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Accounting Research in the Age of AI

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Abstract

Recent developments in artificial intelligence raise fundamental questions about the future of academic accounting research. By integrating core microeconomic principles, a wide range of theoretical perspectives, analyses of current institutional structures, and insights from interviews with senior journal editors and PhD program directors, we investigate the potential impact of AI advancements on accounting research and the institutions that support it. Our analysis highlights four key findings. First, we identify two dimensions where humans can maintain advantages over AI: higher-order reasoning skills and control over data access. AI may reshape research methods and topics based on these advantages, making quantitative studies where neither dimension offers strong protection from AI particularly vulnerable to competition. Second, AI may challenge traditional publishing processes, as lengthy review times risk making research obsolete in a rapidly evolving field. Third, AI may transform doctoral education by emphasizing selection and training of students along the two dimensions where humans can maintain advantages over AI. Fourth and last, these changes may be shaped by broader institutional forces, such as major publishers whose standardized platforms and policies may not fully serve accounting research needs. While our analysis assumes gradual AI progress allowing time for adaptation, we also consider scenarios of faster AI advancement that could create more dramatic disruption. Our findings suggest that accounting research institutions appear remarkably unprepared for these changes.

Keywords: Accounting research; artificial intelligence; research method; academic career; publishing; doctoral education

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1. Introduction

Recent advancements in artificial intelligence (AI) have raised fundamental questions about the future of academic research. For instance, Sakana AI, a Japan-based startup, has introduced technology capable of crafting full, original research papers at a cost of just $15 each (Lu et al., 2024; Yamada et al., 2025). Though currently limited to computer science and of moderate quality (Castelvecchi, 2024), such outputs may soon improve—especially when combined with human input—and expand into other fields, including accounting.[2] While experts differ on the pace of AI development (e.g., Grace et al., 2024), most agree that major advances are inevitable. For example, a *Nature* editorial (2024) exploring the path to artificial general intelligence (AGI) equivalent to human ability confidently states that "more huge advances in AI will certainly happen."

The implications of these advancements for academia are profound and understudied. While previous studies have explored the implications of AI for scientific work (e.g., Binz et al., 2023; Kulkarni et al., 2024; Chen et al., 2025, publicly released the same day as this paper, offers a complementary review of the literature), these studies do not consider the unique challenges AI presents to accounting academia and are relatively narrow in their predictions. Unlike earlier innovations such as the personal computer—which primarily enhanced research tools and data processing (e.g., Efron & Tibshirani, 1991; Orlikowski & Scott, 2008; Weller, 2011)—AI can potentially automate key components of the research process, such as data collection, theory construction, and writing. This development may not merely improve existing methods but fundamentally alter how research is conducted. Because accounting research relies heavily on standardized datasets and archival methods, the field may be especially susceptible to disruption from AI, perhaps more so than other business disciplines.

Anticipating further AI progress, this paper explores the consequences for accounting academia through a pluralistic theoretical lens. We draw on core microeconomic principles—such as comparative advantage and cost–benefit analysis—to show how AI may alter research costs and capabilities, reshaping academic markets and individual decision-making. To capture a more comprehensive range of effects, we also integrate task-based technological change theory (Autor et al., 2003) for skill displacement, network theory (Burt, 1992) and the resource-based view (Barney, 1991) for shifts in competitive advantage, tournament theory (Lazear & Rosen, 1981) for evolving

[2] Ciconte et al. (2025) show that AI can generate accounting research at low cost by exploiting various legal shocks.

academic hierarchies, real options theory (Trigeorgis, 1996) for strategic research choices under uncertainty, and institutional theory (DiMaggio & Powell, 1983) for organizational reactions to disruption. This multi-theoretical approach responds to calls for multi-paradigmatic research on complex organizational phenomena (Lewis & Grimes, 1999; Orlikowski & Scott, 2008). As Laughlin (1995) and Malmi & Granlund (2009) argue in the context of accounting research, applying a range of theoretical perspectives allows researchers to capture different dimensions of complex developments that may be overlooked by single-theory analyses.

Building on this theoretical foundation, existing institutional structures, and interviews with senior editors and program chairs from top journals and programs, we offer several predictions about the future direction of accounting research. Table 1 presents the most persuasive forecasts, along with their supporting theories, underlying rationales, and assessments of novelty. Although grounded in accounting, most of these predictions apply to research more broadly—a characteristic that enhances rather than diminishes their value. The ability of theoretical insights to transfer across fields is a defining feature of strong social science (Campbell & Stanley, 1963; Cook & Campbell, 1979); concepts that explain one area often shed light on comparable dynamics elsewhere (Whetten, 1989). This cross-disciplinary utility proves especially valuable for analyzing technological disruption, where similar forces affect diverse academic domains (Christensen, 1997) and support cumulative knowledge building in organizational studies (Weick, 1989). Accordingly, our forecasts aim to inform not only accounting but also broader discussions of AI's impact on academic research. To the best of our knowledge, most predictions represent new theoretical extensions that combine established principles with evolving technological developments. We summarize our most important findings below.

First, AI has the potential to fundamentally transform the methods and topics of accounting research. We argue that this transformation operates through its impact on two key dimensions where humans currently hold advantages over AI: higher-order reasoning skills (such as complex theorizing and synthesis) and control over data access. The impact of these dimensions varies across research methods. For example, archival research, which constitutes nearly two-thirds of papers in top-six accounting journals (Oler et al., 2010), is particularly exposed to competition from AI-enhanced researchers, as it often relies on standardized methodologies and publicly available datasets. In response, researchers less skilled in AI may shift toward areas requiring higher-order reasoning or access to proprietary data.

Second, AI advancements may have a profound impact on publishing. These technologies can accelerate the research process, contrasting with the trend of accounting journals, which have slowed over time and now lag behind their counterparts in other business disciplines (Hurley et al., 2025). In a rapidly evolving field driven by AI, prolonged review times may lead to research becoming outdated before publication. To remain relevant, accounting journals may need to fundamentally reassess their publishing processes and prioritize faster turnaround times.

Third, AI may reshape PhD programs in accounting by altering their emphasis on the two key dimensions where humans maintain advantages over AI. Admission criteria may shift to emphasize higher-order reasoning skills that maintain human advantages over AI, such as developing innovative research questions and building research agendas. Programs may also increasingly value traits that facilitate access to unique data, including social skills and industry networks that AI cannot replicate. The curriculum may need similar adaptation, teaching efficient AI use while building distinctly human research capabilities in both dimensions.

Fourth and last, AI-driven transformations in accounting may be shaped by broader institutional pressures (DiMaggio & Powell, 1983). For example, most leading accounting journals are managed by large publishers overseeing multiple disciplines, using centralized platforms for manuscript submission and review. These publishers implement broad policies on publishing practices, including AI usage for authors and reviewers. As a result, accounting journals may be compelled to integrate AI tools in ways that align with broader publishing norms, even if the chosen standards are not ideally suited to the unique needs of accounting research.

Many of these processes, such as PhD training and traditional publishing processes, take a lot of time, so fast advancements in AI can generate significant disruption. Yet, it is remarkable how unprepared accounting research related institutions appear to be to these changes. For example, leading PhD programs' web pages and brochures rarely mention AI or its effects, although these programs make significant monetary and human capital investments to their students. Likewise, the publishing processes of accounting journals remain remarkably slow (Hurley et al., 2025). Without swift adaptation, these institutions risk becoming increasingly misaligned with the research environment they aim to serve.

Our paper mainly focuses on a scenario where AI progresses gradually (Ananthaswamy, 2024), giving researchers enough time to adjust to new capabilities. However, we also consider the possibility of faster changes, such as the emergence of AGI already this year, as predicted by the most

optimistic AI entrepreneurs.[3] We take a partial equilibrium approach in our analysis, exploring how AI advancements specifically affect accounting academia. Broader questions, such as whether AI could change the importance of accounting as a profession or the role of universities in society, are beyond the scope of this paper.[4]

This paper contributes to the discussion about the future of accounting research (e.g., Bromwich & Scapens, 2016; Dyckman & Zeff, 2015) in multiple ways. First, it offers a systematic analysis of how AI could reshape key aspects of the accounting research infrastructure. Second, it identifies potential institutional arrangements that may facilitate effective collaboration between human researchers and AI. Lastly, it explores the challenges of maintaining research quality and integrity in an environment where traditional human-centered quality control mechanisms may no longer suffice.

This paper is structured as follows. Section 2 provides a primer on the impact of AI on research production. Section 3 outlines the theoretical framework used to predict the effects of AI advancements. Sections 4 through 6 discuss the consequences for accounting academia, the transformation of research systems, and the redistribution of institutional power. Section 7 examines the effects of AI under scenarios of accelerated growth. Finally, Section 8 concludes.

2. Transformation of research production: a primer

This study examines artificial intelligence (AI), with a primary focus on Large Language Models (LLMs)—AI systems trained on vast datasets to generate and interpret text. While AI includes a range of technologies that mimic human cognition, LLMs currently offer the most relevant application for academic research. Throughout this paper, we use the term "AI" to refer both to present-day LLMs and to future, more advanced systems. Although our discussion centers on existing LLM capabilities, our analysis addresses the broader implications of evolving AI technologies for accounting research.

To understand AI's role in research, it is important to distinguish between AI capabilities and the higher-order reasoning skills central to academic inquiry. In this paper, higher-order reasoning refers

[3] Predictions about AGI's emergence vary widely among industry leaders. Elon Musk (xAI/Grok) believes it could arrive as early as this year (Reuters, 2024), while Jenson Huang (Nvidia) estimates 2029 (Nellis, 2024). Nobel laureate Demis Hassabis (DeepMind/Gemini) suggests a more conservative timeline, expecting AGI around 2035 (Varanasi, 2024). Dario Amodei (Anthropic/Claude) foresees AI surpassing human capabilities in most domains soon after 2027 (Edwards, 2025). Meanwhile, Sam Altman (OpenAI/ChatGPT) predicts that "[i]n a decade, perhaps everyone on earth will be capable of accomplishing more than the most impactful person can today" (Altman, 2025b).

[4] Korinek (2024b) forecasts a substantial decline in demand for traditional educational services and institutions. The emergence of AGI may sharply reduce the value of cognitive skills, thereby diminishing the returns to human capital investment and weakening the case for higher education.

to mental processes such as abstract reasoning, conceptual synthesis, and critical evaluation. These skills enable researchers to develop theoretical frameworks, assess conflicting evidence, and generate novel insights—areas where AI currently exhibits limitations.

AI offers valuable support to academic research in numerous ways. For instance, it can assist in gathering data, proposing analytical methods, and performing data analysis. Additionally, AI contributes to theory development by enabling pattern recognition, generating hypotheses, and facilitating multi-perspective evaluations. These capabilities not only improve research efficiency but can also enhance its quality.

Korinek (2024a) assesses AI's role in research by assigning subjective ratings to its usefulness across 34 tasks, including ideation and feedback, writing, background research, coding, data analysis, math, and research promotion. AI excels in writing, coding, ideation, and research promotion, while its weakest areas include math, feedback, literature research, search-related tasks, simulating human subjects, and generating figures. Despite these limitations, AI receives "highly useful" ratings in 23 tasks and "useful" ratings in the remaining 11.

Despite its usefulness, AI adoption among researchers remains limited in both tool usage and task application. Most are familiar with OpenAI's ChatGPT but have little exposure to other generative AI tools (Hrycyshyn & Eassom, 2025). Nevertheless, researchers acknowledge the increasing relevance of AI skills, with 69% considering them at least somewhat important within two years and more than half viewing them as very important within five years.

Humans struggle to gain expertise in multiple fields, but AI has the potential to do so more easily. AI systems can be trained on data from various fields, potentially enabling them to detect patterns and connect ideas across disciplines (Bommasani et al. 2022; Bubeck et al. 2023). When successful, these capabilities help researchers translate complex, domain-specific jargon into clear language (Noy & Zhang 2023), reducing communication barriers often present in interdisciplinary work. However, researchers tend to incur a reduction in impact when they shift away from their prior work (Hill et al., 2025). Moreover, institutional factors such as tenure evaluation criteria, which favor publications in narrowly defined, discipline-specific journals, and existing departmental structures that restrict cross-disciplinary exchanges, might slow the integration of AI-supported interdisciplinary research (Rafols et al., 2012; Leahey et al., 2017).

The extent to which AI enables cross-disciplinary research depends on its technical capabilities. According to Gans (2025), when AI systems provide broad "coverage"—spanning gaps across domains and connecting distant ideas—they encourage exploration of unfamiliar research areas and promote long-term growth. In contrast, limited coverage supports incremental research, which may raise short-term efficiency but slow the development of new ideas. This suggests that AI's capabilities influence the direction of scientific research, either toward breakthrough innovation or gradual improvement.

Future advancements in AI tools may come not only from improved reasoning but also from autonomous planning, long-term memory, and seamless integration across various applications (Korinek, 2024a). However, greater autonomy raises concerns about safety and control, particularly in unstructured environments (Ananthaswamy, 2024; Shah et al., 2025; Lynch et al., 2025). The key challenge is defining the limits of AI-driven research and developing effective monitoring and intervention mechanisms.

3. Theoretical framework, method, and data

To examine the transformative impact of AI on accounting research, we employ a pluralistic theoretical framework that captures the complexity of this disruption. We begin with core microeconomic principles—such as comparative advantage and cost–benefit analysis—to understand how AI affects research costs, capabilities, and competition within academic markets. We complement this, among others, with task-based technological change theory (Autor et al., 2003) to assess skill displacement; network theory (Burt, 1992) and the resource-based view (Barney, 1991) to examine shifts in competitive positioning; tournament theory (Lazear & Rosen, 1981) to explore changes in academic hierarchies; real options theory (Trigeorgis, 1996) to analyze strategic decision-making under uncertainty; and institutional theory (DiMaggio & Powell, 1983) to evaluate organizational responses to AI.

This multiparadigmatic approach—aligned with calls for comprehensive analyses of complex organizational change (Lewis & Grimes, 1999)—enables us to assess the interrelated effects of AI on research methods, publishing processes, doctoral education, and institutional structures. Our framework provides a structured foundation for anticipating how AI may reshape accounting academia by integrating economic, social, and institutional dimensions. As advocated by Laughlin (1995) and Malmi and Granlund (2009), combining multiple theoretical perspectives allows for insights that single-theory models may overlook.

For example, comparative advantage highlights areas where human researchers retain strengths over AI, while institutional theory explains how standardized publisher platforms might facilitate or constrain AI adoption. In doing so, our framework not only grounds predictions in established theory but also extends them to address the distinct challenges and opportunities AI presents in accounting research, with broader relevance to other academic disciplines (Whetten, 1989).

Our analysis reflects current institutional practices in accounting research, employing a mixed methods approach to provide balanced insights. We collect primary data on these practices from five sources: (1) accounting journal websites, (2) publisher websites, (3) research database websites, (4) publication database websites, and (5) accounting PhD program websites (see Appendix A). In addition, we draw on secondary data from published studies that analyze research methods and topics in leading accounting journals. This triangulation of data sources—combining archival information with qualitative insights from key stakeholders—provides a stronger empirical basis for our theoretical arguments and predictions. Journal data include AI policies, processing times, and revision counts. Other online sources provide information on AI-related policies and services. Website data were collected in June 2025.

To gain deeper insight into the current operations and future direction of accounting research institutions, we conducted interviews with senior accounting scholars. Using a purposive sampling approach, we targeted two groups with authoritative perspectives: senior editors of top-tier accounting journals and PhD program chairs at leading institutions (Creswell & Poth, 2018).[5] These individuals are well positioned not only to understand existing institutional structures but also to influence their future development.

From the first group, we approached all 40 senior editors of the top-six accounting journals, with three agreeing to participate. We also included one additional senior editor from an ABS-3 ranked journal to enrich our analysis. From the second group, we contacted all 19 PhD program directors from a sample of 30 programs (see Appendix A) for which contact information was available, with three consenting to interviews. One participant served dual roles as both a senior editor and PhD program director, resulting in a total of six interviews. This limited sample size aligns with qualitative research practices that prioritize depth from specialized informants (Patton, 2015).

[5] Editorial titles at leading accounting journals differ across publications. For the purposes of this study, "senior editor" refers to individuals in the highest editorial position. When that role is held by a single editor, we also include those in the next-highest tier.

The interviews employed a semi-structured format and were pilot-tested to ensure clarity. Senior editors were invited to discuss AI's influence on research production, peer review practices, and prospective journal policy developments through 2030. PhD program directors addressed AI's potential effects on doctoral training, curriculum development, and admissions criteria. Conducted virtually between March and April 2025, all interviews were audio-recorded with participant consent and averaged 31 minutes in length, balancing depth with practical time considerations. Transcripts were anonymized and analyzed using Braun and Clarke's (2006) iterative thematic analysis. We applied inductive coding to identify emergent themes, followed by deductive mapping onto the study's conceptual framework. Two researchers independently coded a subset of transcripts and reconciled differences through discussion. To enhance the robustness of findings, we triangulated interview data with other sources (Yin, 2018).

4. Implications for the accounting academy

The emergence of advanced AI in accounting research calls for a reassessment of academic training, necessary skill sets, and career paths. These shifts may influence publishing norms, doctoral training, and academic roles, prompting researchers to adopt new tools and approaches.

4.1. Research skills

The skills required for accounting researchers are evolving rapidly. AI is excellent at handling tasks such as data collection, analysis, and method validation—roles that were traditionally done by research assistants or junior staff. Eisfeldt et al. (2024) show that higher analytical skills predict greater exposure to AI, while jobs requiring non-routine interpersonal skills, like coaching or relationship management, face less automation and have lower exposure to AI. Wang and Wang (2024) demonstrate how AI can extract CEO pay ratios and Critical Audit Matters from proxy statements and 10-K filings with human-level accuracy, but at a fraction of the cost of manual collection or commercial database subscriptions.

As predicted by the theory of task-based technological change (Autor et al., 2003), the need for human workers in routine, automatable tasks may decrease. PhD program director 1 points out that "there's just less of a need of [research assistance] if I can relatively quickly get 80% of the way with some kind of LLM or some kind of tool like that…. It's like the end of the job, but that's everywhere in society." Fedyk et al. (2022) find that AI disproportionately affects junior accounting employees, reducing workforce demand in entry-level positions.

Institutional theory suggests that professionals need to adapt to stay relevant (Greenwood et al., 2002). For accounting researchers, this means shifting their skills to areas where AI struggles, such as developing theories and evaluating broader social implications. AI also cannot negotiate access to proprietary data, an advantage researchers can gain through their social connections and professional networks by either collecting data themselves or partnering with those who possess it. These weaknesses in AI incentivize researchers to sharpen the skills that give them an advantage.

AI has the potential to increase efficiency by complementing human labor or replacing it altogether. While job characteristics shape this tradeoff (Felten et al., 2023), researchers can enhance their competitiveness by developing technical skills to work with AI, understanding its biases, and automating aspects of their research.[6] Expertise in both AI and accounting may become a significant advantage, demanding a combination of technical proficiency and deep theoretical knowledge. This synergy promotes collaboration between humans and machines, with each contributing what they do best. As PhD program director 1 put it, "if you are good at using [AI] in your research, that could be a big plus [for placement outcomes]."

While AI boosts productivity, it also presents risks of deskilling by encouraging cognitive offloading—delegating tasks to technology at the expense of critical thinking, learning, and information retention (Lee et al., 2025; Pearson, 2025). Younger, less-educated individuals and those with greater trust in AI are more likely to accept AI outputs uncritically (Gerlich, 2025). For accounting researchers, this cognitive offloading could impair the development of critical analytical skills necessary for evaluating complex accounting issues and regulatory frameworks. Its role in literature review may also alter reading habits and influence how researchers engage with theoretical works (Kulkarni et al., 2024), possibly leading to a shallower understanding of foundational accounting theories and concepts. Senior editor at an ABS-3 journal describes these risks as follows:

> I think [AI] really challenges how we do research and also how we read, think, on the one hand about info, but also research, figuring stuff out. There's this risk that we'll just go into a mode where we pump out papers faster with AI, then we use AI to boil down those papers, and off those summaries we spin yet another round of research.

[6] For example, Levy (2025) shows that commercial AI systems, when not supplemented by other tools, often perform poorly on fundamental accounting tasks. In addition, these tools exhibit look-ahead bias, which accounts for their seemingly strong performance in some predictive applications.

4.2. Research methods and areas

4.2.1. Human expertise and AI's transformative effects

AI's impact on accounting research may vary across research methods and areas. In some methods, researchers can more readily use AI to enhance productivity than in others. We suggest that this variation is shaped by two dimensions in which humans currently retain an advantage: (1) higher-order reasoning cognitive skills, such as theorizing and synthesizing, and (2) control over data access. In the first dimension, state-of-the-art systems still perform modestly on more demanding tasks, such as those featured in Humanity's Last Exam (Kavukcuoglu, 2025). In the second dimension, humans retain an advantage by managing access to data. This latter advantage appears more stable, as it is upheld by institutional gatekeepers, whereas the first remains exposed to the evolving pace of AI advancements.[7]

To assess how these dimensions shape exposure to AI-assisted competition, we locate established accounting research methods on a two-axis map. Fig. 1 shows the results. The seven methods listed by Oler et al. (2010) are positioned according to their need for higher-order reasoning (horizontal) and their control over data access (vertical).[8] The size of each circle represents the method's share of 1,196 publications in top-six accounting journals during the 2000s, as identified by Oler et al. (2010). The placement of methods is based on our subjective assessment of their typical requirements, with supporting arguments presented later. To guide interpretation, we highlight regions of the map likely to face high, moderate, or low AI competition.

Understanding these methodological dynamics also requires considering how uneven AI proficiency among individual researchers shapes competitive outcomes within each tradition. Those with stronger skills can automate routine tasks, experiment efficiently with multiple methods, and analyze larger datasets, giving them a clear advantage in scaling analytical work (Noy & Zhang, 2023). Consistent with the winner-takes-all theory (Frank & Cook, 1995), this expertise gap may widen disparities in research productivity, particularly in tasks where AI performs well. As AI-proficient researchers generate more high-quality output, they may capture a disproportionate share of publications, citations, and professional opportunities. In contrast, less adept users—including the median

[7] Lynch et al. (2025) demonstrate that AI systems from all major providers, when granted significant autonomy and confronted with obstacles to their goals, consistently exhibit a willingness to engage in harmful behaviors commonly associated with insider threats. The consistency of these behaviors across providers points to a fundamental risk inherent in current AI architectures, raising the bar for granting such systems access to sensitive data.

[8] Coyne et al. (2010) and Bloomfield et al. (2016) provide alternative and largely similar classifications of the methods.

researcher within each methodological tradition—may contribute a diminishing share of scholarly output. These patterns reflect a digital divide that parallels broader concerns about AI-driven inequality in the labor market (Acemoglu & Restrepo, 2022).

As shown in Fig. 1, archival research, the most prevalent method (65% of publications), falls into the high-competition quadrant due to its reliance on public data and standardized analytical methods. This quadrant also includes theoretical (15%), experimental (12%), and survey research (2.2%). Review (2.3%) and normative research (2.0%) are positioned in the moderate-competition zone, while field studies (1.5%) remain the only method in the low-competition quadrant, where human advantages are most pronounced.

This visualization suggests that over 90% of accounting research is concentrated in areas highly susceptible to AI-assisted competition. The least affected methods—field studies and normative research—account for only 3.5% of publications in top journals.[9] Of the 42 papers using these methods, 69% were published in *Accounting, Organizations, and Society*, with 14% each in the *Accounting Review* and *Contemporary Accounting Research*; the remaining top-6 journals published virtually none. This distribution suggests that *Accounting, Organizations, and Society* may face less AI disruption risk than other leading journals due to its methodological preferences, creating uneven impacts across accounting publication outlets.

The following discussion evaluates each research method's vulnerability to AI competition. Additionally, we explore potential human responses to the challenges posed by AI in each method.

4.2.2. AI's impact across research methods

AI is highly effective at handling well-defined tasks, making it a significant competitor for quantitative research that relies on easily available data. Archival research, as discussed by Oler et al. in the context of capital markets studies (e.g., Kothari, 2001; Blankespoor et al., 2020), often depends on standardized, publicly available historical market data. For example, Berninger et al. (2024) document that 74% of empirical finance papers use at least one widely used database. This reliance makes it particularly susceptible to AI advancements, except when proprietary data is used, as it remains inaccessible to AI. Researchers without a comparative advantage in AI or confidence in adapting to intensified competition may increasingly resort to proprietary data to shield their work.

[9] Examining papers published in a narrower set of top accounting journals from 2003 to 2013, Bloomfield et al. (2016) found that only two out of 1,638 studies relied on field experiment data. This suggests that field studies in accounting are overwhelmingly qualitative.

This strategy reflects a classic approach to raising barriers to entry (Bain, 1956; Porter, 1980) by securing exclusive control over a key research input. Alternatively, researchers may reduce their exposure to AI-driven competition by emphasizing methods that continue to favor human expertise, thereby leveraging their comparative advantage.

AI's ability to identify patterns and suggest relationships in large datasets can transform hypothesis generation in accounting research. AI lowers the cost of data analysis, making iterative, data-driven hypothesis generation more feasible from a cost-benefit perspective. By analyzing archival data, AI can propose novel hypotheses that researchers might not have considered, enabling faster cycles of testing and refinement (Wang et al., 2023). This shift may enhance research efficiency but risks over-reliance on data-driven insights, potentially sidelining theory-driven inquiry.

The methods used in theoretical research (referred to as analytical by Coyne et al., 2010) are straightforward to codify. Like other applied theorists, accounting researchers typically use existing methods to solve accounting problems instead of creating new ones. Since these methods are also accessible to AI, humans do not have a clear advantage in this area. AI can already propose proof strategies and draft solutions, but it still makes mistakes and needs human validation (Tao, 2025). PhD program director 2 describes how they encourage students to use AI in building simple models as a way to clarify and structure their thinking:

> And in particular, I think what's really fascinating is that it's lowering the barrier to do analytical work. I'm not a theorist, but I like to have toy models in my mind to help me understand what's going on, or the economics of a particular environment… now with LLMs, that barrier has lowered, like our ability to write a few models down ourselves without having to go seek out theorists, experts in our field. That barrier really has come down.

Over time, AI may learn how to build realistic models for accounting phenomena. As a result, theoretical research may not offer researchers lasting protection against AI-supported competition. In response, researchers may adapt by supporting their models with empirical evidence, which also improves their real-world relevance. These models and supporting evidence could focus on topics involving proprietary data, helping researchers limit competition.

AI advancements have already made it possible to carry out experimental and survey research without human participants. AI can simulate average survey responses to test hypotheses and act as experimental confederates, modeling interactions and decision-making in agent-based models

(Grossmann et al., 2023). In addition to gathering data, AI can assist in designing experiments and processing and analyzing results (Chang et al., 2024). Using AI-generated data instead of human responses could also simplify the research process by potentially bypassing university institutional review board approvals for human subjects. This can save time and money, enabling researchers to complete projects faster and use larger sample sizes.

While AI offers many advantages that make it a useful complement to human-based experimental and survey research, it has notable limitations when applied as a standalone tool. First, experiments are often designed to explore questions where no observational data exist, making it implausible for AI to accurately infer what the relevant data would look like. Second, AI has difficulty producing accurate variance estimates and capturing extreme attitudes (Bail, 2024; Mei et al., 2024; Gao et al., 2025), and it is unable to replicate outcomes observed in financial markets (Henning et al., 2025). Third, in areas requiring specialized domain knowledge—such as the perspectives of accounting professionals or corporate executives—AI is unlikely to match human respondents due to limitations in domain-specific training data. In response to these limitations, experimental and survey researchers may increasingly focus on questions involving human participants whose views and behaviors AI cannot easily replicate.

AI is good at summarizing individual research papers, but it struggles to synthesize an entire body of literature, which requires a more holistic approach. Its limitations include restricted access to paywalled studies and the inability to incorporate research beyond its training data (Pearson, 2024). AI is also subject to hallucinations, inventing references and data. While these errors can be reduced, they cannot be fully eliminated because they are built into the way AI functions (Jones, 2025). This requires significant human efforts to ensure the accuracy of the results.

Recent advances in AI technology that combine text generation with targeted information retrieval have the potential to improve AI's ability to synthesize disparate research findings (Lewis et al., 2020). These developments may enable AI to autonomously produce meta-analyses by identifying shared themes, contrasting theoretical perspectives, and evaluating empirical patterns across studies. As such tools mature, meta-analyses could become more frequent, given AI’s ability to efficiently process large volumes of literature. However, ensuring the reliability and comprehensiveness of AI-generated syntheses remains a key challenge, as AI may introduce biases in selecting and summarizing literature (Li et al., 2022).

Normative accounting research asks what ought to be rather than what is. Balancing aims such as transparency against privacy or standardization against flexibility needs rich background knowledge from history, law, ethics, and everyday practice—knowledge that is mostly tacit and hard to spell out in code. While AI can already draft policy text that sounds as persuasive as human writing (Matz et al., 2024), it struggles to adapt arguments across contexts (Liu et al., 2025) and to maintain consistent ethical reasoning across cultures and languages (Zangari et al., 2025). Past experience also warns that good rhetoric is not enough: ideas like current-value accounting and price-level adjustments lost support once their behavioral assumptions seemed unrealistic (American Accounting Association, 1977; Watts & Zimmerman, 1979). Although initiatives such as the United Arab Emirates' use of AI to draft and revise legislation point to a growing interest in automated reasoning (Cornish, 2025), human judgement may still be essential in normative accounting contexts.

Field studies rely on data gathered through direct observation. These studies often use small sample sizes, typically focusing on a single firm, but provide rich, descriptive insights. AI can facilitate qualitative research by conducting and transcribing interviews in multiple languages, reducing reliance on human interviewers and annotators (Chopra & Haaland, 2024). Additionally, AI assists in analyzing large volumes of both qualitative and quantitative data, such as organizational records and communications (Ranta et al., 2023). However, since AI cannot independently access such data, field studies face limited competition from AI, potentially increasing their appeal among researchers. Moreover, field experiments conducted in collaboration with institutions can help bridge the gap between accounting theory and practice (e.g., Kaplan, 1986; Rynes et al., 2001; Hopwood, 2007).

While AI is expected to enhance all areas of research, its development may be uneven and shaped by sudden breakthroughs. These dynamics could create varying levels of pressure across research methods. For example, accelerated progress in processing structured financial data could put more pressure on researchers using archival methods, whereas slower improvement in qualitative analysis could insulate field research from immediate disruption. As AI continues to develop, revisiting methodological choices may become a regular necessity.

Interviewees offer differing perspectives on how AI might influence methodological preferences in accounting research. PhD program director 2 suggests that "we as a profession should go back to doing more descriptive research," arguing that AI "allows us to industrialize the packaging of results that have the necessary attributes of what would be acceptable as causal inference." In contrast, director 3 believes AI will not fundamentally alter researchers' preferences: "We do research based on what we are interested in, and then we utilize a tool to help us to achieve our goals."

4.2.3. AI's impact across research areas

The advancement of AI may influence not only how accounting research is conducted but also what topics are explored. Because research method is often linked to the area of study, the effect of AI is unlikely to be uniform across the field. Using four broad method categories—archival, theoretical, experimental, and other methods—Coyne et al. (2010) analyzed papers from 11 accounting journals and found that archival research was most prevalent in financial accounting, where 76% of papers employed this approach.[10] This methodological concentration, combined with the frequent use of standardized data sets, may make financial accounting research particularly susceptible to AI-driven competition. This is consistent with the theory of task-based technological change, which predicts greater automation risk for tasks that are routine and data-intensive (Autor et al., 2003). The share of "other" methods, which are plausibly less susceptible to such disruption, varies notably across subfields. In tax and audit, they appeared in only 10% and 23% of papers, respectively, whereas in managerial accounting, accounting information systems, and "other" topics, they featured in at least 40% of papers. These patterns may influence how research agendas evolve in response to advances in AI.

4.3. Research and teaching employment

AI may change the job market in academic accounting, shifting the balance between research and teaching roles. In research, AI threatens to automate tasks traditionally performed by junior researchers or assistants, potentially lowering the demand for human researchers as the share of automated outputs grows. This shift could lead to smaller research teams, with demand concentrating on a smaller, more specialized workforce skilled in guiding AI systems (for a related argument, see Hassabis, 2024). Senior editor 1 notes that AI may also influence accounting research funding through indirect channels:

> We get paid money because of the fact that we teach in programs, and those programs fund the universities, allow us to do our research. But if the underlying demand for accounting programs diminishes, that will need mean fewer need for accounting researchers and fewer need for like accounting PhDs and all those kind of things. So there's going to be an indirect demand shock, which is already happening.

[10] Despite analyzing a narrower set of journals and a different sample period, Bloomfield et al. (2016) report the same figure of 76%.

In addition to the indirect effects noted above, AI may directly impact teaching by raising its productivity, particularly in courses with abundant training material. For example, it could lower the cost of personalized instruction, a method shown to be significantly more effective than traditional teaching (Bloom, 1984). If AI matches or exceeds average faculty instruction quality, demand for teaching staff could decline sharply. As PhD program director 2 notes, this represents an "existential threat" to the profession. Yet they express cautious optimism:

> Do we need humans to deliver the content? My sense is yes. But I think we have to deliver the content in a way that really resonates, that gives people incentives to come to the classroom and justifies why they are paying a tuition.

The lasting value of human educators may lie in their ability to mentor, motivate, and adapt to student needs.[11] Education is in demand not only because it builds students' human capital but also because they enjoy its consumption (Lazear, 1977). Interactions with instructors—both formal and informal—remain a key part of this experience. Whether AI can eventually replicate these aspects of the student experience, as it has begun to do in mental health services (e.g., Li et al., 2023), may shape the future relevance of human teaching roles.

4.4. Doctoral education

As an initial step in evaluating the role of AI in doctoral education, we examine the websites of 30 prominent accounting PhD programs across North America, Europe, and Asia, as listed in Appendix A. In addition to website content, we analyze brochures dedicated to accounting doctoral programs, as well as accounting-related content within general PhD program brochures. Our review indicates that AI is rarely mentioned, and when it is, the references are typically indirect.[12] Although these websites are often rudimentary, their general silence on AI suggests that it is not currently a focus for accounting PhD programs.

[11] High dropout rates in massive open online courses (MOOCs) remain a significant challenge, largely driven by low learner engagement and limited personal support (Zawacki-Richter et al., 2018).

[12] "Machine learning and big data" is among the nine core areas highlighted by HKUST's department. At the University of Rochester, all accounting PhD students are required to complete a course titled "Advanced Causal Inference plus Machine Learning." University of Iowa's webpage advertises that accounting PhD students will "dig into the latest innovations in the field, like using computational linguistics to determine the intent behind annual report numbers." Tilburg University's introduction video includes AI in a list of topics linked to accounting and described as among the most pressing questions of our time. Additionally, many universities highlight individual studies by faculty and students, some of which focus on AI.

Accounting PhD programs' measured response to AI can be viewed through two lenses. First, change in academia is usually slow, because faculty and administrators must find ways to adopt new technologies without lowering existing standards (DiMaggio & Powell, 1983). Second, those committed to traditional teaching methods and long-established evaluation systems—often with limited AI expertise—may resist reform (Meyer & Rowan, 1977; Suddaby & Greenwood, 2005; Khanfar et al., 2024a, 2024b). For them, the arrival of AI can seem to threaten both core values and the legitimacy of current assessment practices.

Earning a PhD in accounting typically takes five years (Brink et al., 2012). Given the rapid pace of AI advancement, the field of accounting research may change significantly between the time students start their program and when they finish. We discuss two specific ways PhD programs may adapt to the challenges and opportunities posed by AI.

First, admission criteria may shift to focus more on skills where humans have a comparative advantage over AI. Following the logic of Fig. 1, this shift encompasses two dimensions: higher-order reasoning skills and traits enabling access to valuable unique data. Higher-order reasoning skills include higher-level abilities such as asking innovative questions and developing ideas into research agendas. Additionally, as AI facilitates connections between accounting and other fields, interdisciplinary aptitude may become more important. The second dimension involves social skills, industry contacts, and other valuable networks. These networks and social skills are crucial for accessing unique data and collaborating effectively with colleagues and students. However, since strong networks often correlate with socioeconomic status (Luo et al., 2017), this shift in criteria could exacerbate inequalities among applicants.

PhD program directors point to a shift in selection criteria, with decreasing emphasis on hard skills and the intellectual capacity to acquire them, and increasing attention to soft skills, as described below:

> I feel that has already happened… There's less emphasis on these kinds of hard-core skills probably than there was once. (PhD program director 1)

> It might be, maybe the premium on IQ per se is not going to be as high as before because the most valuable papers, let's say, in business fields, are going to be the ones that ask the right questions about the right phenomena that people care about… Then what are you competing on? Like who can get there first so that that might be hustle. And then if it requires you to go

> inside a company or be the first to collect the data, it might be not just hustle, but also ability to interface with other humans who work on the company side or the data provider side. And like, convince them to partner with you or something like that. So yeah, it might be other softer attributes like that rather than just hard IQ. (PhD program director 2)

Evaluating soft attributes differs from assessing technical skills and is likely more challenging. This challenge is compounded by a potential decline in applicants' research experience, as traditional research assistant roles may become less common. Consequently, fewer applicants may have had the chance to evaluate their motivation for committing to a five-year program, or to secure strong recommendation letters from senior researchers.

As a result, both applicants and admissions committees may be making long-term commitments based on narrower and less reliable information than in the past. Reduced access to traditional research experiences and fewer opportunities for faculty interaction may limit applicants' ability to assess fit and constrain committees' evaluations. Programs may respond by admitting fewer students and devoting more resources to interviews.

A second way doctoral programs may respond to advances in AI is by updating their curriculum. While technical training may remain important, programs may seek to focus more on building the unique skills of human researchers. This reflects an effort to align training with areas of comparative advantage, such as tasks requiring contextual understanding, human judgment, and interaction. For example, a possible increase in interest in fieldwork would require expanded training in ethnography, case study methods, and interview techniques. PhD program director 2 acknowledges the value of this shift but is cautious about departing from the profession's established norms, highlighting the role of institutional pressures in shaping program design:

> Maybe [descriptive research] ought to be a big a component of our training: doing fieldwork, going into companies, collecting data, running experiments inside companies, maybe that's something we need to invest a bit more into…. The challenging part there is, if the profession doesn't value it, then for us to deviate this way would seem to be doing students a disservice, even if we think it's the right thing to be doing.

A less controversial way to address AI advancements in the curriculum is to include dedicated content on the topic. As PhD program director 1 observes, "there isn't necessarily resistance to the use in coursework." Similarly, director 2 notes that "for example, we are starting to read papers, having to

do with the implications of large language models for topics we care about in accounting." Given the growing influence of AI on accounting research, programs may need to revise their curricula regularly.

Another approach is to enhance students' technological fluency—not only by teaching technical skills but also by helping them understand AI's limitations and apply it meaningfully in research. As director 2 adds, "we are thinking actively about various ways in which we can get students up to speed, to help them figure out how to make LLMs something that can help accelerate their work or to give them new ideas to explore." As a result of these measures, there may be growing demand for faculty who can help students to leverage AI. Director 1 observes that for job market candidates who can integrate AI tools into accounting instruction, "there's no doubt that... universities will go out and look for that." However, Senior Editor 1 cautions that institutional constraints may limit what PhD programs can realistically offer, noting, "Who's going to be doing the training? The older faculty may not be up to the state of the art."

AI acts as a supplemental mentor by offering structured, timely feedback where faculty capacity is thin (Heldt, 2025). Because many accounting departments are small and lack depth in certain specialties, doctoral students can struggle to secure expert guidance. Advanced AI tools fill this gap, enabling students to pursue topics that might otherwise be inaccessible and raising the overall quality of feedback. This could narrow the disparities in PhD training across institutions.

AI increases productivity and could allow PhD students to complete their degrees faster. However, rising expectations for research quality could counterbalance these efficiency gains, keeping completion times largely unchanged.

4.5. Publication and knowledge validation processes

4.5.1. Publication policies governing authors' AI use

Panel A of Internet Appendix B summarizes the policies governing authors' use of AI across the top seven publishers of accounting journals.[13] These journals typically refer to their publisher's general

[13] We identified the seven publishers by examining journals listed under "Accounting & Finance" in the Journal Quality List by Subject Area (Harzing, 2024). Using keyword filtering, we selected journals with titles containing "accounting," "audit/auditing," "accountability," "financial reporting," or "taxation," and included the *Journal of Information Systems* and *Abacus* due to their recognized focus on accounting. This process yielded 49 journals, of which 48 are published by seven key publishers: Elsevier (14), American Accounting Association (10), Wiley (9), Emerald (7), Taylor & Francis (4), SAGE (2), and Springer (2). We excluded *Comptabilité - Contrôle - Audit* (French Accounting Association) due to its limited geographic reach and primary use of French.

policies in their author guidelines, which are largely consistent. For example, all seven publishers permit the use of AI for language editing, hold authors accountable for its application, and prohibit listing AI as a coauthor. The main difference lies in the use of generative AI beyond writing: four publishers allow it, while two do not and one remains unclear. This divergence reflects varying priorities between preserving established norms of research integrity and adapting to technological advancement.

4.5.2. Dimensions of quality

Ellison's (2002) q-r theory models two key aspects of academic paper quality. Q-quality refers to the importance of the main ideas, while r-quality includes elements like robustness checks, literature reviews, and polish that can be improved through revisions. The theory suggests that academic norms influence how these aspects are valued, with referees and editors using them to judge papers. Over time, these norms may evolve due to factors like referee learning and biases (e.g., overconfidence). This could explain why papers have become longer and more thoroughly revised.

AI could affect both dimensions. It could automate many r-quality tasks, such as literature reviews and formatting, making revisions faster and easier. AI might also help with q-quality by generating and refining ideas, though major breakthroughs may require human insight. If AI has a larger impact on r-quality than q-quality, academic evaluation may shift to focus more on the originality and significance of ideas (q-quality) rather than the completeness of presentation (r-quality). In other words, when easily produced contributions become more abundant, the relative value of scarce components increases. PhD program directors 1 and 3 support the increasing focus on q-quality, with the former stressing the value of "creativity coming up with the right idea" and the latter noting that "the idea part…differentiates a good researcher from a mediocre [one]." This focus on originality aligns with Gamez-Djokic et al. (2025), who find that individuals prioritize creativity as a competitive advantage when faced with automation in the job market.

4.5.3. Dealing with obsolescence risks

Publishing a research paper in accounting takes a long time. Hurley et al. (2025) found that the average time from submission to acceptance in top accounting journals is 20 months, with a median of 18 months, and this has increased over time.[14] Since 2019, these journals have been about eight

[14] Elsevier journals provide data on submission-to-acceptance timelines, indicating that delays are common across a broad range of accounting journals. Among 14 Elsevier accounting journals, 10 report these statistics, showing both the average and median submission-to-acceptance time to be 21 months.

months slower than top journals in other business disciplines. This does not include the time spent conducting the research or revising the paper for other journals before acceptance. Acceptance rates for top accounting journals are estimated to be around 10% (Moizer, 2009), though exact rates are generally not publicly available (Hurley et al., 2025). This means researchers often need to submit their work to multiple journals to get it published.

The long process of publishing a research paper means AI capabilities could evolve significantly during that time. This has at least the following implications.

First, advances in AI that expand research boundaries may change what journals expect from papers. A paper might be a good fit for the first journal it is submitted to but still get rejected for idiosyncratic reasons. In a fast-moving scientific field, the delay caused by this rejection can lower the value of the paper's contribution, making it less suitable for another journal of the same level. While the risk of becoming outdated is not new, rapid AI advances and the multiple rounds required by accounting journals can make this problem worse. In 2023, the *Journal of Accounting Research* (n.d.) accepted only 2% of papers during the second round and rejected 27% at that stage. For papers that made it to the third round, 29% were accepted at that point. This statistical reality highlights the substantial time investment and inherent publication uncertainty required by the traditional review process at a moment when the pace of AI development threatens to accelerate knowledge obsolescence.

Second, as AI raises research productivity, much like a technological advancement in a production function (Solow, 1957), researchers may complete projects more quickly, increasing the perceived cost of delay in the publication process. At the same time, AI lowers the marginal cost of revision, making frequent updates to working papers more appealing from a cost-benefit perspective. Together, these developments elevate the opportunity cost of slow publication, as researchers forgo timely dissemination and updates while awaiting reviews, making protracted and uncertain timelines increasingly untenable. As the risk of obsolescence grows, researchers may become less willing to submit to top-tier journals with low acceptance rates. Risk-averse researchers, in particular, may prioritize faster publication in lower-tier journals to minimize the chance that their work becomes outdated. More broadly, and consistent with real options theory (Trigeorgis, 1996) and models of investment under uncertainty (Dixit and Pindyck, 1994; Bloom, 2009), researchers may converge more quickly on journals aligned with their paper's quality, bypassing prolonged rounds of review. For the same reason, opportunities such as reject-and-resubmit or extensive revise-and-resubmit invitations could lose appeal, with researchers prioritizing quicker publication over lengthy uncertainty.

Third, researchers may adapt their research agenda to reduce vulnerability to obsolescence. One response is to choose topics where entry barriers slow down progress in the field. Research using unique, non-public data offers such barriers, protecting against both AI and human competition. Another response, consistent with real options theory (Trigeorgis, 1996) and models of investment under uncertainty (Dixit and Pindyck, 1994; Bloom, 2009), is to pursue projects that are narrower in scope and quicker to complete. Such studies are less exposed to the competitive risks and rapid changes in the research environment. If this strategy becomes common, it may gradually erode the overall ambition and depth of scholarship in accounting.

4.5.4. Hybrid review systems

As AI improves research efficiency and lowers production costs, the equilibrium quantity of research output rises (see Lindebaum, 2024, for a related argument). Consistent with this prediction, editor 1 anticipates "an increase in the number of papers people are writing," while a senior editor at an ABS-3 journal observes that "the amount of drafts circulating in the academic world has grown massively." Editor 2 further predicts that "the still good journals … will be flooded by a lot of papers," echoing recent accounts of a surge in poor-quality biomedical papers using public datasets (Naddaf, 2025). This surge in submissions, particularly to lower-tier journals, aligns with the theory of vertical differentiation (e.g., Gabszewicz & Thisse, 1979), as AI slashes the cost of producing low-effort, derivative manuscripts—the segment screened out by top journals. Researchers with less competitive papers will thus target more accessible outlets. Editor 1 further notes, "unless journals increase the number of publication slots—which they may or may not—publishing might just become a whole lot more difficult because you have more papers chasing the same number of publication slots."

The increasing volume of submissions places additional pressure on existing review systems. As an ABS-3 editor observes, "it's clear that our existing way of working can't cope if the number of drafts coming to us increases significantly." Editor 2 adds, "this, of course, has an impact on how we review. We might have to spend more time on reviewing." This highlights that review labor is constrained, forcing a trade-off between review quality and the quantity processed. Editor 1 notes that the rising demand for reviewers "might actually also increase the usage of AI in the reviewing process because people get asked to review more." In short, human capacity constraints may prompt journals and conferences to adopt hybrid review systems that integrate AI with human judgment. In addition to alleviating reviewer workload, these systems can reduce average screening costs as submission volume grows, making them economically attractive under scale.

A common strategy—one that, according to an ABS-3 editor, "is being done and has been done"—is to "raise the bar for being able to send a paper to us for review." This can take at least the following forms. One approach is the use of AI to prescreen submissions, as hinted earlier by Editor 1. AI systems could desk-reject papers that fail to meet basic technical standards, allowing human reviewers to focus on higher-quality work. In the future, AI might take on more complex tasks, such as evaluating the technical aspects of a paper's method, while human reviewers focus on judging its broader significance and creativity. Another approach is to increase submission fees. As AI accelerates content creation but remains limited in its ability to support peer review, it creates excess demand for qualified reviewers. Journals may respond by raising submission fees to manage volume and help fund the peer review process. The *Journal of Financial Economics*, for instance, has a history of adjusting fee levels for this purpose, with part of the revenue used to compensate reviewers and encourage timely feedback (Schwert, 2021).

Panel B of Internet Appendix B summarizes the AI policies applicable to referees and editors across the top seven publishers of accounting journals. A key area of divergence concerns whether reviewers are permitted to incorporate AI-generated insights into their evaluations. The American Accounting Association, through the *Accounting Review*, allows reviewers to use AI tools as aids, provided these tools do not serve as the sole basis for evaluation. Springer Nature, publisher of *Review of Accounting Studies*, implicitly permits the use of AI tools under certain restrictions.[15] In contrast, the remaining five publishers prohibit the use of AI in the review process, with limited exceptions such as language improvement. Together, these policies illustrate a cautious and varied approach to balancing technological assistance with the need to preserve editorial standards.

Caution toward AI-assisted reviewing among academic publishers reflects ongoing concerns about the technology's limitations. AI-generated reviews are often too general, offering vague or irrelevant feedback instead of detailed critiques (Giray, 2024). Ye et al. (2024) find that AI reviewers are prone to hallucinations and are vulnerable to various manipulation tactics. They also tend to favor longer papers and those written by well-known authors compared to human reviewers. Additionally, reliance on AI may reduce reviewers' critical thinking and analytical engagement, resulting in superficial

[15] The journal does not explicitly address the issue but, in the context of advising on AI-generated figures, provides a link to its publisher's page. This page, after discussing the responsibilities of human reviewers and advising against uploading manuscripts into generative AI tools, states: "If any part of the evaluation of the claims made in the manuscript was in any way supported by an AI tool, we ask peer reviewers to declare the use of such tools transparently in the peer review report." https://www.springer.com/us/editorial-policies/artificial-intelligence--ai-/25428500

evaluations (Giray, 2024). Survey results from Hrycyshyn & Eassom (2025) show that most researchers still prefer human-led peer review over AI.

Despite these concerns, publisher or journal policies on AI-assisted reviewing may evolve over time. For instance, *Science* initially banned AI-assisted writing in January 2023 but revised its stance ten months later (Thorp, 2023; Grove, 2023). Two of the top-six accounting journals, *Journal of Accounting and Economics* and *Accounting, Organizations and Society*, explicitly acknowledge that their current prohibition policy may be subject to change. One reason for this flexibility is the difficulty of monitoring AI use in the review process. Blankespoor et al. (2024) find that many employees use generalized AI for financial reporting without formal approval, often without their supervisors' knowledge. Similarly, Liang et al. (2024) analyzed writing styles and word patterns, estimating that in 2023–24, 7–17% of sentences written by reviewers in computer science conferences were AI-generated. It is possible that some accounting reviewers are also quietly using AI to assist their work, although such use appears to be uncommon for now. As senior editor 2 states, “I have not actively seen it,” and the ABS-3 editor similarly reports, “not so far.”

4.5.5. Research fraud

AI offers powerful tools to catch research fraud by spotting manipulated data, verifying statistical analyses, and detecting plagiarism. These tools improve research integrity and discourage dishonest practices. Senior editor 2 anticipates that “journals will demand more information on, for example, the code to ensure replicability.” However, the same technology can enable sophisticated deception, such as generating fake data or automating the production of fabricated research. This could lead to an "arms race" where new tools are constantly needed to keep up with more advanced fraud methods. Whether research fraud rises or falls may depend on how effectively the scientific community implements fraud detection tools and raises the risks for those engaging in misconduct.

4.6. Correlation between research actions

The increasing use of shared AI tools in research can lead to commonalities in researcher behavior. These tools assist in identifying trending topics, relevant literature, and standard methods, which can result in convergence around particular research questions or approaches. They may also recommend similar writing styles, structure, and terminology, leading to greater uniformity in presentation. Evidence from creative-writing experiments offer a cautionary example: use of AI raises each story’s originality score but draws the stories toward a shared style, reducing the group’s overall variety

(Doshi & Hauser, 2024). A similar compression may occur in accounting if researchers increasingly rely on shared AI tools.

Herding theory (Banerjee, 1992; Bikhchandani et al., 1992) predicts that this convergence can amplify booms and busts in research. When AI tools identify and promote emerging topics, many researchers may quickly shift their focus toward these areas, creating concentrated periods of high activity—a boom. However, because AI also accelerates the production and dissemination of research, these fields may become saturated more quickly. As the perceived marginal value of further contributions declines, attention can shift away just as rapidly, resulting in a bust. The coordination enabled by shared AI tools may thus increase the speed and magnitude of these cycles.

Institutional dynamics may contribute to these patterns. DiMaggio & Powell's (1983) concept of isomorphism predicts that coercive forces such as editorial policies, mimetic forces such as emulating perceived winners, and normative forces embedded in doctoral curricula will converge toward a common model. When AI encodes these preferences into algorithmic standards for "rigor" or "novelty," work that deviates from prevailing norms may appear excessively risky.[16] This dynamic can create a reinforcing cycle: researchers adopt AI-driven research agendas, journals reward such outputs, and doctoral curricula replicate these patterns, leading to a gradual decline in intellectual diversity.

AI-driven monitoring systems can detect regulatory changes within days and rapidly disseminate this information across research networks, prompting a wave of similar project ideas well before any publication. Given that the median publication lag in top accounting journals is eighteen months (Hurley et al., 2025), researchers' attention may already have shifted by the time early studies are published. Consequently, the field risks trading depth for speed, with promising questions being abandoned before they mature into a coherent body of evidence.

4.7. Readiness, resistance, and adoption of AI tools

Interest in artificial intelligence is rising across academia, yet the supporting infrastructure remains thin. A recent 88-page report on "Improving the publication process in economics" (Altonji et al., 2025) by a prestigious committee of representatives from top economics associations demonstrates these limitations. Despite the report's comprehensive scope, the committee explicitly acknowledged

[16] Analyzing numeric and textual data from SSRN posted papers in finance and related fields, including accounting, Dai et al. (2023) find that semantic similarity to existing research increases both readership and publication likelihood. In contrast, studies that do not align clearly with established subfields face a higher hurdle.

lacking "expertise to discuss the impact AI can have on the generation of research," offering only basic recommendations on manuscript handling and disclosure. This limited engagement with AI's implications in a major disciplinary review suggests that institutional inertia in the face of technological change represents a broader academic phenomenon. Supporting this, Jiao et al. (2024) find that AI policies at 80 universities show major gaps—especially in discipline-specific guidance—highlighting how institutions across fields remain ill-prepared for the challenges posed by AI. Accounting follows the same path: our review of doctoral program websites uncovered almost no plans for AI integration, indicating limited institutional preparedness.

Classic technology acceptance work shows that researchers adopt new tools when they see clear value. Scholars who watch AI speed up coding or data cleaning may assume it will help elsewhere as well, strengthening their belief in its usefulness (Davis, 1989; Venkatesh & Davis, 2000; Liao et al., 2024). However, visible benefits do not necessarily alleviate deeper concerns. Organizational studies highlight persistent barriers, including anxiety about job loss, limited opportunities for skill development, weak governance structures, inadequate technical support, and unclear incentives (Khanfar et al., 2024a, 2024b). As a result, researchers invested in traditional methods may defend their existing expertise rather than pursue AI-related skills. Moreover, external pressures—such as regulatory mandates, institutional competition, and employer demand for AI-skilled graduates—further complicate the picture.

Senior editors 1 and 2, along with the editor at an ABS-3 journal, note that both internal factors (such as association rules) and external factors (such as publisher policies) influence the adoption of AI. Editor 2 adds, “External factors, I think, are a bit stronger. And to be honest, I think the econ and the finance journals are usually the frontrunners in this.” Acknowledging these institutional constraints, ABS-3 journal editor predicts that review processes at the top accounting journals are unlikely to undergo major changes over the coming 5-year period: “I think at this point there's enough inertia that it won't change massively in that timeframe.”

When asked about the journal’s readiness for advancements in AI, editor 2 responded, “No, we are not. I mean, how can you be prepared for that?” Similarly, ABS-3 journal editor commented, “We are on the map, not in the front, not in the back.” Offering a more detailed view, they added:

> “We are in the research community still at a pretty early stage in using AI—especially when it comes to large-scale, high-level applications… We don't really see the big picture yet, how much of an impact it’ll have when we really start using it effectively… It's completely

> impossible to try and say, 'this is how it's going to be,' because it's constantly changing. That's why, for me, the question of whether I see a need to change – yeah, I do, but how? No clue."

Social learning and network effects may lead to uneven AI adoption, dividing accounting research units into high- and low-use clusters (Rogers, 2003). As researchers observe colleagues' success with AI tools, adoption spreads through close professional networks, creating reinforcing feedback loops that accelerate implementation among early adopters while leaving resistant groups increasingly isolated. This clustering may deepen existing research hierarchies, with AI-integrated units advancing more rapidly while traditional groups risk marginalization in an increasingly AI-oriented field (Merton, 1968).

5. Transformation of research through integration of AI into research information systems

AI is becoming a key component of research information systems, altering the ways in which accounting knowledge is developed and reviewed. This section examines how AI adoption by publishers, database providers, and publication platforms contributes to this transformation. The analysis draws on a comprehensive set of institutional information, with full details and references provided in Internet Appendix C.

5.1. Integration of AI with publishers

Most leading accounting journals are published by large academic publishers such as Elsevier (e.g., *Journal of Accounting and Economics* and *Accounting, Organizations, and Society*), Wiley (e.g., *Journal of Accounting Research* and *Contemporary Accounting Research*), and Springer Nature (e.g., *Review of Accounting Studies*).[17] These publishers cover many disciplines, with accounting journals comprising less than 1% of their total portfolio. They rely on centralized platforms for manuscript processing, allowing them to spread the fixed costs of system development and maintenance. Some have also incorporated AI tools into these platforms, as detailed in Panel C of Internet Appendix B. Currently, AI is used to support tasks such as pre-submission checks, research-integrity screening, and reviewer matching. However, AI systems do not make editorial decisions after pre-screens; they only highlight potential issues for editors to consider.

Although publishers use similar tools, the extent of AI integration varies significantly. Some rely on basic automation for surface-level checks, while others apply AI throughout the editorial process,

[17] The *Accounting Review*, published by the American Accounting Association, is a notable exception.

including drafting editor notes and suggesting referees. This means the journal a researcher selects affects the degree of AI involvement, introducing a new dimension to submission strategy.

AI-powered automation speeds up validation and helps minimize human mistakes. If publishers expand their use of AI tools in manuscript handling, these tools are likely to be implemented across all journals via shared editorial platforms, including those in accounting. This, combined with publishers' general guidelines on AI use in the review process, could occur even if accounting scholars do not fully agree with the idea. Following institutional theory's concept of coercive isomorphism, shared platforms and instructions could push accounting journals to adopt AI tools as a standard. While publishers might not require accounting journals to use AI, mimetic isomorphism suggests that journals not using AI would likely follow the lead of others that do, especially since the technology would already be available.

These institutional pressures not only affect journal operations but may also shape the nature of academic work itself. AI systems used by publishers to evaluate scientific work would likely be centralized and designed to meet the needs of the broader scientific community, not just accounting. If a cross-disciplinary platform cannot be adjusted to recognize standards of evidence specific to accounting, researchers may feel the need to reshape their work to match a general format, thereby narrowing the field's intellectual latitude. This could also change researchers' incentives, pushing them to focus on topics, methods, or writing styles that meet AI standards instead of pursuing their own research interests. As a result, AI advancements could reduce the independence of accounting researchers by discouraging them from following their preferred research agendas.

5.2. Integration of AI with commercial research database providers

Commercial research database providers represent another important institutional force shaping accounting research. Most archival studies rely on such databases, typically accessed through institutional subscriptions. The integration of AI capabilities into these platforms may significantly alter how researchers interact with data. At present, such integration occurs primarily in two ways.

First, database vendors use AI to extract features and indicators from unstructured sources like news headlines, earnings calls, and social media. This method achieves scale economies by performing intensive processing once at the source, rather than repeatedly by each end user.

Second, vendors now provide AI as a front-end service. These tools create brief summaries from existing data tailored to the user's needs. Although they do not produce new information, they can save researchers time by performing the first step of reviewing filings, news, and market data.

Integration of AI tools to databases could influence research in at least the following ways. First, built-in AI tools might steer researchers toward certain types of analyses or research questions that are easier to implement with the provider's AI infrastructure. Second, if competing providers implement different AI solutions—such as in sentiment analysis—methodological divergence might emerge based on which platform researchers use. This situation parallels how the availability and structure of existing databases have historically influenced research choices in accounting (Kothari, 2001), but with AI integration, the effect could be even more pronounced. The combination of AI-enhanced databases and researchers' own AI tools could significantly increase research productivity and output speed.

5.3. Integration of AI with publication databases

Databases are incorporating AI for search, summarization, and citation analysis. Since academic articles are frequently paywalled, publishers can apply AI to full-text content that is inaccessible to others. This data advantage reduces competitive pressure and may explain why publishers have implemented such features cautiously, often through limited pilots.

Outside these proprietary "walled gardens," three types of open ecosystems have emerged, arguably demonstrating a more experimental use of AI. The first consists of large-scale public indexers that provide semantic search and access to open-access metadata and full texts. The second includes AI tools that generate evidence summaries, citation mappings, or structured literature overviews by querying these public datasets. The third involves platforms that allow researchers to upload their own documents for AI-assisted exploration.

AI integration may substantially accelerate literature reviews and meta-analyses, supporting more frequent or even continuously updated research. Since most AI tools rely on similar architectures, access to high-quality, timely data may be crucial for the quality of these analyses. Proprietary AI tools operate within "walled gardens," excluding articles outside those systems. In contrast, tools in open ecosystems can access preprints and recent open-access publications but lack access to paywalled content. To address these constraints, accounting scholars may need to balance speed

against completeness, evaluate AI-generated outputs critically, and ensure transparent documentation of data sources in future reviews.

6. Institutional power shifts

Institutional theory helps explain how AI could drive change in academic accounting research. According to DiMaggio & Powell (1983), institutional structures create stability but are susceptible to disruption from technological advancements. This disruption may lead to a reevaluation of established research approaches and the development of new academic conventions.

6.1. Ownership of research

The long publication process in accounting journals creates problems in a world where AI can quickly replicate and modify analyses to claim originality. Although working papers are usually considered "owned" when first circulated, this is based on informal norms, not formal rules. Papers released around the same time are often regarded as contemporaneous, making it harder to determine who came first.

In the past, replicating and adapting research took a lot of time and effort, so disputes over intellectual ownership were relatively rare. However, AI has made these tasks much easier, which could lead to more conflicts over original ideas. Without stronger protections for intellectual ownership, powerful actors might use their influence to claim credit, even for work that is just a quick variation of the original. Hurley et al. (2025) found that authors from less prestigious institutions face longer submission-to-acceptance times, making them more vulnerable to being exploited by better-connected researchers. Senior editor at an ABS-3 journal expresses concerns about declining intellectual ownership and its potential impact on researchers' ability to present their work publicly, stating:

> So, the question under the whole infrastructure, the logic that's been in place for a long time—that we present research and discuss it at the stage when it's still in progress. Well, this is challenged pretty strongly in my opinion… Like who will dare to present their best stuff beforehand anymore, because someone will steal it.

In Demsetz (1967), property rights systems develop when the benefits from exclusive control over a resource exceed the costs of establishing and enforcing those rights. Applied to academic publishing, this implies that formal intellectual property protections for working papers would develop if the

benefits (preventing idea theft, encouraging knowledge sharing) outweigh the costs (enforcement mechanisms, legal frameworks). Historically, these costs may have outweighed the benefits, but the rise of AI, which lowers the cost of replicating research, may shift this balance.

6.2. Transformation of traditional gatekeepers

AI may significantly accelerate the research process, pressuring traditional accounting journals to evolve or risk becoming less relevant. This reflects Schumpeter's (1942) concept of creative destruction, where new technologies disrupt existing institutional arrangements. Without adaptation, alternative publication models—such as conference proceedings, already prominent in disciplines like computer science and electrical engineering—could gain traction. Additionally, the academic community could place greater emphasis on observable quality indicators for working papers, such as citation counts. This shift could diminish the status of top journals, with profound incentive effects, particularly for junior faculty whose tenure prospects often depend on publications in these outlets.

However, this outcome is not inevitable. A rise in research output could strengthen the need for credible quality signals, reinforcing the role of established journals. As Schumpeter (1942) notes, innovation may also generate new forms of organization that preserve essential functions—in this case, the role of journals in certifying research quality.

Institutional theory offers other ways to explain how AI might be adopted in accounting research. For example, under coercive isomorphism, deans who see AI as strategically important might withhold faculty positions unless the department agrees to hire researchers skilled in using AI. Funding agencies could also prioritize research that incorporates AI, and accreditation bodies like AACSB might require AI to be integrated into accounting programs and research. Additionally, mimetic isomorphism could drive AI adoption, as accounting researchers may learn and adopt best practices from colleagues in other departments, especially those leading in AI development. For example, Liao et al. (2024) document that computer science researchers accept and use AI more than those in social sciences or biology.

6.3. Evolution of academic hierarchies

AI could change the balance of power between established and upcoming researchers. Established researchers, with their deep expertise and ability to ask the “right” questions, are well placed to direct AI toward high-value problems. They also have better access to proprietary data and the financial means to license premium models. If a flood of AI-augmented, high-quality papers starts to

overwhelm traditional review systems, their reputation and editorial connections could still secure priority for their submissions. Nevertheless, many auxiliary tasks that once demanded grant funding—statistical troubleshooting, programming support, manuscript polishing—can now be performed by readily available AI tools, reducing the resource advantage traditionally held by established researchers.

Upcoming researchers, by contrast, often adopt new tools quickly. Hopwood (2007) observed that doctoral students spearheaded earlier methodological shifts in accounting; a similar pattern may re-emerge. Their adaptability helps them overcome barriers to doing complex research, enabling them to produce competitive work quickly. AI further levels the field by tutoring novices in coding, econometrics, and rhetorical framing while also offering topic suggestions and feedback that previously flowed only through elite networks. Consistent with the tournament theory of Lazear & Rosen (1981), PhD program director 2 predicts that gains in junior researchers' productivity may prompt revisions to tenure criteria:

> Ultimately, I think what this means is by the next generation of folks who are getting tenure, the bar is going to be at like ten papers. Or something crazy.

Tournament theory also suggests that when AI changes the productivity of competitors differently, it will alter their optimal effort levels. In academic tournaments, researchers compete for limited positions and recognition, with rewards based on relative performance rather than absolute output. If AI primarily benefits upcoming researchers by reducing their disadvantages in access to resources, established researchers may need to increase their effort to maintain their competitive position. Conversely, if upcoming researchers can now produce high-quality work more easily, they face incentives to exert greater effort since the marginal return to effort has increased.

The effect of AI on research might depend on how advanced it is and how central it becomes to scholarly practice. During the exploratory phase, fast-learning juniors may enjoy a temporary edge as seniors experiment cautiously. As AI becomes more advanced, easier to use, and more powerful, almost all researchers may start using it. At that point, experience, data ownership, and editorial influence may again tip the scales, but the route from newcomer to incumbent may have become quicker, less dependent on personal networks, and marked by greater early-career autonomy.

The accelerated transition in academic status reflects how AI weakens traditional sources of competitive advantage. From Burt's (1992) network theory perspective, AI reduces the value of

occupying central positions in academic networks by making research advice widely accessible. Similarly, from Barney's (1991) resource-based view, AI lowers barriers by democratizing access to previously scarce resources such as grant proposal writing assistance. As a result, established advantages erode, allowing newcomers to reach incumbent status more quickly.

6.4. AI and the shifting global balance of research power

Advanced AI is reshaping the global research landscape through two opposing forces: increasing strategic competition (Yang, 2025) and potential democratization of research capabilities (Parashar, 2024).

At the strategic level, AI is now viewed as a critical resource, leading to international tensions. The United States, considered the leading AI power, exemplifies this by restricting China's access to microchips and AI technology (Freifeld, 2025). These restrictions could affect research access and collaboration patterns.

Regulatory developments add another layer of complexity. While regulation generally lags behind AI advancement (Jauhiainen & Lehner, 2022), public pressure for oversight is growing, as shown by polls in the United States and United Kingdom (Hashim, 2025; Perrigo, 2025). The European Union has already enacted AI regulations, though research is currently exempt (Gibney, 2024). However, future regulations, particularly regarding sensitive data research, may vary by region, with the US and China potentially maintaining lighter oversight to support their AI industries.

These dynamics could affect research inequality in multiple ways. Differential access to AI might widen gaps between regions and institutions, potentially leading to new collaboration patterns where researchers with limited AI access partner with better-resourced colleagues. Resource allocation might also shift, with increased funding directed toward AI systems rather than human capital. For accounting departments, this could mean prioritizing investments in AI infrastructure over traditional research support such as research assistants.

However, AI simultaneously offers potential for democratization. Decreasing costs and technical barriers, exemplified by new AI models since DeepSeek's launch (Normile, 2025), could expand access to advanced research tools. These developments might help level the playing field by reducing resource requirements for sophisticated research, particularly benefiting less-resourced institutions. Senior editor at an ABS-3 journal expresses cautious optimism about the potential for democratization, as follows:

> Research in accounting, for example, it's kinda an elite hobby…I hope that [AI] would lower the barriers, making it so that to do high-quality research, the threshold isn't so high that you need certain educational backgrounds or whatever, having to jump through the hoops, to be able to do that.

7. Faster AI growth scenarios

According to standard institutional theory (DiMaggio & Powell, 1983), organizations tend to converge due to isomorphic pressures. This convergence process requires organizations to observe successful practices, assess their effectiveness, and implement necessary changes. Up to this point, we have considered scenarios where AI progresses gradually, allowing time for this institutional learning process. However, if AI advances extremely rapidly—such as achieving AGI already this year—this process may break down, as organizations would struggle to identify and replicate effective strategies quickly enough.[18]

Under such conditions, we would expect greater divergence in organizational responses to AI advancements. Institutions differ in their capacity to adapt, and these differences become more pronounced in times of extreme change (Pfeffer & Salancik, 1978). Short-term survival concerns may take precedence over long-term strategy, leading to hasty and uncoordinated responses. For accounting departments, this might manifest as rapid curriculum overhauls, emergency adoption of AI tools without adequate integration planning, or abrupt shifts in research priorities.

Predicting the impact of extreme AI-driven change is inherently difficult, but such shifts could have significant consequences for doctoral programs. These programs do not function as profit centers; rather, they sustain themselves by contributing to a university's prestige and providing low-cost teaching and research assistance. In times of extreme uncertainty, the value of their prestige component would become less reliable, except perhaps at the most elite institutions, increasing pressures for their discontinuation or significant transformation.

Rapid advances in AI capabilities could also reshape academic hierarchies. Under slower AI development, senior faculty might be reluctant to adopt new technologies. However, rapid improvements in both reasoning and usability would encourage faster adaptation. This would reduce

[18] Korinek & Suh (2024) examine such scenarios from an economic perspective, demonstrating that while economic output grows exponentially, wages collapse as machines replace human labor.

the advantage junior faculty gain from early adoption, limiting their competitive edge and shortening their window of opportunity.

The varying abilities of senior and junior faculty to adapt to AI reflect a classic organizational challenge. At both individual and institutional levels, the speed of adaptation often conflicts with established routines and behaviors. Hannan & Freeman (1977) highlight this trade-off between reliability and adaptability, arguing that organizations strengthen their legitimacy and survival by maintaining consistent performance and predictable outcomes. Under stable conditions, the inertia created by these characteristics is advantageous, but during times of significant change, it becomes a liability. The very traits that once supported survival—reliability and consistency—can hinder the rapid adaptation necessary to navigate disruption.

Academic publishing reflects this tension between reliability and adaptability. Peer review maintains research quality but slows the publication process. Since peer review operates through a dispersed network of volunteers who participate infrequently, changing these practices is inherently slow. Ellison (2002) shows why: reviewers tend to apply the same norms they experienced as authors.[19] For example, a reviewer whose own papers typically required multiple revision rounds may be reluctant to approve another paper after just one or two. This institutional inertia becomes particularly problematic if AI-driven advancements accelerate the demand for rapid dissemination, potentially making the traditional peer review model unsustainable.

These conditions create evolutionary pressure for hybrid organizational forms that combine reliability with faster adaptation. However, such hybrid models face challenges: maintaining sufficient quality control to preserve academic credibility while reducing publication delays and ensuring faster tracks don't become viewed as lower-quality outlets, which could create a two-tier reputation system that undermines their purpose.

The effectiveness of hybrid review models could be potentially improved through the adoption of innovative practices. Accounting journals might employ AI-assisted pre-screening to detect major flaws and assess baseline research quality. Separately, a tiered review process could assign varying levels of scrutiny depending on a paper's claims and potential impact. Journals might also explore post-publication review systems, wherein papers are published following basic quality checks and

[19] Actually, Ellison (2002) suggests that authors tend to be stricter as reviewers because they overestimate the quality of their own work. This overconfidence leads them to impose higher standards when evaluating others, creating a self-reinforcing cycle.

subsequently subjected to ongoing peer evaluation. The success of such models could depend on journals' openness to replication studies, particularly those that challenge original findings—an area where publication remains challenging in major accounting journals.

Specific approaches to hybrid models are emerging. Hurley et al. (2025) suggest that accounting journals consider fast-track systems or enforced review timelines to expedite the process. For example, journals could offer both standard and accelerated review options, with rapid reviews for time-sensitive research while maintaining traditional review processes for other papers. Another approach is registration-based editorial processes, where journals conditionally accept studies based on detailed research plans before results are known. Although this model demands significant upfront investment, it simplifies later stages of the research process if initial editorial feedback is favorable (Bloomfield et al., 2018).

8. Conclusion

Nobel laureate Demis Hassabis (DeepMind/Gemini) has stated that the goal of artificial intelligence is "solving intelligence, and then using that to solve everything else" (Simonite, 2016). Sam Altman (OpenAI/ChatGPT) echoes this perspective, stressing that AI's true potential lies in superintelligence. He asserts that such advanced systems could "massively accelerate scientific discovery and innovation well beyond what we are capable of doing on our own…" (Altman, 2025a).

This paper explores how AI's progression toward human-equivalent intelligence and beyond impacts accounting research and its supporting institutions. We examine AI's influence on research production, validation processes, and academic power structures. Our findings suggest that while AI may transform accounting research institutions within a short time frame, they remain largely unprepared. Without swift adaptation, they risk becoming misaligned with the evolving research environment.

AI is not merely a research tool; it is a transformative force altering the foundations of academic inquiry. The analysis presented in this paper yields a rich set of predictions about AI's potential impact on accounting scholarship. Future empirical research can test these predictions, offering insights into how AI may influence research practices, academic careers, and institutional arrangements.

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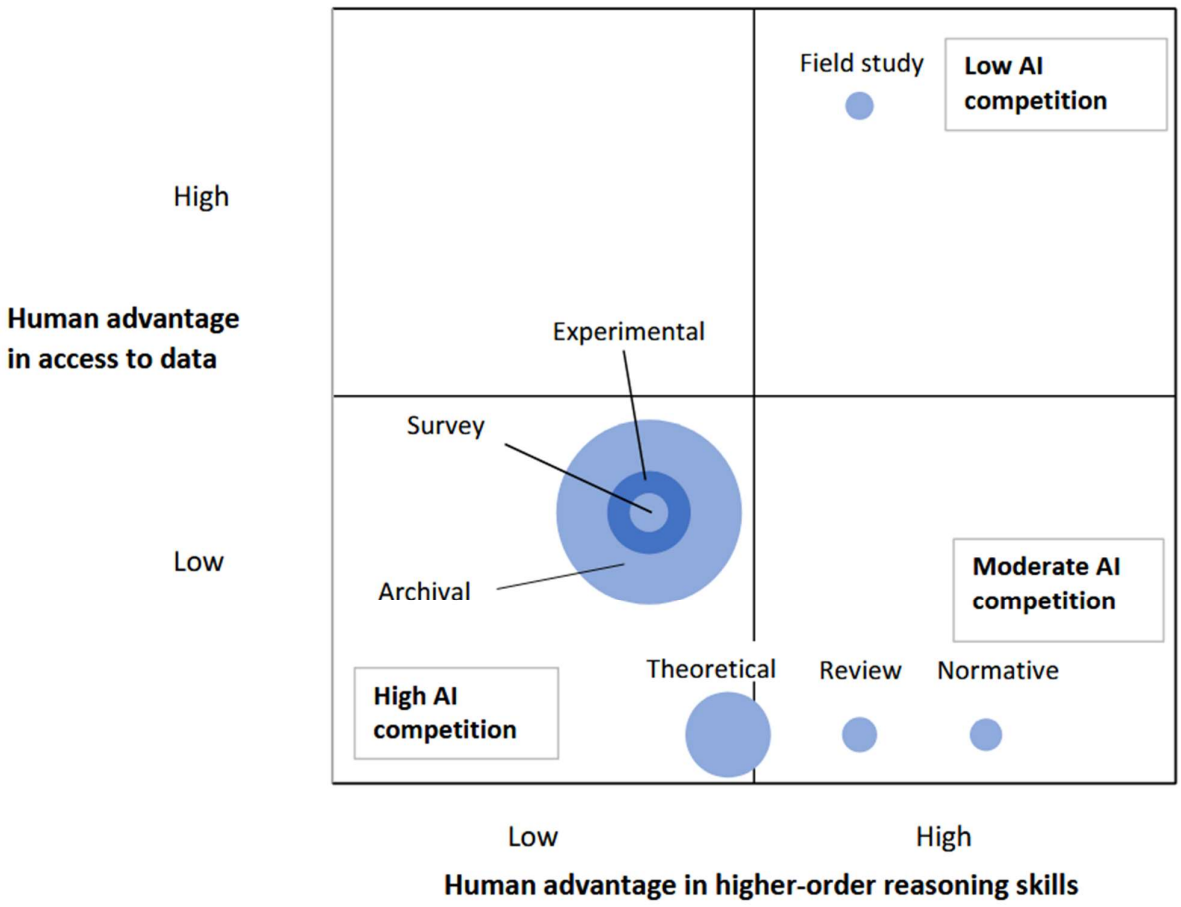

Fig. 1. Research methods' vulnerability to AI competition. Accounting research methods, classified by Oler et al. (2010), are shown on two dimensions that highlight areas where humans have an edge over AI. Each method is represented as a circle, with the size of the circle showing its share of publications in the top-six accounting journals during the 2000s, based on Oler et al.'s data. The placement of methods is based on our subjective assessment of their typical requirements, with supporting arguments provided in Section 4.2. The figure highlights areas likely to experience high, moderate, or low AI competition to aid interpretation.

Table 1. Main predictions

This table summarizes the paper's main predictions. Each entry includes the theoretical framework (underlined), rationale behind the prediction, an assessment of its novelty (with "Yes" suggesting likely novelty), and a reference to the relevant subsection where the prediction and related prior work are discussed in more detail. The word "may" is used intentionally in all predictions.

No	Subsection	Prediction	Theoretical framework & Justification	Novel
1	4.1. Research skills	AI may displace routine research-assistant tasks	Task-based technological change: Skilled labor complements new technology, while less skilled routine tasks are automated away	No
2	4.2.1. Human expertise and AI's transformative effects	Inequality in research productivity may increase, especially in areas where AI excels	Winner-takes-all theory: Scale effects let top performers capture outsized rewards, widening inequality	No
3	4.2.2. AI's impact across research methods	Researchers who lack an edge in using AI may increasingly rely on proprietary data	Barriers to entry: Proprietary data raises entry costs and limits competition	Yes
4	4.2.2. AI's impact across research methods	Researchers who lack an edge in using AI may shift toward methods where AI struggles	Comparative advantage: To remain competitive, researchers specialize in tasks where humans continue to outperform AI	Yes
5	4.2.2. AI's impact across research methods	Hypothesis generation may become more iterative and data-driven	Cost-benefit analysis: AI lowers the cost of data analysis, making iterative, data-driven hypothesis generation more feasible	No
6	4.2.3. AI's impact across research areas	Financial accounting research may be especially exposed to AI-driven competition	Task-based technological change: Financial accounting largely relies on archival methods and publicly available data, areas where AI excels	Yes
7	4.3. Research and teaching employment	Research teams may become smaller	Supply & demand: AI increases the supply of automated research outputs, reducing demand for human researchers in teams	No

No	Subsection	Prediction	Theoretical framework & Justification	Novel
8	4.4. Doctoral education	PhD admissions may shift focus from technical skills to higher-order reasoning and social skills	Comparative advantage: To stay competitive, programs emphasize areas of human comparative advantage	Yes
9	4.4. Doctoral education	PhD curricula may shift toward developing skills where humans retain an advantage over AI	Comparative advantage: To stay competitive, programs emphasize areas of human comparative advantage	Yes
10	4.5.2. Dimensions of quality	Academic evaluation may increasingly emphasize the originality and quality of research ideas	Supply & demand and scarcity: When easily produced contributions become more abundant, the relative value of scarce components increases	No
11	4.5.3. Dealing with obsolescence risks	Researchers may complete their studies more quickly	Technological change theory: Technological progress shifts research production function upward, allowing same output with fewer inputs	No
12	4.5.3. Dealing with obsolescence risks	Researchers may update their work more often during the research process	Cost-benefit analysis: Lower revision costs due to AI make frequent updates more economically viable	Yes
13	4.5.3. Dealing with obsolescence risks	Researchers may converge more quickly to journals of appropriate quality	Real options theory: As obsolescence risk rises, the option value of waiting for better journal match loses value	Yes
14	4.5.3. Dealing with obsolescence risks	Reject-and-resubmit and extensive revise-and-resubmit invitations may lose appeal	Real options theory: As obsolescence risk rises, costly and uncertain options lose value	Yes

No	Subsection	Prediction	Theoretical framework & Justification	Novel
15	4.5.3. Dealing with obsolescence risks	Research projects may become quicker and narrower in scope	Real options theory: As obsolescence risk rises, projects with longer duration and higher uncertainty lose value	Yes
16	4.5.4. Hybrid review systems	Submission volumes to journals may rise	Supply & demand: When production cost falls, equilibrium quantity supplied rises	No
17	4.5.4. Hybrid review systems	Submission volumes to lower-tier journals may rise relative more than to higher-tier journals	Vertical differentiation: AI slashes the cost of producing low-effort, derivative manuscript, the segment screened out by top journals	Yes
18	4.5.4. Hybrid review systems	Journals may adopt AI-assisted pre-screening and hybrid human–AI review systems	Supply & demand and economies of scale: Publishers adapt to increased submissions by using automated pre-screening, which reduces average screening costs as volume grows	No
19	4.5.4. Hybrid review systems	Peer review quality may decline due to reviewer overload	Capacity constraints: Review labor is constrained, forcing a trade-off between review quality and the quantity processed	No
20	4.5.4. Hybrid review systems	Submission fees may increase	Supply & demand price-mechanism: AI accelerates content creation but struggles with review, generating excess demand for quality review that leads journals to raise submission fees	Yes

No	Subsection	Prediction	Theoretical framework & Justification	Novel
21	4.6. Correlation between research actions	Boom and bust patterns in research interests may become stronger	Herding theory: Common AI tools direct researchers toward trending areas, but this can also accelerate saturation in those fields	Yes
22	4.7. Readiness, resistance, and adoption of AI tools	Institutions may separate into high- and low-AI-use clusters	Social learning and network effects: Social learning and network effects drive AI adoption	No
23	5.1. Integration of AI with publishers	Publisher platforms may drive AI adoption	Institutional theory: Centralized AI adoption by publishers may pressure accounting journals to incorporate AI tools	Yes
24	6.1. Ownership of research	Conflicts over intellectual ownership may increase	Property rights theory: AI reduces replication costs, and without clearly defined property rights, promotes intellectual appropriation and increases ownership conflicts.	Yes
25	6.2. Transformation of traditional gatekeepers	Alternative publication models may emerge	Creative destruction: New publishing models displace incumbents unwilling to adapt	No
26	6.3. Evolution of academic hierarchies	Tenure standards may rise	Tournament theory: As average output rises, tenure committees raise standards to maintain selectivity	Yes
27	6.3. Evolution of academic hierarchies	Newcomers may reach incumbent status faster	Network theory and resource-based view: AI weakens network advantages and amplifies newcomer capabilities	Yes

Accounting research in the age of AI

Internet Appendix

Appendix A. List of accounting PhD programs analyzed in this study

This paper analyzes the websites of accounting PhD programs from 30 universities. Of these, 20 appear in the top 20 of Stephens et al.'s (2011) program rankings based on alumni research productivity within six years of graduation during 2001–2009. To enhance coverage of top institutions and geographical representation, we subjectively add two U.S. universities (Columbia University and Massachusetts Institute of Technology), one Canadian university (University of Toronto), four European schools (HEC Paris, London Business School, London School of Economics, and Tilburg University), and three Asian institutions (Hong Kong University of Science and Technology, National University of Singapore, and Singapore Management University).

North America
Arizona State University
Columbia University
Cornell University
Harvard University
Indiana University at Bloomington
Massachusetts Institute of Technology
New York University
Northwestern University
Ohio State University
Pennsylvania State University
Stanford University
U. of Arizona
U. of Chicago
U. of Illinois at Urbana-Champaign
U. of Iowa
U. of Michigan at Ann Arbor
U. of North Carolina at Chapel Hill
U. of Pennsylvania
U. of Rochester
U. of Southern California
U. of Texas at Austin
U. of Toronto
U. of Washington at Seattle

Europe
HEC Paris
London Business School
London School of Economics
Tilburg University

Asia
Hong Kong U. of Science and Technology
National University of Singapore
Singapore Management University

Appendix B. AI policies and integration among major accounting journal publishers

This table summarizes how seven accounting journal publishers address AI across three domains: author policies (Panel A), reviewer and editor policies (Panel B), and the integration of AI tools in editorial workflows (Panel C). In Panels A and B, a dash (-) in the disclosure column indicates that disclosure is not applicable because the corresponding AI use is not permitted. In Panel A, *AI recognized as content owner* refers to cases where AI retains rights or ownership of generated content. In Panel B, *Content upload to AI permitted* refers to cases where uploading is allowed only if the AI tool ensures anonymity, adheres to RELX Responsible AI principles (RELX, n.d.), and excludes the content from model training. In Panel C, *Image screening* denotes the automated analysis of scientific images to detect duplication or manipulation. The information is based on journal guidelines and responsible AI policies, collected in June 2025. Full sources are listed in the reference section.

Panel A: Publisher AI policy for authors

	Publisher						
Publisher policy	American Accounting Association	Elsevier	Emerald	SAGE	Springer Nature	Taylor & Francis	Wiley
AI assistance permitted for:							
Language editing	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Content generation	Yes	No	No	Yes	Not stated	Yes	Yes
Use of AI-generated images permitted	No	No	No	Yes	No	No	Not stated
Use of AI-generated data permitted	Not stated	Not stated	No	No	Not stated	No	No
Disclosure of AI use required for:							
Language editing	Yes	Yes	Yes	No	No	Yes	No
Content generation	Yes	-	-	Yes	Not stated	Yes	Yes
Author retains full responsibility for AI use	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AI recognized as content owner	No	Not stated	Not stated	Not stated	Not stated	No	No
AI authorship permitted	No	No	No	No	No	No	No

Panel B: Publisher AI policy for editors / reviewers

	Publisher						
Publisher policy	American Accounting Association	Elsevier	Emerald	SAGE	Springer Nature	Taylor & Francis	Wiley
AI assistance permitted for:							
Reviewer selection	Yes	Yes	Yes	Yes	Not stated	Not stated	Not stated
Language editing	Not stated	No	No	Yes	Not stated	Yes	Yes
Manuscript evaluation	With restrictions	No	No	No	With disclosure	No	No
Content upload to AI permitted	With restrictions	No	No	No	No	No	No
Disclosure of AI use required for							
Language editing	Yes	-	-	No	Not stated	No	Yes
Manuscript evaluation	Yes	-	-	-	Yes	-	-
Editor / reviewer responsibility for AI use	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Publisher AI tool integration in editorial workflows

	Publisher						
AI tool application	American Accounting Association	Elsevier	Emerald	SAGE	Springer Nature	Taylor & Francis	Wiley
Pre-submission checks	Yes	No	No	No	No	No	No
Integrity screening	Yes	Yes	No	Yes	Yes	No	Yes
Image screening	No	No	No	No	Yes	No	No
Relevance evaluation	No	No	No	Yes	Planned	No	Yes
Reviewer search	No	Yes	No	No	No	No	No

Appendix C. Expanded descriptions of AI tool integration

This appendix provides detailed empirical support for the claims presented in Section 5 regarding the integration of AI into the research infrastructure relevant to accounting scholarship. Each subsection expands on a specific domain—publisher platforms, data vendors, and publisher databases—by documenting the actual systems, services, and implementations currently in use.

C.1 AI tool integration within publisher platforms

Major accounting journals use submission platforms that are shared with much larger disciplinary portfolios. Publishers have begun to embed AI services into these platforms, though with different levels of depth and ambition. The American Accounting Association now asks authors to run manuscripts through Paperpal Preflight, a gateway that scans for missing structural elements, language problems, and formatting errors before the file can proceed (Isakhov, 2022). Wiley, in collaboration with Sage and IEEE, is testing Papermill Detection, a service that flags tortured phrases, verifies author identity, detects generative text, and checks whether the topic fits the journal's scope (Wiley, 2024). Elsevier has augmented its long-standing plagiarism and completeness checks with a machine-learning Reviewer Recommender that suggests suitable referees based on prior publications (Bazari, 2018; Elsevier A, n.d.). Springer Nature deploys Geppetto to detect AI-generated passages and SnappShot to spot manipulated images; in 2025 it added an editor-assist dashboard that produces structured summaries and highlights ethical issues (Springer Nature, 2024, 2025). Oxford University Press is piloting Alchemist Review, a generative assistant that digests methods, cross-checks citations, and scores originality, with the goal of shortening handling times (Bennett, 2025; Hum Works, n.d.). Together, these initiatives suggest a modular strategy where tools are first tested in a subset of journals and then, if successful, extended across the catalogue.

C.2 AI tool integration by commercial data vendors

Database providers influence research agendas by deciding which AI outputs become off-the-shelf variables and which remain unstructured. One current focus is sentiment analysis. Platforms such as WRDS and LSEG convert news headlines, earnings calls, and social-media messages into sentiment scores that researchers can download like any other time series (WRDS, n.d.; LSEG, 2024). Studies by Jeon et al. (2022) and Aggarwal et al. (2024) show how these ready-made indicators have already entered archival work. Vendors are also building conversational layers that synthesise existing fields into coherent briefings. S&P Global's ChatIQ stitches together fundamentals, disclosures, and analyst

forecasts into on-demand company or industry summaries (S&P Global, 2024). Bloomberg has integrated BloombergGPT into its terminal, allowing users to query filings in plain language and receive sentence-level event summaries (Bloomberg, 2023). Centralizing these heavy computations at source yields scale economies for end users but also guides attention toward the vendor's preferred constructs and taxonomies.

C.3 AI tool integration within publisher databases

Publisher platforms enjoy a data advantage because copyrighted articles sit behind paywalls. They have embedded AI for search, summarization, and citation mapping. Elsevier has embedded such features into ScienceDirect and Scopus, including document comparison tools, expert identification systems, and semantic search interfaces (Elsevier B, n.d.; Elsevier C, n.d.; Elsevier 2024; Research Information, 2025; Hochschule Anhalt, 2025). JSTOR now allows natural-language querying of its historical archives (JSTOR, 2024), while Wiley is piloting a conversational search engine developed with Perplexity that draws from textbooks and selected web content (Wiley, 2025; Perplexity, 2025). These features remain limited to subscribers or participants in early-access programs, reflecting a cautious, controlled rollout strategy.

Outside these proprietary "walled gardens," three open ecosystems have emerged. First, open-access aggregators such as Semantic Scholar, CORE, and OpenAlex index hundreds of millions of freely available papers and provide semantic search and TLDR-style summaries (Semantic Scholar, n.d.; CORE, n.d.; OpenAlex, n.d.). Second, application-layer tools such as Elicit, Scite, and Consensus use these datasets to generate evidence tables, classify citation intent, or produce structured literature overviews (Elicit, n.d.; Scite, n.d.; Consensus, n.d.). Third, user-curated platforms such as Anara and Scholarcy allow researchers to upload private documents like PDFs and apply AI-based summarization, question answering, or keyword extraction locally (Anara, n.d.; Scholarcy, n.d.). Although these open tools explore a broader range of AI capabilities, their access ends at the paywall, limiting coverage compared to publisher platforms.

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