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From Search to Delegation: PhD Scholars' Reliance on Agentic AI for Scholarly Information Discovery in Zambia

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Abstract

Context: Academic information discovery is changing as agentic AI systems identify, filter, summarize, compare, and recommend scholarly information. This rapid transformation raises questions about increasing reliance on AI and the continuing need for human oversight of these tasks.

Aim: The study aimed to explore how PhD scholars in Zambia use, delegate, rely on, and verify agentic AI for academic information discovery.

Approach: A quantitative, descriptive, cross-sectional survey was conducted at four Zambian universities. A total of 220 pen-and-paper questionnaires were distributed between 1 June and 25 July 2026, and 180 complete responses were received. The data were analyzed using frequencies, percentages, means, and standard deviations.

Key Findings: Participants used agentic AI for numerous information-discovery tasks, with initial summarization being the most commonly delegated task. Reliance was strongest for making scholarly discovery faster and easier. Participants perceived AI as useful and relevant, but confidence in its accuracy and credibility was lower. Verification was consistently high, especially for research claims, citations, bibliographic details, and source existence.

Interpretation: Delegation did not indicate unconditional dependence; rather, scholars combined AI-enabled efficiency with continued human verification.

Contribution: The study identifies a pattern of verified reliance and provides evidence of AI-mediated scholarly information behavior in the underrepresented Zambian and Global South contexts.

Keywords: agentic AI; scholarly information discovery; delegation; reliance; verification; PhD scholars; Zambia

1. Introduction

Generative artificial intelligence (GenAI) is reshaping higher education and scholarly information practices. Large language models (LLMs) and AI-enabled academic tools support searching, summarizing, comparing, and organizing scholarly information through natural-language interaction, although adoption varies across nations, disciplines, and user groups (Mohammadi et al., 2026). This advancement extends the shift from library-centered information seeking toward diverse digital resources, which have enhanced access while increasing challenges related to information overload, credibility, and evaluation (Bipasha et al., 2026). Unlike conventional retrieval systems, LLM-based systems can also synthesize retrieved information and provide conversational responses (Chowdhury & Chowdhury, 2025).

Agentic AI generally refers to AI systems capable of pursuing complex goals with limited direct human supervision through goal-directed reasoning, planning, task decomposition, tool use,

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action, and adaptation across multiple steps (Shavit et al., 2023; OECD, 2026). Unlike conventional generative AI, which primarily generates content in response to user prompts, genuinely agentic systems can determine and execute sequences of actions toward a specified objective, often interacting with external tools or information environments and adapting their actions as tasks progress (OECD, 2026).

In the present study, however, agentic AI is used operationally in a broader, human-in-the-loop sense to describe AI-enabled scholarly tools and systems to which PhD scholars delegate selected information-discovery tasks, including literature searching and identification, information filtering, preliminary summarization, source comparison, and literature recommendation. These activities vary in their degree of agency: some may be performed by genuinely agentic systems involving multi-step planning and execution, whereas others may represent conventional GenAI or AI-assisted search rather than full technical agency. The term is therefore used in this study to emphasize the movement from passive information retrieval toward AI-assisted task delegation, while recognizing that the tools and activities examined do not necessarily exhibit full autonomous agency. This operational distinction is important because the study investigates scholars' delegation and reliance behaviors rather than evaluating the technical architecture or degree of autonomy of individual AI systems.

These competences are particularly relevant to doctoral researchers, who are primarily engaged in identifying, evaluating, and synthesizing academic literature. AI can support keyword development, literature identification, and information extraction (Gavgani et al., 2026). Ringo (2025) found that ChatGPT use was associated with doctoral research progress but stressed that AI should complement, rather than replace, critical thinking. Similarly, greater AI knowledge among doctoral students has been associated with lower AI dependence (He et al., 2026a).

The distinction between use, delegation, and reliance is therefore critical. Using AI does not necessarily mean accepting its outputs without judgment. Reliance may instead involve selective and conditionally validated use in which AI outputs are independently verified (Pudasaini, 2026). Individual decision-making styles also matter: users who are more inclined to defer decisions may rely more on AI, whereas more vigilant users examine AI explanations more closely (Mei et al., 2026).

For AI-generated academic information, verifying accuracy and reliability is essential. In a domain-specific evaluation of LLM-assisted literature searching on inguinal hernia repair, Kasakewitch et al. (2025) found limitations in the accuracy of identified studies, illustrating the need for caution when relying on AI-assisted literature discovery. False or non-existent AI-generated citations have also been reported (Oladokun et al., 2025), emphasizing the need to verify references and scholarly evidence (Han et al., 2026). AI literacy is critical for addressing these risks, involving the assessment of AI tools and outputs and their appropriate and ethical use (Cao & Mao, 2026). While GenAI offers advantages such as efficiency and writing assistance, it also poses challenges such as dependence, plagiarism, bias, and accessibility disparities (Abdelrahman et al., 2026).

These issues are especially important in the Global South, which remains underrepresented in GenAI research (Bhardwaj & Choudhary, 2026). Institutional contexts can influence digital engagement (Bipasha et al., 2026), while GenAI adoption and associated concerns vary across geographic and disciplinary contexts (Mohammadi et al., 2026). Findings from other contexts therefore cannot automatically be assumed to represent PhD scholars in Zambia.

Despite the expansion of GenAI research, limited evidence exists on how PhD scholars in Zambia use agentic AI for scholarly information discovery and progress from use to delegation, reliance, and verification (Bhardwaj & Choudhary, 2026). This study addresses this gap by examining AI use, task delegation, reliance, perceived usefulness, trustworthiness, and verification among PhD scholars in Zambia. It thereby provides evidence on whether AI-supported scholarly discovery reflects dependence or a more conditional form of reliance in which scholars retain human oversight.

1.1 Research Objectives

The study aims to:

- Examine PhD scholars' use of agentic AI for scholarly information discovery.
- Assess the extent to which PhD scholars delegate scholarly information-discovery tasks to agentic AI.
- Determine PhD scholars' reliance on agentic AI for scholarly information discovery.
- Assess PhD scholars' perceptions of the usefulness, accuracy, and credibility of AI-discovered scholarly information.
- Examine the verification practices used by PhD scholars when using scholarly information discovered through agentic AI.

2. Review of Literature

2.1 Agentic AI in Scholarly Information Discovery

Artificial intelligence is increasingly reshaping scholarly information discovery by extending conventional keyword searching through natural-language interaction, topic exploration, relevance identification, summarization, and retrieval. Lund et al. (2026), surveying 236 university students, found that AI tools function as both complements to and competitors of search engines and library resources, indicating a shift toward a more diverse scholarly information ecosystem.

Comparative studies show that AI-assisted and conventional search tools have different strengths. Tomczyk et al. (2026) found that Scopus and Web of Science performed better at identifying accurate, high-quality literature, whereas Elicit and SciSpace identified some unique publications missed by traditional searches. Gavgani et al. (2026) reported accuracy rates of 86% for Consensus, 75.5% for Semantic Scholar, and 72% for Google Scholar. These results suggest that AI can improve academic discovery but is most effective when used alongside established databases rather than as a replacement for them.

AI also assists in constructing searches and developing research topics. Yadav et al. (2026) noted that systematic prompting can translate researchers' keywords into database-specific search strategies, and Zhao et al. (2026) found that conversational AI can help researchers refine their topics and locate credible sources. Reliability remains a concern, however: Acut et al. (2025) found that more comprehensive prompts were more likely to generate non-existent references.

2.2 Delegation and Reliance on AI in Scholarly Information Seeking

As AI becomes increasingly embedded in academic research, it functions not only as a tool but also as a means of delegating specific research tasks. Delegation occurs when a researcher assigns part of a research task to an AI system rather than using it merely as an information source. Suchikova et al. (2026), in the Generative AI Delegation Taxonomy (GAIDeT), identify literature searching, literature systematization, and parts of literature-review preparation as research activities that can be delegated to GenAI. Importantly, such delegation does not remove human responsibility: researchers remain responsible for overseeing the process, assessing the outputs, and deciding whether AI-generated or AI-discovered information is appropriate for scholarly use.

Delegation is especially relevant to scholarly information seeking because information-discovery tasks vary in the amount of intellectual judgment they require. AI can reduce researchers' information-processing burden when brainstorming keywords, sifting through potentially relevant literature, filtering large volumes of information, producing initial summaries, and structuring retrieved information. More advanced AI research systems can extend this support to multi-step research processes. For instance, SciSciGPT illustrates how LLM-based research tools can streamline complex research workflows, provide analytical support, and accelerate research prototyping while preserving human–AI collaboration (Shao et al., 2026). Delegation

should therefore be interpreted not as the complete surrender of scholarly authority to AI but as a redistribution of selected tasks within the human–AI research process.

It is also important to distinguish delegation from reliance. Delegation refers to assigning a specific task or part of a task to AI, whereas reliance refers to the extent to which the researcher depends on AI to complete research tasks. Frequent use of AI to make research tasks quicker, easier, or less cognitively demanding does not necessarily indicate dependence. Recent literature distinguishes two types of AI dependency: adaptive or instrumental dependency, in which AI tools enhance an individual's efficiency in tasks such as summarization or feedback, and problematic dependency, in which an individual's autonomy is reduced or the individual feels unable to complete a task without AI (He et al., 2026b). Using AI for cognitive offloading is therefore not necessarily maladaptive and can facilitate academic work while the researcher maintains control over judgment and verification.

This is particularly important for doctoral research. Ringo (2025) found that ChatGPT use was positively correlated with students' academic research progress but argued that AI should be used alongside, not in place of, critical thinking and intellectual effort. Likewise, He et al. (2026a), in a study of 607 doctoral students, found that stronger AI knowledge was associated with lower AI dependence, indicating that AI knowledge can reduce dependence while still enabling doctoral researchers to benefit from AI. These results suggest that the key issue is not whether PhD scholars use or delegate tasks to AI, but whether their independent intellectual judgment and engagement are maintained.

Reliance also depends on individual decision-making behavior. Mei et al. (2026) found that individuals with a greater tendency to defer decisions were more likely to consult and use AI-generated information, whereas those with a more vigilant decision-making style spent more time evaluating AI explanations. Reliance is therefore shaped not only by the technological capability of AI but also by users' approaches to judgment, responsibility, and decision-making. Consequently, scholars who use or delegate tasks to AI to a similar extent may still differ in their actual levels of reliance.

The literature thus indicates a spectrum extending from use to delegation, reliance, and, potentially, dependency on AI. Delegation refers to using AI for selected information-related tasks, reliance occurs when researchers increasingly depend on AI assistance or outputs, and dependency is a more problematic state in which autonomy and self-regulation are weakened (He et al., 2026b). Delegation and reliance are not, however, inherently problematic in scholarly information discovery. Their appropriateness depends on the task being delegated and on PhD scholars' ability to critically evaluate, make independent decisions about, and verify the information they receive from AI.

2.3 Verification of AI-Discovered Scholarly Information

Verification is critical because AI-generated or AI-recommended information cannot automatically be considered reliable academic evidence. While GenAI can enhance access to knowledge and research efficiency, it may also compromise research integrity, reproducibility, and reliability if not adequately validated (Hosseini et al., 2025).

This concern is reinforced by evidence on false citations. Oladokun et al. (2025) reported that 42.9% and 51.8% of the outputs generated by ChatGPT-3.5 and ChatGPT-4o, respectively, were false. In line with this, Watson (2024) identified issues in 45 of 46 suspected AI-generated citations, including incorrect or misleading URLs and DOIs. The results confirm that seemingly credible references must be verified independently.

Verification is therefore a key component of responsible AI use. According to Shomotova and ElSayary (2026), human validation, multi-source cross-checking, and transparency are measures that protect scholarly research, and Flores et al. (2025) reiterated the importance of developing students' evaluation skills. Boretti (2026) noted that false papers, incorrect DOIs, and unsubstantiated claims can be introduced into the academic landscape undetected, while

Kamińska (2026) emphasized the role of libraries in strengthening critical AI literacy and source evaluation.

The literature shows that responsible use of agentic AI for academic information discovery requires a balance between efficiency and human oversight. Researchers should verify the existence of sources, bibliographic details, citations, claims, and original publications before incorporating AI-discovered information into scholarly work.

2.4 Research Gap

Despite increasing research on AI-supported scholarly searching, delegation, reliance, credibility, and verification, there is inadequate evidence on how these dimensions function together among PhD scholars. Existing studies largely examine individual aspects of GenAI use and are predominantly situated outside sub-Saharan Africa. In particular, little is known about how PhD scholars in Zambia advance from using AI to delegating academic information-discovery tasks, relying on its outputs, and verifying them. Given the limited representation of Global South contexts in GenAI research (Bhardwaj & Choudhary, 2026), this study addresses this gap by examining these interconnected practices among PhD scholars in Zambia.

3. Research Methodology

3.1 Research Design

The study employed a quantitative, descriptive, cross-sectional survey design to examine PhD scholars' use of agentic AI for scholarly information discovery in Zambia. The design was appropriate because the study sought to describe scholars' practices and perceptions at a specific point in time rather than establish causal relationships. Five dimensions were examined: use of agentic AI, delegation of scholarly information-discovery tasks, reliance on agentic AI, perceived usefulness, accuracy, and credibility of AI-discovered scholarly information, and verification practices.

3.2 Study Setting, Population, and Sampling

The study involved PhD scholars from four universities in Zambia, comprising two public and two private institutions. The identities of the participating universities were withheld to maintain institutional anonymity, and the institutions were not treated as comparative units. PhD scholars at different stages of their doctoral programs were eligible to participate.

A voluntary-response sampling technique was used. This non-probability approach was considered practical for reaching eligible PhD scholars across the four participating universities while allowing potential participants to decide freely whether to take part. A total of 220 questionnaires were distributed, of which 180 complete and usable questionnaires were returned, yielding an 81.8% usable response rate. Responses from the four universities were pooled and analyzed as a single sample.

The voluntary-response approach may, however, introduce self-selection bias. Because participation depended on individuals choosing to respond, PhD scholars with greater interest in, familiarity with, or experience of AI-supported scholarly information discovery may have been more likely to participate. The resulting sample, therefore, cannot be assumed to be statistically representative of all PhD scholars in Zambia, and generalization of the findings should be made cautiously.

3.3 Research Instrument and Measurement

Data were collected using a structured, self-administered questionnaire developed specifically for the objectives of the study. The questionnaire items were organized around the five dimensions examined in the research: AI use, task delegation, reliance, perceived usefulness, accuracy, and credibility, and verification practices. The items were designed to capture activities and

perceptions directly related to the research objectives rather than to constitute an established psychometric scale.

The questionnaire comprised six sections. Section A collected demographic information. Section B contained five items measuring the use of agentic AI for scholarly information discovery. Section C contained five items addressing the delegation of scholarly information-discovery tasks. Section D consisted of five items examining reliance on agentic AI. Section E contained five items assessing perceived usefulness, accuracy, and credibility, while Section F contained seven items examining verification practices.

The items covered scholarly activities such as searching for and identifying literature, exploring unfamiliar topics, identifying search terms, summarizing scholarly materials, narrowing information, comparing sources, receiving literature recommendations, relying on AI during scholarly discovery, evaluating the usefulness and credibility of AI-supported information, and verifying sources, bibliographic information, citations, summaries, and research claims. A brief description of agentic AI and its application to scholarly information discovery was provided to respondents to promote a common understanding of the concept.

Items in Sections B–F were measured using a five-point Likert scale: 5 = Strongly Agree, 4 = Agree, 3 = Neutral, 2 = Disagree, and 1 = Strongly Disagree. Higher scores therefore indicated greater agreement with the respective statements.

No documented pilot study, formal content- or construct-validation procedure, or reliability testing was conducted for the questionnaire. The study consequently does not present the questionnaire as a formally validated psychometric instrument. This absence of formal validation and reliability testing limits conclusions regarding the instrument's internal consistency and psychometric properties and is explicitly acknowledged as a methodological limitation. Future studies should subject the questionnaire to expert assessment, pilot testing, construct validation, and appropriate reliability analysis before treating it as a standardized measurement instrument. To improve transparency and facilitate replication and future validation, the complete questionnaire used in this study is provided in Appendix A.

3.4 Data Collection Procedure

Data were collected through pen-and-paper questionnaires between 1 June and 25 July 2026. During this period, 220 questionnaires were distributed to eligible PhD scholars across the four participating universities. Before participation, respondents were informed about the purpose of the research, the voluntary nature of participation, and the study's focus on agentic AI and scholarly information discovery. A brief explanation of agentic AI in the context of the study was also provided.

Participation was voluntary, and informed consent was obtained before respondents completed the questionnaire. Participants were free to decline participation, and no personally identifying information was requested through the questionnaire. Returned questionnaires were screened for completeness and suitability for analysis, after which 180 complete questionnaires were retained.

3.5 Data Processing and Analysis

The completed questionnaires were coded and analyzed using descriptive statistics. Frequencies and percentages were used to summarize demographic characteristics and response distributions, while means and standard deviations were used to describe individual Likert-scale items.

For comparison across the five study dimensions, an overall mean was calculated from the item means within each dimension. The resulting overall means were 3.84 for AI use, 3.73 for delegation, 3.69 for reliance, 3.73 for perceived usefulness, accuracy, and credibility, and 4.01 for verification. These summary scores facilitate direct comparison of the dimensions and show that verification recorded the highest overall mean, whereas reliance recorded the lowest.

Composite standard deviations were not estimated by averaging the item-level standard deviations, because a valid dimension-level standard deviation should be calculated from respondent-level composite scores. Accordingly, the study retains the observed standard deviations for individual items and reports dimension-level means primarily as descriptive summaries. All 180 respondents were analyzed as one sample, and no institution-level or public-private university comparisons were undertaken.

3.6 Ethical Considerations

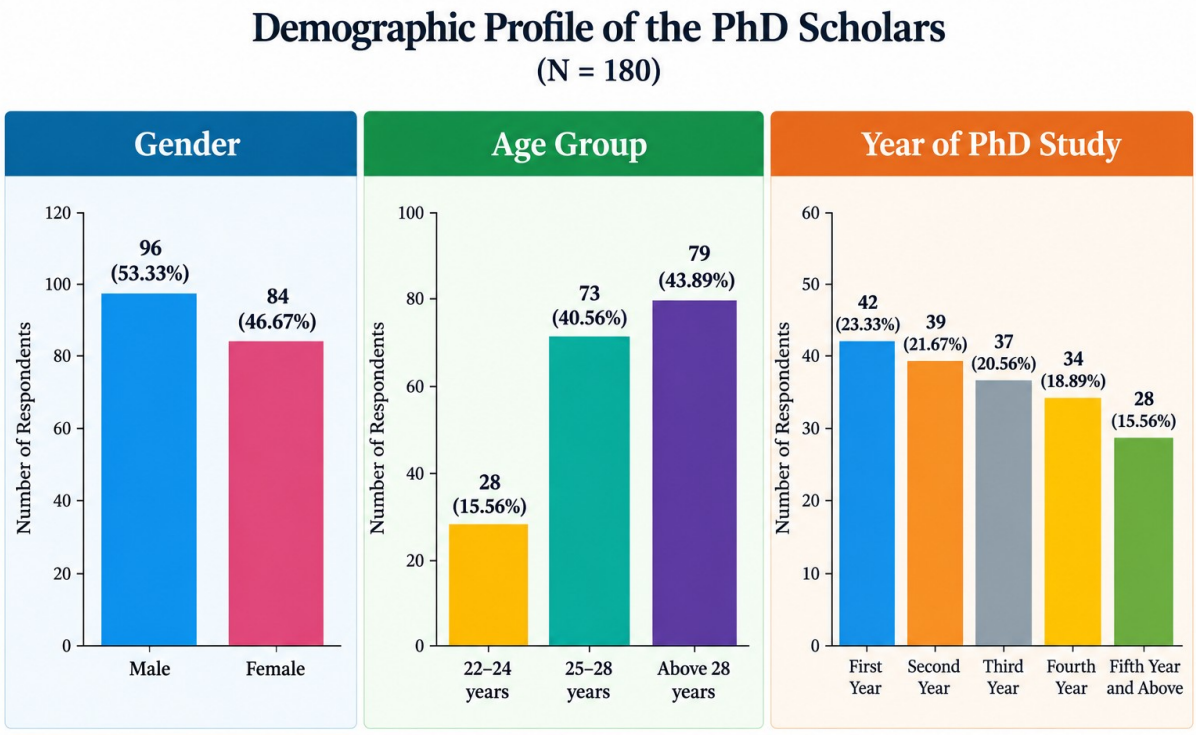
Participation was voluntary, and informed consent was obtained from all respondents before data collection. Participants were adults enrolled in PhD programs and were informed of the purpose of the study and their freedom to decide whether to participate. No personally identifying information was collected through the questionnaire. The identities of individual participants and the participating universities were not disclosed, university affiliation was not used for comparative analysis, and findings were reported only in aggregate form to maintain anonymity and confidentiality.

Formal approval from an Institutional Ethics Committee (IEC) was not sought before data collection. At the time of the study, the study was regarded by the researcher as a minimal-risk, non-interventional social-science survey involving consenting adult participants and collecting information about scholarly information-discovery practices and perceptions rather than clinical, biomedical, or personally identifying information. No physical intervention, clinical procedure, experimental treatment, or collection of biological material was involved.

This description reflects the basis on which the study was conducted and should not be interpreted as a formal IEC exemption, since no prospective exemption determination was obtained from an ethics committee. The absence of prospective formal ethics review is therefore acknowledged transparently. Throughout data collection and reporting, voluntary participation, informed consent, anonymity, confidentiality, and aggregate reporting were maintained.

4. Results

Figure 1. Demographic Profile of the PhD Scholars (N = 180)



Source: Author's own work based on primary survey data (2026).

Figure 1 presents the demographic profile of the 180 PhD scholars who participated in the study according to gender, age group, and year of PhD study. Regarding gender, 96 (53.33%) respondents were male and 84 (46.67%) were female, indicating a relatively balanced gender distribution, with a slight majority of male PhD scholars. In terms of age, the largest proportion of respondents were above 28 years (n = 79, 43.89%), followed by those aged 25–28 years (n = 73, 40.56%), while those aged 22–24 years constituted the smallest group (n = 28, 15.56%). With respect to year of PhD study, first-year scholars represented the largest group (n = 42, 23.33%), followed by second-year (n = 39, 21.67%), third-year (n = 37, 20.56%), and fourth-year scholars (n = 34, 18.89%). PhD scholars in their fifth year and above constituted the smallest group (n = 28, 15.56%). The demographic profile shows representation across gender, age groups, and all stages of PhD study, providing a diverse sample of PhD scholars for examining the use of agentic AI for scholarly information discovery.

Table 1. Use of Agentic AI for Scholarly Information Discovery

Statement	Strongly Agree, n (%)	Agree, n (%)	Neutral, n (%)	Disagree, n (%)	Strongly Disagree, n (%)	Mean	SD
I use agentic AI to search for scholarly information related to my research topic.	58 (32.2%)	69 (38.3%)	31 (17.2%)	15 (8.3%)	7 (3.9%)	3.87	1.08
I use agentic AI to identify relevant academic articles and research materials.	54 (30.0%)	72 (40.0%)	33 (18.3%)	14 (7.8%)	7 (3.9%)	3.84	1.06
I use agentic AI to explore unfamiliar research topics and concepts.	61 (33.9%)	67 (37.2%)	30 (16.7%)	15 (8.3%)	7 (3.9%)	3.89	1.09
I use agentic AI to identify keywords and search terms for scholarly literature searches.	56 (31.1%)	70 (38.9%)	32 (17.8%)	15 (8.3%)	7 (3.9%)	3.85	1.08
I use agentic AI at different stages of scholarly information searching.	49 (27.2%)	71 (39.4%)	36 (20.0%)	17 (9.4%)	7 (3.9%)	3.77	1.07

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Source: Author's own work based on primary survey data (2026).

Table 1 shows generally high use of agentic AI for scholarly information discovery, with mean scores ranging from 3.77 to 3.89. The highest-rated use was exploring unfamiliar research topics and concepts (M = 3.89, SD = 1.09; 71.1% agreement), followed by searching for research-related scholarly information (M = 3.87, SD = 1.08; 70.5%). Identifying keywords and search terms (M = 3.85) and relevant academic materials (M = 3.84) also recorded high agreement. Using agentic AI at different stages of scholarly searching received the lowest mean (M = 3.77), although 66.6% still agreed. The findings indicate substantial use of agentic AI across multiple scholarly information-discovery activities.

Table 2. Delegation of Scholarly Information Discovery Tasks

Statement	Strongly Agree, n (%)	Agree, n (%)	Neutral, n (%)	Disagree, n (%)	Strongly Disagree, n (%)	Mean	SD
I delegate the task of identifying relevant scholarly literature to agentic AI.	45 (25.0%)	66 (36.7%)	40 (22.2%)	20 (11.1%)	9 (5.0%)	3.66	1.12
I use agentic AI to narrow down large amounts of scholarly information.	48 (26.7%)	69 (38.3%)	37 (20.6%)	18 (10.0%)	8 (4.4%)	3.73	1.10
I delegate the initial summarization of scholarly materials to agentic AI.	57 (31.7%)	70 (38.9%)	31 (17.2%)	15 (8.3%)	7 (3.9%)	3.86	1.08
I use agentic AI to compare scholarly sources.	46 (25.6%)	65 (36.1%)	40 (22.2%)	20 (11.1%)	9 (5.0%)	3.66	1.12
I allow agentic AI to recommend further literature or research directions.	50 (27.8%)	67 (37.2%)	36 (20.0%)	18 (10.0%)	9 (5.0%)	3.73	1.12

Source: Author's own work based on primary survey data (2026).

Table 2 shows that PhD scholars delegated various scholarly information-discovery tasks to agentic AI, with mean scores ranging from 3.66 to 3.86. Initial summarization of scholarly materials was the most frequently delegated task (M = 3.86, SD = 1.08; 70.6% agreement).

Narrowing large amounts of information and recommending further literature or research directions both recorded a mean of 3.73 and 65.0% agreement. Identifying relevant literature and comparing scholarly sources recorded the lowest means (M = 3.66), with 61.7% agreement each. The findings suggest that respondents were more willing to delegate preliminary information-processing tasks, particularly summarization, than tasks requiring greater scholarly judgment, such as literature identification and source comparison.

Table 3. Reliance on Agentic AI for Scholarly Information Discovery

Statement	Strongly Agree, n (%)	Agree, n (%)	Neutral, n (%)	Disagree, n (%)	Strongly Disagree, n (%)	Mean	SD
I rely on agentic AI when I have difficulty finding relevant scholarly information independently.	44 (24.4%)	64 (35.6%)	41 (22.8%)	22 (12.2%)	9 (5.0%)	3.62	1.13
Agentic AI has become an important part of my scholarly information-searching process.	52 (28.9%)	68 (37.8%)	35 (19.4%)	17 (9.4%)	8 (4.4%)	3.77	1.10
I rely on agentic AI to help me decide which scholarly sources deserve further examination.	42 (23.3%)	65 (36.1%)	42 (23.3%)	22 (12.2%)	9 (5.0%)	3.61	1.12
I rely on agentic AI to make scholarly information discovery faster and easier.	63 (35.0%)	70 (38.9%)	29 (16.1%)	12 (6.7%)	6 (3.3%)	3.96	1.04
I would find scholarly information discovery more difficult without agentic AI.	39 (21.7%)	58 (32.2%)	45 (25.0%)	26 (14.4%)	12 (6.7%)	3.48	1.17

Source: Author’s own work based on primary survey data (2026).

Table 3 shows moderate to high reliance on agentic AI, with mean scores ranging from 3.48 to 3.96. Reliance was highest for making scholarly information discovery faster and easier (M = 3.96,

SD = 1.04; 73.9% agreement), followed by AI becoming an important part of the scholarly searching process (M = 3.77; 66.7%). Reliance when relevant information was difficult to find (M = 3.62) and prioritizing sources for further examination (M = 3.61) was moderate. The lowest mean concerned finding scholarly discovery more difficult without AI (M = 3.48; 53.9% agreement). Respondents relied primarily on agentic AI for efficiency and support rather than showing complete dependence on it.

Table 4. Perceived Usefulness, Accuracy, and Credibility of Agentic AI

Statement	Strongly Agree, n (%)	Agree, n (%)	Neutral, n (%)	Disagree, n (%)	Strongly Disagree, n (%)	Mean	SD
I find scholarly information provided by agentic AI useful for my research activities.	64 (35.6%)	72 (40.0%)	28 (15.6%)	11 (6.1%)	5 (2.8%)	3.99	1.01
Agentic AI generally provides scholarly information relevant to my research needs.	55 (30.6%)	72 (40.0%)	33 (18.3%)	14 (7.8%)	6 (3.3%)	3.87	1.04
I consider the scholarly information provided by agentic AI to be generally accurate.	37 (20.6%)	64 (35.6%)	47 (26.1%)	23 (12.8%)	9 (5.0%)	3.54	1.11
I consider scholarly sources recommended by agentic AI to be generally credible.	35 (19.4%)	62 (34.4%)	49 (27.2%)	24 (13.3%)	10 (5.6%)	3.49	1.12
I am confident in using agentic AI as a supporting tool for scholarly information discovery.	49 (27.2%)	69 (38.3%)	38 (21.1%)	17 (9.4%)	7 (3.9%)	3.76	1.08

Source: Author’s own work based on primary survey data (2026).

Table 4 shows that respondents viewed agentic AI more positively for usefulness and relevance than for accuracy and credibility. Usefulness recorded the highest mean (M = 3.99, SD = 1.01;

75.6% agreement), followed by relevance to research needs (M = 3.87; 70.6%). Confidence in using AI as a supporting tool was also relatively high (M = 3.76; 65.5%). However, perceived accuracy (M = 3.54; 56.2%) and the credibility of AI-recommended sources (M = 3.49; 53.8%) were lower. The results show that PhD scholars considered agentic AI useful for scholarly information discovery but remained comparatively cautious about the accuracy and credibility of its outputs.

Table 5. Verification Practices for AI-Discovered Scholarly Information

Statement	Strongly Agree, n (%)	Agree, n (%)	Neutral, n (%)	Disagree, n (%)	Strongly Disagree, n (%)	Mean	SD
I verify whether scholarly sources suggested by agentic AI actually exist.	69 (38.3%)	68 (37.8%)	27 (15.0%)	11 (6.1%)	5 (2.8%)	4.03	1.02
I check the bibliographic details of references provided by agentic AI before using them.	72 (40.0%)	67 (37.2%)	26 (14.4%)	10 (5.6%)	5 (2.8%)	4.06	1.01
I compare scholarly information provided by agentic AI with reliable academic sources.	65 (36.1%)	71 (39.4%)	29 (16.1%)	10 (5.6%)	5 (2.8%)	4.01	1.00
I access the original scholarly source before using information recommended by agentic AI.	61 (33.9%)	69 (38.3%)	31 (17.2%)	13 (7.2%)	6 (3.3%)	3.92	1.05
I verify the accuracy of AI-generated summaries before relying on them.	58 (32.2%)	70 (38.9%)	33 (18.3%)	13 (7.2%)	6 (3.3%)	3.89	1.04

I verify AI-provided citations or references before including them in my research work.	74 (41.1%)	66 (36.7%)	25 (13.9%)	10 (5.6%)	5 (2.8%)	4.08	1.01
I verify important research claims provided by agentic AI before using them in my thesis or publications.	77 (42.8%)	65 (36.1%)	24 (13.3%)	9 (5.0%)	5 (2.8%)	4.11	1.00

Source: Author's own work based on primary survey data (2026).

Table 5 shows consistently high verification of AI-discovered scholarly information, with mean scores ranging from 3.89 to 4.11. Verification was highest for important research claims before use in theses or publications (M = 4.11, SD = 1.00; 78.9% agreement), followed by citations or references (M = 4.08; 77.8%) and bibliographic details (M = 4.06; 77.2%). Respondents also frequently verified source existence (M = 4.03), compared AI information with reliable academic sources (M = 4.01), and accessed original sources (M = 3.92). Verification of AI-generated summaries recorded the lowest mean (M = 3.89), although agreement remained high at 71.1%. The findings indicate strong human oversight and suggest that respondents generally verified AI-generated information rather than accepting it uncritically.

5. Discussion

The findings demonstrate that agentic AI is becoming integrated into PhD scholars' scholarly information-discovery practices in Zambia, but its use does not appear to represent unconditional dependence. Respondents used AI across numerous discovery activities, particularly for exploring unfamiliar topics, searching for scholarly information, and identifying search terms. This supports evidence that AI is becoming part of the wider scholarly information environment alongside conventional search and library resources (Lund et al., 2026). AI can also support keyword development and research-topic refinement, strengthening its role as an intermediary in academic discovery (Yadav et al., 2026; Zhao et al., 2026).

Delegation was evident but selective. Initial summarization was the most frequently delegated activity, whereas literature identification and source comparison received comparatively lower agreement. This suggests that scholars may be more willing to delegate preliminary information-processing tasks than activities requiring greater scholarly judgment. This is consistent with Suchikova et al. (2026), who argue that research tasks can be delegated to GenAI while human oversight and accountability are maintained. Thus, delegation should not necessarily be interpreted as transferring complete academic authority to AI.

Reliance was strongest for making academic information discovery faster and easier, whereas respondents were less likely to indicate that discovery would become difficult without AI. This difference suggests efficiency-oriented reliance rather than complete dependence. It corresponds with Pudasaini's (2026) characterization of AI reliance as potentially selective and conditionally validated. This distinction is particularly important for doctoral researchers because excessive AI dependence may affect independent scholarly and innovative capabilities (He et al., 2026a).

Another important finding was the difference between usefulness and trustworthiness. Respondents rated AI highly for usefulness and relevance, but were more cautious about accuracy

and credibility. Similar concerns about the accuracy of GenAI-generated information have been reported among academics internationally (Mohammadi et al., 2026). Such caution is warranted because AI can produce plausible yet inaccurate or false academic information (Tang et al., 2024).

Most importantly, verification recorded consistently high scores. Respondents reported checking research claims, citations, bibliographic details, source existence, and original publications. This is particularly significant given documented problems with fabricated AI-generated citations (Oladokun et al., 2025; Watson, 2024). The coexistence of delegation, reliance, caution, and verification, therefore, supports the concept of verified reliance: PhD scholars benefit from AI-assisted efficiency while retaining human responsibility for evaluating scholarly evidence. However, because verification was self-reported, the findings cannot establish the rigor with which such checks were performed (Pudasaini, 2026).

5.1 Study Implications

The findings indicate that universities should approach agentic AI as a complementary scholarly tool rather than a replacement for established research practices. Doctoral education should reinforce AI literacy alongside traditional information literacy skills, specifically in source evaluation, citation verification, bibliographic checking, and comparison of AI-generated information with authoritative academic sources. Academic libraries can support PhD scholars by integrating responsible AI use into research support and information literacy programs. Doctoral supervisors should also encourage suitable task delegation while ensuring that scholars retain responsibility for literature selection, critical reading, interpretation, and evaluation. Provision of clear institutional guidance on acceptable AI use would help scholars distinguish productive AI assistance from excessive dependence. Generally, the findings suggest that effective academic use of agentic AI requires balancing efficiency and delegation with independent judgment, verification, and human oversight.

5.2 Study Limitations

The results should be interpreted in light of several limitations. First, voluntary-response sampling may have introduced self-selection bias, as PhD scholars with greater interest in or experience with AI may have been more inclined to participate. Because the sample comprised 180 PhD scholars from four universities, the results should not be generalized statistically to all PhD scholars in Zambia or to other contexts. Second, the cross-sectional design captured practices and perceptions at a single point in time and cannot establish causal relationships or changes over time. Third, the findings are based on self-reported responses and may not fully reflect participants' actual AI use or the rigor of their verification practices. Fourth, because all variables were measured using the same self-administered questionnaire, common method bias cannot be excluded. Fifth, no documented pilot study, formal content- or construct-validation procedure, or reliability coefficient was available for the questionnaire; the dimension-level findings should therefore be interpreted as descriptive evidence rather than results from a validated measurement scale. Finally, responses from the four universities were pooled, so institution-level and public–private comparisons were beyond the scope of the study.

6. Conclusion

This study shows that agentic AI is emerging as a significant means of scholarly information discovery among PhD scholars in Zambia. The results indicate a shift from traditional searching toward the delegation of specific information-discovery tasks, such as literature identification, summarization, filtering, comparison, and recommendation. However, reliance on agentic AI was associated mainly with making scholarly information discovery faster and easier rather than with complete dependence on the technology. Although respondents found AI-provided scholarly information useful and relevant, they were more skeptical about its accuracy and credibility. Importantly, respondents reported strong verification practices, including checking source

existence, bibliographic details, citations, original publications, and research claims. Overall, agentic AI appears to serve primarily as a supplementary scholarly tool in which efficiency and delegation are combined with human judgment and verification.

In practice, universities should incorporate responsible AI use into doctoral research training and provide specific guidance on appropriate AI use in scholarly work. Academic libraries should strengthen AI- and information-literacy programs that train PhD scholars to check citations, bibliographic information, research claims, and AI-suggested sources against authoritative academic databases and publications. Doctoral supervisors should help students distinguish tasks that can be delegated to AI from those that require independent thinking, reading, interpretation, and evaluation. PhD scholars should use agentic AI tools alongside, not in place of, established scholarly information-discovery tools and should verify the accuracy of AI-generated content before including it in a thesis, publication, or other academic work. These measures can help universities gain efficiency from agentic AI while maintaining scholarly independence, research integrity, and the trustworthiness of doctoral research.

Declarations

Funding

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Conflict of Interest

The author declares no conflict of interest.

Author Contributions (CRediT)

Dalitso Mvula: Conceptualization, Methodology, Investigation, Data Curation, Formal Analysis, Writing – Original Draft, Writing – Review & Editing.

Ethics Statement

Formal approval from an institutional ethics committee was not obtained for this study. The study was an anonymous, minimal-risk, non-interventional questionnaire survey of consenting adult PhD scholars and did not collect clinical, biomedical, or personally identifying information. It was conducted in accordance with the principles of voluntary participation, informed consent, anonymity, and confidentiality, as described in Section 3.6.

Informed Consent

Informed consent was obtained from all participants prior to data collection.

Data Availability

The data supporting the findings of this study are available from the author upon reasonable request.

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Appendix A. Research Instrument

Section A: Demographic Information	
A1. Gender	**Response**
Male	
Female	
A2. Age Group	**Response**
22–24 years	
25–28 years	
Above 28 years	
A3. Year of PhD Study	**Response**
First Year	
Second Year	
Third Year	
Fourth Year	
Fifth Year and Above	

Section B: Use of Agentic AI for Scholarly Information Discovery
Objective: To examine PhD scholars' use of agentic AI for scholarly information discovery.

No.	Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
B1	I use agentic AI to search for scholarly information related to my research topic (e.g., finding research articles, reports, or academic literature).					
B2	I use agentic AI to identify relevant academic articles and research materials (e.g., asking AI to suggest papers, journals, or scholarly sources).					
B3	I use agentic AI to explore unfamiliar research topics and concepts (e.g., obtaining an initial understanding of a new theory, concept, or research area).					

B4	I use agentic AI to identify keywords and search terms for scholarly literature searches (e.g., generating related keywords for Google Scholar or academic databases).					
B5	I use agentic AI at different stages of scholarly information searching (e.g., topic exploration, literature searching, source identification, or follow-up searching).					
Section C: Delegation of Scholarly Information Discovery Tasks **Objective: To assess the extent to which PhD scholars delegate scholarly information discovery tasks to agentic AI.**						
No.	**Statement**	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
C1	I delegate the task of identifying relevant scholarly literature to agentic AI (e.g., asking AI to locate important studies related to my research topic).					
C2	I use agentic AI to narrow down large amounts of scholarly information (e.g., asking AI to identify the most relevant studies from many available sources).					
C3	I delegate the initial summarization of scholarly materials to agentic AI (e.g., obtaining article summaries before deciding which papers require detailed reading).					
C4	I use agentic AI to compare scholarly sources (e.g., comparing the findings, methods, theories, or arguments of different studies).					

C5	I allow agentic AI to recommend further literature or research directions (e.g., asking AI to suggest additional studies, authors, keywords, or subtopics to explore).					
Section D: Reliance on Agentic AI for Scholarly Information Discovery **Objective: To assess PhD scholars' level of reliance on agentic AI for scholarly information discovery.**						
No.	**Statement**	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
D1	I rely on agentic AI when I have difficulty finding relevant scholarly information independently (e.g., using AI when database searches do not provide sufficient relevant results).					
D2	Agentic AI has become an important part of my scholarly information-searching process (e.g., regularly using AI alongside Google Scholar, Scopus, Web of Science, or other databases).					
D3	I rely on agentic AI to help me decide which scholarly sources deserve further examination (e.g., using AI recommendations to prioritize articles for reading).					
D4	I rely on agentic AI to make scholarly information discovery faster and easier (e.g., reducing the time required to identify relevant literature).					
D5	I would find scholarly information discovery more difficult without agentic AI (e.g., locating and filtering relevant research literature would require more time and effort).					

Section E: Perceived Usefulness, Accuracy, and Credibility **Objective: To examine PhD scholars' perceptions of the usefulness, accuracy, and credibility of scholarly information provided by agentic AI.**						
No.	**Statement**	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
E1	I find scholarly information provided by agentic AI useful for my research activities (e.g., literature reviews, research proposals, thesis work, or manuscript preparation).					
E2	Agentic AI generally provides scholarly information relevant to my research needs (e.g., suggested literature corresponds closely to my research topic or question).					
E3	I consider the scholarly information provided by agentic AI to be generally accurate (e.g., explanations of research concepts or findings correspond with reliable academic sources).					
E4	I consider scholarly sources recommended by agentic AI to be generally credible (e.g., recommendations refer to legitimate articles, journals, researchers, or academic sources).					
E5	I am confident in using agentic AI as a supporting tool for scholarly information discovery (e.g., using AI together with established scholarly databases and search systems).					
Section F: Verification Practices for AI-Discovered Scholarly Information **Objective: To assess PhD scholars' verification practices when using scholarly information discovered through agentic AI.**						
No.	**Statement**	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**

F1	I verify whether scholarly sources suggested by agentic AI actually exist (e.g., searching the article title in Google Scholar, Crossref, Scopus, or the publisher's website).					
F2	I check the bibliographic details of references provided by agentic AI before using them (e.g., verifying author, title, journal, year, volume, pages, or DOI).					
F3	I compare scholarly information provided by agentic AI with reliable academic sources (e.g., checking AI-generated information against journal articles, databases, books, or official sources).					
F4	I access the original scholarly source before using information recommended by agentic AI (e.g., opening and reading the original article rather than relying only on an AI-generated summary).					
F5	I verify the accuracy of AI-generated summaries before relying on them (e.g., comparing an AI summary with the abstract, full text, results, or conclusions of the original article).					
F6	I verify AI-provided citations or references before including them in my research work (e.g., checking that the DOI, authors, journal, and article actually exist before citing them).					

F7	I verify important research claims provided by agentic AI before using them in my thesis or publications (e.g., tracing a claim to the original scholarly source and confirming that the source actually supports it).					