talenta PUBLISHER

Data Science : Journal Of Computing And Applied Informatics

Journal homepage: https://jocai.usu.ac.id

Applied Informatics: Librarian Scepticism of Artificial Intelligence in Information Retrieval — Does AI Promote Library Usage or Displace It? Evidence from the Nigerian University Library Landscape

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ARTICLE INFO

Article history:
Received 3 June 2026
Revised 20 July 2026
Accepted 21 July 2026
Available online 31 July 2026

E-ISSN: 2580-829X
P-ISSN: 2580-6769

How to cite:
Dada, K.S.J. "Applied Informatics: Librarians sceptisim of Artificial Intelligence in Information Retrieval - Does AI promote Library Usage or Displace it? Evidence from the Nigerian University Library Landscape," Data Science: Journal of Computing and Applied Informatics, vol. V10, no.2, Jul. 2026, doi: 10.32734/jocai.v10i2.25832

ABSTRACT

Librarian scepticism towards artificial intelligence (AI) tools in information retrieval is routinely reframed in African higher education discourse as a capacity gap. This paper challenges that reframing. Using a convergent mixed-methods design — a survey of 214 librarians across 27 Nigerian universities, 32 semi-structured interviews, and documentary analysis of 81 institutional documents spanning 2015–2025 — the study pursues three objectives: (1) to examine the nature and structural determinants of librarian scepticism towards AI-assisted retrieval; (2) to determine whether AI adoption promotes or displaces substantive library usage in resource-constrained institutions; and (3) to investigate gendered and geographic dimensions of differential AI scepticism. Findings confirm that scepticism is epistemically rational and structurally grounded. In institutions where AI chatbots generate citation lists that the local collection cannot fulfil, the information outcome is zero regardless of interface sophistication — what the study theorises as an information supply chain failure (ISCF), structurally analogous to a health system that achieves a correct diagnosis but cannot dispense the medication. Only 27.1% of librarians reported that AI-generated references were typically retrievable locally (17.8% in rural institutions). Female librarians in northern Nigeria reported the highest scepticism and the lowest institutional support. No sampled institution held an operational AI-resource integration policy. The study concludes that AI adoption without collection integrity undermines library utility, and recommends a policy-first, resource-second integration framework.

Keyword: Artificial intelligence Scepticism, Information retrieval, Information supply chain failure, Librarian professional identity, Nigerian university libraries

1. Introduction

The arrival of large language model (LLM)-based research tools has restructured professional conversation in library and information science (LIS) globally. In Nigeria, this conversation carries a distinctive pathology: practising librarians' scepticism towards AI-assisted retrieval is routinely diagnosed as a deficit requiring training intervention rather than a signal requiring structural response [2], [27], [30]. The present study begins from a different premise and pursues it to an empirically grounded conclusion.

Consider the scenario that anchors this inquiry. A librarian at a rural Nigerian federal university is approached by a postgraduate researcher carrying an AI-generated reference list for community-acquired pneumonia treatment protocols. Examining the list, the repository librarian employs artificial intelligence tools such as large language models, including Ex Libris Alma (AI Metadata Assistant) and Iris.ai. These systems can analyze institutional assets, suggest optimized repository catalog descriptions, and automate index processing by identifying abstract concepts within texts and assigning accurate disciplinary keywords.

However, the structural logic of this failure remains the same as that described by pharmaceutical supply chain scholars: a health worker may correctly diagnose pneumonia but cannot prescribe amoxicillin because the supply chain has failed [5], [39]. The clinical outcome is zero, and the information outcome is equally zero. No chatbot can fix a supply chain failure [3]. This structural critique is largely absent from Nigerian LIS scholarship, which has predominantly focused on readiness, awareness, and competence [19], [33]. This paper addresses that gap by making three key contributions: theoretically, it proposes the Information Supply Chain Failure (ISCF) model; empirically, it presents the first multi-zone mixed-methods study of librarian AI scepticism across Nigerian federal and state universities; and methodologically, it introduces a convergent parallel design incorporating temporal documentary analysis, which is particularly applicable to applied informatics research in the Global South.

1.1. Research Objectives

The following research objectives guided the study:

1. To examine the nature, prevalence, and structural determinants of librarian scepticism towards AI-assisted information retrieval in Nigerian university libraries, distinguishing structurally grounded scepticism from unfamiliarity-based resistance.
2. To determine whether AI tool adoption promotes substantive library usage — defined as verified engagement with locally held collections — or functions as a displacement mechanism redirecting users towards inaccessible or non-existent sources.
3. To investigate gendered and geographic dimensions of differential AI scepticism among Nigerian library professionals, with particular attention to female librarians in rural northern institutions, and to assess whether institutional policy frameworks reflect these dimensions.

2. Literature Review

2.1. AI in Libraries: Global Optimism, African Divergence

Global LIS scholarship has engaged AI integration optimistically across cataloguing [9], reference services [25], collection development [36], and learning analytics [37]. This optimism is anchored in resource-rich institutional contexts where collection integrity is assumed rather than theorised [8]. Comparative African evidence complicates this framing: Zimba and Zulu [40] found that Zambian librarians' scepticism was most strongly predicted by collection inadequacy, not digital literacy deficits; Owusu-Ansah and Amoah [32] found that Ghanaian librarians who had trialled AI tools reported greater post-trial scepticism than those who had not. Fulton [15] and Fulton and Vondracek [16] have consistently argued that information systems must be evaluated for functional fit within specific information ecologies, not in abstraction from them. Nigerian contributions have reproduced the capacity-gap framing without adequately theorising the structural conditions that make scepticism rational [30], [33].

2.2. Information Infrastructure Deficits in Nigerian Universities

The NUC [29] identified library resource inadequacy in 68% of assessed federal universities. NITDA [28] found that 42% of rural-campus libraries operated below minimum bandwidth thresholds for reliable database access. Average library acquisitions budgets fell from 4.2% of institutional expenditure in federal universities in 2015 to 1.8% in 2023, while ICT expenditure rose by 112% over the same period [31], [28]. These conditions constitute structural information poverty [24], [10]: AI tools trained on globally accessible English-language content will systematically underperform in contexts where locally relevant resources are not globally accessible [4]. The hallucination problem — confident generation of incorrect or non-existent citations — compounds retrieval failure in these contexts [20].

2.3. Professional Scepticism and Epistemic Injustice

Professional scepticism in librarianship has been theoretically underexplored. Abbott's [1] jurisdictional framework positions practitioner scepticism as a cognitive claim grounded in contextual expertise — an assertion that local knowledge of collection conditions constitutes an irreducible professional asset [18], [22]. Fricker [14] concept of testimonial injustice — the discounting of a knower's testimony on the basis of identity prejudice — is directly applicable when female librarians' evidence-based scepticism is reinterpreted as technophobia. Kwon et al. [21] and Singh and Nair [34] document that female library professionals in lower-income country contexts report higher scepticism attributable to structurally unequal institutional support, not lower digital literacy — a pattern this study tests in the Nigerian context through an intersectional lens [11], [13].

2.4. Theoretical Framework: The Information Supply Chain Failure Model

The ISCF model integrates supply chain theory [23]), information poverty theory ([10], [24], and professional epistemology ([1], [14]). Lee et al. [23] bullwhip effect — in which small upstream demand distortions produce large downstream supply disruptions — maps analytically onto the AI retrieval context: the chatbot introduces demand distortion by generating citation requests that misrepresent local availability. The library, as supply-chain fulfilment node, receives signals it cannot honour. The downstream consequence is what this study names expectation debt: a structural gap between AI-generated retrieval demand and collection-bounded supply capacity.

The ISCF model specifies four intervention points: (1) collection development, creating the supply-chain substrate; (2) AI-collection integration, calibrating tools to verified holdings; (3) practitioner mediation, recognising librarians' contextual intelligence as a governance resource; and (4) policy architecture, linking AI promotion to collection adequacy assessment. The model is explicitly normative: it identifies not only how ISCF occurs but the conditions under which it can be prevented. Critically, ISCF becomes institutionally entrenched when practitioners best positioned to diagnose it — librarians — are denied epistemic authority over that diagnosis through the misclassification of their scepticism as incapacity.

3. Methodology

This study employed a convergent parallel mixed-methods design [12]: a quantitative survey, semi-structured interviews, and documentary analysis were conducted concurrently, analysed independently, and integrated through joint display analysis [17]. The design responds to Teddlie and Tashakkori [35] argument that complex sociotechnical phenomena require multi-strand designs capable of capturing different structural and temporal dimensions.

3.1. Participants and Sampling

A stratified purposive sampling framework was applied across all six Nigerian geopolitical zones. The NUC [29] accredited university list served as the sampling frame; 27 institutions were selected (15 federal, 12 state), deliberately over-sampling rural-campus universities. Survey instruments were administered to all available professional librarians (LRCN-qualified) within each institution, yielding 214 respondents (response rate: 78.4%). A maximum variation sample of 32 librarians (18 female, 14 male) was drawn for semi-structured interviews, varying on gender, zone, institutional type, and expressed scepticism level. Documentary analysis covered 81 institutional documents across all 27 institutions for the period 2015–2025.

3.2. Instruments and Analysis

The 48-item survey questionnaire (ASCAQ) assessed AI tool awareness and use, scepticism orientation adapted from Luo et al. [26], collection adequacy perceptions, gender-related support disparity, and institutional policy environment (overall $\alpha = .87$). The instrument was piloted with 18 librarians at two non-sampled institutions. Quantitative data were analysed using IBM SPSS v.29 and R v.4.3.1; multiple linear regression examined scepticism predictors and two-way ANOVA tested gender × zone interaction effects. Semi-structured interviews (22 questions; 45–75 minutes) were transcribed, member-checked, and analysed through reflexive thematic analysis [7]; Cohen's $\kappa = 0.79$ on a 20% random sample). Documentary analysis followed Bowen [6] protocol, coded in NVivo 14 using a provisional framework derived from the ISCF model. Ethical approval was obtained from UNN/REC/2024/108 and FUD/IRB/2024/067.

4. Result and Discussion

4.1. Research Objective 1: Nature and Determinants of Librarian Scepticism

Overall scepticism scores were moderate-to-high (M = 3.71, SD = 0.84). The Collection Mismatch Concern subdimension was highest (M = 4.23, SD = 0.71), followed by Hallucination Awareness (M = 3.89, SD = 0.93). Collection Adequacy Perception (M = 2.14, SD = 0.96) and Institutional AI Support (M = 1.87, SD = 0.79) scores were markedly low (Table 1). Multiple regression (Table 2) identified collection adequacy as the strongest scepticism predictor ($\beta = -.47$, $p < .001$), followed by institutional AI support ($\beta = -.31$, $p < .001$), geographic location ($\beta = .22$, $p = .004$), gender ($\beta = .18$, $p = .007$), and internet bandwidth adequacy ($\beta = -.19$, $p = .009$), explaining 54% of variance ($R^2 = .54$).

Table 1. Descriptive Statistics for Key Survey Subscales (N = 214)

Subscale	M	SD	α	Item range
AI Scepticism (Overall)	3.71	0.84	.87	1–5
Collection Mismatch Concern	4.23	0.71	.81	1–5
Hallucination Awareness	3.89	0.93	.78	1–5
Jurisdictional Displacement Concern	3.62	0.88	.75	1–5
Collection Adequacy Perception	2.14	0.96	.82	1–5
Institutional AI Support	1.87	0.79	.84	1–5
Gender-Related Support Disparity	3.44	1.02	.80	1–5

Note. Higher scores on AI Scepticism and subdimensions indicate greater concern. Higher scores on Collection Adequacy Perception and Institutional AI Support indicate more positive assessments. α = Cronbach's alpha.

Table 2. Multiple Regression: Predictors of AI Scepticism (N = 214)

Predictor	B	SE B	β	t	p
Collection Adequacy Perception	−0.46	0.07	−.47	−6.57	< .001
Institutional AI Support	−0.33	0.09	−.31	−3.67	< .001
Geographic Location (rural = 1)	0.29	0.10	.22	2.90	.004
Gender (female = 1)	0.19	0.07	.18	2.71	.007
Internet Bandwidth Adequacy	−0.21	0.08	−.19	−2.63	.009
Constant	5.12	0.41		12.49	< .001

Note. $R^2 = .54$; Adjusted $R^2 = .52$; $F(5, 208) = 48.91$, $p < .001$. Geographic Location: 1 = rural, 0 = urban; Gender: 1 = female, 0 = male. β = standardised coefficient.

Qualitative analysis generated three superordinate themes. First, Rational Scepticism Grounded in Collection Experience: present in 28 of 32 transcripts, articulated not as antipathy towards technology but as a precise assessment of collection-AI mismatch. A senior librarian in the North-West stated:

The chatbot gives the student a reference list that looks excellent. Seven papers, perfectly formatted. But three of those papers — those journals we do not subscribe to. Two citations, I could not find them anywhere. The DOIs are wrong. The AI did not help. It created work for us and confusion for the student. (F-NW-07)

The supply-chain analogy emerged independently across zones: 'It is like being told there is medicine for your patient, but when you go to the pharmacy, there is no medicine. The prescription is perfect. The shelf is empty' (F-SE-14). Second, Scepticism as Professional Jurisdiction: 17 of 32 participants explicitly distinguished between contextual professional judgment and generalised resistance. Third, Institutional

Abandonment and the Erosion of Trust: particularly prevalent in state universities and northern zones, characterised by disinvestment in both collections and professional expertise.

4.2. Research Objective 2: AI Displacement and Collection Integrity

Table 3 presents AI use, library visit, and retrieval fulfilment data by campus location. The critical finding: only 27.1% of librarians reported AI-generated references as typically retrievable locally, falling to 17.8% in rural institutions. Thirty-six percent reported users returning after AI referral failure — the 'failure visit' — in which the library's role is reduced to managing the gap between AI-generated expectation and collection-bounded reality.

Table 3. AI Tool Use, Library Engagement, and Retrieval Fulfilment by Location

Variable	Urban (n=124)	Rural (n=90)	Total (N=214)	Test statistic
Weekly AI tool use (% yes)	61.3%	38.9%	51.9%	$\chi^2(1)=10.74$, p=.001
Weekly library visits (M, SD)	3.41 (1.22)	2.87 (1.34)	3.18 (1.30)	t(212)=2.87, p=.005
AI references retrievable locally (% yes)	34.2%	17.8%	27.1%	$\chi^2(1)=8.13$, p=.004
Users returning after AI failure (% yes)	41.2%	28.9%	36.0%	$\chi^2(1)=4.06$, p=.044
Awareness of institutional AI policy (% yes)	8.1%	4.4%	6.5%	$\chi^2(1)=1.64$, p=.200

Note. AI references retrievable locally = proportion reporting AI-suggested references typically locatable in the institutional collection. Users returning after AI failure = librarians' estimates of users who returned to the library following unsuccessful AI retrieval.

Documentary analysis of 81 institutional documents across 27 universities confirmed the structural picture. None held an operational AI-library integration policy. Of 27 institutions, 19 held collection development policies but only three had revised them since 2019. Library acquisitions budgets fell from an average 4.2% (federal) and 3.1% (state) of institutional expenditure in 2015 to 1.8% and 1.4% respectively by 2023. All 27 institutions referenced AI tools in their 2023 annual library reports; none linked those references to collection coverage assessments. As a principal librarian observed: 'The university is now telling us: promote AI research tools in orientation sessions. Then the student does not come to the library. And when they do come, they come with a list we cannot fill. We have promoted our own displacement' (M-SS-03).

4.3. Research Objective 3: Gender, Geography, and Epistemic Injustice

Female librarians reported significantly higher scepticism than male librarians (M = 3.85 vs. 3.50, t(212) = 3.01, p = .003, d = 0.43). Two-way ANOVA revealed a significant gender × zone interaction, F(5, 203) = 3.24, p = .008, $\eta p^2 = .07$, with the largest gap in the North-West ($\Delta M = 0.78$), North-East ($\Delta M = 0.57$), and North-Central ($\Delta M = 0.37$). Table 4 presents the joint display integrating these quantitative patterns with qualitative themes.

Table 4. Joint Display: Scepticism Scores, Qualitative Themes, and Participant Voices by Zone

Zone	Male M	Female M	Dominant theme	Representative voice
North-West	3.39	4.17	Epistemic dismissal	'My concern was seen as resistance to change, not professional judgment.' (F-NW-11)
North-East	3.44	4.01	Professional jurisdiction	'We know our collection. The AI does not. That should count.' (F-NE-06)
North-Central	3.51	3.88	Infrastructure deficit	'Even if AI was perfect, we cannot load

Zone	Male M	Female M	Dominant theme	Representative voice
				the full text. Bandwidth collapses.' (F-NC-04)
South-East	3.62	3.74	Supply chain analogy	'The prescription is perfect. The shelf is empty.' (F-SE-14)
South-South	3.55	3.69	Displacement	'We have promoted our own displacement.' (M-SS-03)
South-West	3.48	3.62	Balanced concern	'The tool is useful. The collection is not. Fix the collection.' (M-SW-08)

Note. Joint display integrates quantitative scepticism scores (AI Scepticism Scale, range 1–5) with dominant themes from reflexive thematic analysis. The gender gap in scepticism is largest in the three northern zones, where qualitative evidence of epistemic dismissal is most pronounced. M = mean scepticism score.

Qualitative data produced the third superordinate theme, Institutional Abandonment, most sharply from female participants in northern institutions. The pattern is not lower digital literacy but structurally unequal access to institutional recognition, professional development, and decision-making:

When I raised this issue — that the AI was giving students references we do not have — the university librarian said: 'Maybe the students should be more flexible.' Flexible how? We do not have the journals. But because I am a woman and younger, my concern was not seen as valid. (F-NW-11)

This constitutes testimonial injustice [14]: evidence-based professional testimony discounted on the basis of gender and seniority. The consequence is institutional: the practitioners most capable of diagnosing ISCF are excluded from the processes through which that diagnosis could become policy.

5. Discussion

5.1. Scepticism as Structural Intelligence

The dominant framing in extant Nigerian LIS scholarship — scepticism as capacity deficit, remedy as training [2], [30] — is empirically unsupported. The regression model ($R^2 = .54$) demonstrates that scepticism is most powerfully predicted by collection adequacy, institutional support, and infrastructure constraints, not by AI awareness or prior experience. Librarians who are most sceptical are those who know their collections best and who have observed AI-generated demand that their collections cannot fulfil. This is precisely the form of embedded expertise Abbott [1] identifies as the defining characteristic of professional jurisdiction. Dismissing it as technophobia is both theoretically incorrect and practically self-defeating: it redirects scarce institutional resources towards training interventions that do not address the structural dysfunction.

The ISCF model provides the analytical vocabulary this literature has lacked. The 'bullwhip effect' [23] names the mechanism: AI tools distort retrieval demand upstream, and the library absorbs the downstream disruption. The failure visit — identified by 36% of librarians — represents the second-order consequence: the library's service identity degraded from primary information delivery to disappointment management. Yadav [39] concept of demand shifting applies: persistent supply failure produces not escalating advocacy for supply improvement but declining user expectations of service quality, a new degraded equilibrium that is difficult to reverse.

5.2. Gender, Structural Disadvantage, and Policy Failure

The gender × zone interaction ($\eta p^2 = .07$) is both statistically significant and theoretically revealing. The scepticism gap between male and female librarians is not uniform; it is amplified precisely where structural gender inequality in professional access is most severe. Kwon et al. [21] and Singh and Nair [34] identified this pattern cross-nationally; the present study confirms and extends it to the Nigerian context. The reinterpretation of female librarians' scepticism as personal limitation — documented across multiple northern zone interview transcripts — is a concrete institutional mechanism through which the ISCF is perpetuated: the diagnostic intelligence required to fix the supply chain is systematically suppressed by the governance processes that should be drawing on it.

The documentary finding that no institution holds an AI-library integration policy is the capstone of the structural analysis. Nigerian universities have adopted AI tools as a gesture towards modernity while declining to govern the relationship between those tools and the collections that give them local meaning. This is not an oversight; it is a policy choice, and it is a costly one. The sector's insistence on reframing rational, evidence-based scepticism as a capacity gap is costing users information outcomes, costing librarians professional recognition, and costing institutions the opportunity to build information systems that actually function within their own collection constraints.

6. Conclusion

This study has demonstrated, through convergent mixed-methods evidence, that surveyed librarians in Nigerian university libraries expressed skepticism towards AI, while also highlighting how gendered institutional dynamics shape its reception and implementation. The ISCF model introduced here provides a theoretically generative framework for understanding why AI tools fail as information delivery instruments in resource-constrained library contexts, and why the practitioners who diagnose this failure are the most important and most systematically disregarded resource available to institutions seeking to address it. The evidence base for scepticism is solid. The structural case for prioritising collection integrity over AI adoption elegance is compelling. No chatbot fixes a supply chain failure — but a policy framework that is honest about what is broken can begin to do so.

7. Recommendations

For National Policy Bodies (NUC, NITDA, Federal Ministry of Education)

1. Establish a minimum collection retrievability threshold (recommended: 60% of AI-generated citations retrievable within the institutional collection) as a prerequisite for institutional AI tool promotion, integrated into NUC accreditation standards.

2. Develop a national AI-library integration policy framework in consultation with the NLA and LRCN, specifying governance obligations linking AI adoption to collection development.

3. Mandate minimum bandwidth standards for university library buildings with differentiated support for rural-campus institutions, and fund a national institutional repository audit benchmarked against ROARMAP standards.

For University Management and Library Administrators

4. Constitute AI-resource integration committees with mandatory librarian representation at all grades and explicit gender parity requirements, with deliberative rather than merely advisory authority over AI adoption decisions.

5. Link every institutional AI tool promotion decision to a prior collection coverage assessment and targeted acquisition allocation for relevant subject areas.

6. Implement systematic AI-referral failure tracking, reporting quarterly to institutional governance bodies as evidence for library investment advocacy.

7. Design professional development programmes with gender-equitable access architecture: remote attendance options, device lending, and travel parity for female librarians in rural institutions.

For Library Professionals and Researchers

8. Document and formally report supply chain failure incidents through NLA chapters, institutional governance submissions, and peer networks, converting practitioner knowledge into institutional evidence.

9. Develop local information literacy programmes that explicitly address hallucination risk and collection-mismatch limitations of AI tools, positioning the library as the infrastructure that gives AI outputs local operational meaning.

10. Prioritise longitudinal and experimental research designs in Nigerian LIS scholarship, moving beyond cross-sectional attitude surveys to causal investigation of the relationship between collection investment, AI adoption, and retrieval outcomes. Extend ISCF model testing to other Global South information contexts — health information, agricultural extension, legal aid — where analogous supply-demand structural mismatches are likely to obtain.

8. Acknowledgements

The authors express profound gratitude to the 214 librarians who completed the survey and the 32 colleagues who gave their time for in-depth interviews. Their candour about structural realities provided the empirical and intellectual foundation of this research. Gratitude is extended to institutional library directors at all 27 sampled universities for facilitating data access, and to the four research assistants — Adaeze N. Okonkwo, Musa K. Ibrahim, Temitope A. Bankole, and Hafsat Y. Danmusa — whose logistical and linguistic contributions were indispensable. The Nigerian Library Association is acknowledged for endorsing the research design and facilitating survey distribution. Two anonymous reviewers of a conference draft materially strengthened the paper's methodology and discussion. The views expressed are solely those of the authors.

9. Conflict of Interest

The author declares no conflict of interest in relation to this research. This study was conducted independently without any financial support or sponsorship from external organizations that could have influenced its outcomes.

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