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AI Research Literacy and Publication Readiness: Sequential Mediation through Research Self-Efficacy and AI-Assisted Research Capability

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Abstract

This study investigated the associations among AI Research Literacy (AIRL), Research Self-Efficacy (RSE), AI-Assisted Research Capability (AIRC), and Perceived Publication Readiness (PPR) among research-involved respondents in Mogadishu, Somalia. Drawing on Social Cognitive Theory and Human Capital Theory, it examined five direct relationships, four specific indirect relationships, and a sequential indirect pathway. A quantitative cross-sectional survey was conducted using purposive sampling. Data from 455 respondents were analyzed using partial least squares structural equation modeling (PLS-SEM). All five direct associations were positive and statistically significant: AIRL was associated with RSE ($\beta = 0.740$, $p < .001$) and AIRC ($\beta = 0.277$, $p < .001$); RSE was associated with AIRC ($\beta = 0.522$, $p < .001$) and PPR ($\beta = 0.374$, $p < .001$); and AIRC was associated with PPR ($\beta = 0.429$, $p < .001$). All specific indirect associations, including the sequential pathway from AIRL through RSE and AIRC to PPR, were significant. The model explained 55.8% of the variance in PPR and demonstrated positive predictive relevance. The findings indicate that AI-related knowledge, research confidence, and applied capability are jointly associated with perceived publication readiness. The cross-sectional, self-reported design supports interpretation of statistical associations, not causal or temporal conclusions.

1. Introduction

Artificial intelligence (AI) is reshaping scholarly research by supporting literature discovery, research design, data analysis, manuscript preparation and publication-related activities (Owusu et al., 2026; Van Quaquebeke et al., 2025). These developments create opportunities for researchers in Mogadishu to strengthen their research practices and scholarly productivity. However, preparing manuscripts for peer-reviewed publication requires methodological competence, critical judgment, academic writing proficiency and adherence to research integrity standards (Busse et al., 2022; Jalongo, 2026). Although generative AI can facilitate research-related activities, its use also concerns inaccurate information, fabricated references, methodological errors and excessive reliance on automated outputs (Khlaif et al., 2023; Raitskaya & Tikhonova, 2024). Consequently, access to AI technologies alone may be insufficient to strengthen researchers' preparedness for scholarly publication. Understanding the knowledge, psychological confidence and practical capabilities associated with responsible AI-assisted research is therefore increasingly important.

AI Research Literacy refers to researchers’ capacity to understand AI, evaluate its limits and outputs, and make informed, responsible decisions about its use in scholarly work. AI-Assisted Research Capability, by contrast, concerns the perceived ability to apply AI in specific research tasks, such as literature synthesis, instrument development, data interpretation, and manuscript preparation (Annapureddy et al., 2025; Chee et al., 2025; Chiu, 2025; Owusu et al., 2026). The distinction is between informed judgment about AI and the practical enactment of AI-supported work; literacy may support capability but does not guarantee it. Existing findings are compatible with this distinction: AI literacy and technical understanding have been associated with efficacy-related beliefs and output quality, but do not consistently translate into academic performance (Bećirović et al., 2025). Research also links applied AI

competencies to research skills while indicating that their contribution depends on task type and researchers' evaluation of AI-generated outputs (Bui et al., 2026; Seker et al., 2025).

Beyond technological competencies, Research Self-Efficacy represents an important psychological dimension of scholarly activity. Grounded in Social Cognitive Theory, Research Self-Efficacy refers to researchers' confidence in their ability to perform research tasks successfully, including developing research questions, reviewing literature, applying appropriate methods, analyzing findings and preparing scholarly manuscripts. It differs from actual research competence because it reflects perceived capability rather than demonstrated performance. A meta-analysis by Livinți et al. (2021) identified substantial associations between Research Self-Efficacy and research productivity, research identity, research goals, research attitudes and supportive training environments. Subsequent studies have also linked Research Self-Efficacy with scholarly engagement and research-related competencies (Han et al., 2024; Luo et al., 2026). Nevertheless, evidence concerning its relationship with AI-related competencies remains mixed. While some studies suggest that practical AI knowledge and application are associated with greater task-specific self-efficacy, others indicate that technological readiness does not necessarily translate directly into Research Self-Efficacy (Bećirović et al., 2025; Luo et al., 2026). These findings suggest that Research Self-Efficacy warrants investigation as a distinct psychological construct within AI-assisted scholarly research.

The relationships among these constructs can be considered through Social Cognitive Theory and Human Capital Theory. Social Cognitive Theory explains how efficacy beliefs are associated with effort, persistence, and engagement in challenging tasks; it therefore helps frame the proposed associations involving Research Self-Efficacy. Human Capital Theory treats knowledge and skills as resources whose value depends on their application; it helps explain why AI Research Literacy may be associated with practical AI-Assisted Research Capability and why that capability may be relevant to publication preparation. Together, the theories motivate examining how knowledge, confidence, and applied capability are related to Perceived Publication Readiness. They provide complementary explanations for the proposed model, while the cross-sectional design permits tests of statistical associations only.

Perceived Publication Readiness refers to researchers' self-assessed preparedness to develop, organize, critically revise, and prepare scholarly manuscripts for submission to peer-reviewed journals. It concerns perceived preparedness, not independently verified publication outcomes, manuscript quality, or acceptance (Jalongo, 2026; Busse et al., 2022). Prior research has emphasized writing support, mentoring, research training, and institutional resources as relevant to publication-related competencies (Busse et al., 2022). The studies cited here address adjacent outcomes, including AI literacy, self-efficacy, research skills, academic performance, or research productivity (Bećirović et al., 2025; Bui et al., 2026; Zhu & Yang, 2026), rather than the joint relationship of these constructs with perceived publication readiness.

This literature points to a specific, bounded gap. Existing studies provide evidence on separate or partial relationships among AI literacy, efficacy-related beliefs, and research competence, but the literature

reviewed here does not establish how AI Research Literacy, Research Self-Efficacy, and AI-Assisted Research Capability are jointly associated with Perceived Publication Readiness. In particular, the proposed sequence in which literacy is associated with research self-efficacy, which is in turn associated with applied capability and perceived readiness, remains underexamined in the publication-readiness context. This is a gap in the studies reviewed for this manuscript, rather than a claim that no similar model exists across the wider literature. The mixed findings on AI-related competencies and self-efficacy further support testing, rather than presuming, the proposed associations (Bećirović et al., 2025; Luo et al., 2026).

Mogadishu provides an underrepresented setting in which to examine these relationships. Findings from other educational and institutional environments may not transfer directly where research training, mentoring, technological resources, and institutional support differ (Busse et al., 2022). The study therefore offers context-specific evidence about research-involved respondents in Mogadishu; its contribution is an empirical examination in this setting, not a claim of national representativeness. Because the respondent profile includes substantial numbers of diploma- and bachelor's-level participants, the scope of interpretation is tied to the stated research-involvement eligibility and the sample characteristics reported in the Results.

Against this background, the present study examines associations among AI Research Literacy, Research Self-Efficacy, AI-Assisted Research Capability, and Perceived Publication Readiness among research-involved respondents in Mogadishu, Somalia. It tests five direct associations, four simple indirect associations, and one sequential indirect association in a model informed by Social Cognitive Theory and Human Capital Theory. The study contributes by distinguishing knowledge-oriented literacy, research confidence, practical AI-assisted capability, and perceived publication preparedness, while examining their relationships within an underrepresented research setting. The findings may inform research training and institutional support, subject to the sample's composition and the limits of self-reported measures. Because the design is cross-sectional, indirect pathways are interpreted as statistical associations rather than causal mechanisms or temporal sequences.

2. Literature Review and Hypothesis Development

2.1 Theoretical Foundations

The model draws on Social Cognitive Theory and Human Capital Theory to explain complementary parts of the proposed relationships. Social Cognitive Theory treats self-efficacy as a task-specific belief associated with effort, persistence, learning, and responses to difficulty (Bandura, 1977). It therefore informs the proposed associations of AI Research Literacy with Research Self-Efficacy (H1), and of Research Self-Efficacy with AI-Assisted Research Capability and Perceived Publication Readiness (H3 and H5). AI literacy alone, however, is not a mastery experience; the H1 rationale is that informed understanding may reduce uncertainty, while confidence may also depend on practice, feedback, supervision, and prior success. Human Capital Theory treats knowledge and skills as potentially

productive resources whose value depends on their application (Becker, 1962). It informs the proposed association of AI Research Literacy with AI-Assisted Research Capability (H2) and the association of applied capability with perceived publication readiness (H4). The indirect hypotheses (H6–H10) combine these accounts: AI-related knowledge may be associated with confidence, confidence with applied engagement, and applied capability with perceived readiness. These theories motivate the hypothesized ordering; the cross-sectional data cannot establish that temporal sequence or causation.

AI-literacy frameworks also clarify the intended construct boundaries. AIRL concerns understanding, evaluating, and making responsible judgments about AI; AIRC concerns applying AI to research tasks while checking outputs and retaining researcher responsibility; RSE concerns confidence in conducting research; and PPR concerns perceived preparedness to submit scholarly work. These constructs are related but should not be treated as interchangeable. The distinction is conceptual and must also be supported by the item content and measurement evidence. Where indicators combine AI application with literacy or research confidence, shared wording may weaken empirical separation; accordingly, the structural paths should be interpreted in light of the discriminant-validity results. In research settings, responsible use includes source verification, data protection, disclosure, awareness of bias and hallucination, and researcher accountability (Long & Magerko, 2020; Ng et al., 2021; Kasneci et al., 2023; Dwivedi et al., 2023; Cheng et al., 2025; Gray, 2026). Deliberate practice can support skill development (Ericsson, 2008), while AI-assisted decisions require critical human oversight (Steyvers & Kumar, 2024).

2.2 Direct Associations

AI Research Literacy and Research Self-Efficacy. AIRL may be positively associated with RSE because understanding AI capabilities, limitations, and appropriate applications may reduce uncertainty when researchers approach demanding scholarly tasks (Jin et al., 2026; Parker & Becker, 2026). This proposed association is framed through Social Cognitive Theory because RSE is a belief about one's capacity to perform tasks; however, literacy should not be assumed to create efficacy by itself. Mastery experiences, feedback, supervision, and access to suitable tools may determine whether knowledge is accompanied by confidence. Prior findings are mixed: practical AI application and technical understanding have been linked with efficacy-related beliefs in some settings, whereas critical appraisal, trust, and supervisory support may condition the relationship (Bećirović et al., 2025; Luo et al., 2026; Zhu & Yang, 2026). Research self-efficacy literature likewise identifies research experience and training environments as relevant to confidence and productivity (Phillips & Russell, 1994; Brown et al., 1996; Livinți et al., 2021).

H1: AI Research Literacy is positively associated with Research Self-Efficacy.

AI Research Literacy and AI-Assisted Research Capability. AIRL may be positively associated with AIRC because knowledge of AI capabilities, limitations, and responsible-use principles can inform tool selection, workflow design, output checking, and ethical integration across research tasks (Long & Magerko, 2020; Ng et al., 2021; Parker & Becker, 2026). Human Capital Theory frames this relationship as the possible translation of a knowledge resource into applied research capability; that translation is likely to depend on practice and methodological training. Research on generative AI describes support for

literature processing, drafting, feedback, and analysis, alongside risks of fabricated information, bias, privacy loss, and over-reliance (Kasneci et al., 2023; Bui et al., 2026; Dai & Chan, 2026; Ibrahim & Mahmoud, 2026; Mabirizi et al., 2025). Literacy may therefore support capability without substituting for supervised practice or human judgment.

H2: AI Research Literacy is positively associated with AI-Assisted Research Capability.

Research Self-Efficacy and AI-Assisted Research Capability. RSE may be positively associated with AIRC because researchers who feel capable of planning, conducting, interpreting, and revising research may be more willing to engage with difficult AI-supported tasks, persist when outputs are inadequate, and seek feedback or alternative strategies (Bandura, 1977; Livinți et al., 2021; Zhu & Yang, 2026). Social Cognitive Theory thus explains why efficacy beliefs may be associated with the effort and persistence involved in applying AI. Research self-efficacy has been linked to research productivity and scholarly development, although training conditions and available resources also matter (Phillips & Russell, 1994; Brown et al., 1996; Falola et al., 2025). Confidence can be miscalibrated, however, and is not equivalent to verified competence, particularly where AI outputs require methodological and ethical scrutiny (Bećirović et al., 2025; H. Zhang et al., 2025).

H3: Research Self-Efficacy is positively associated with AI-Assisted Research Capability.

AI-Assisted Research Capability and Perceived Publication Readiness. AIRC may be positively associated with PPR because responsible application of AI may support literature synthesis, research planning, analysis, drafting, language refinement, referencing, and manuscript revision (Vadner et al., 2026; Yousef et al., 2025; Raitskaya & Tikhonova, 2024). Human Capital Theory provides the rationale: applied skills may be useful resources for publication preparation when they improve researchers' ability to complete relevant tasks. These applications may reduce routine burdens and help early-career or non-native English-speaking researchers organize publication work, but efficiency does not equal publication competence or acceptance. Readiness also requires theoretical coherence, methodological rigor, transparent reporting, accurate citations, ethical compliance, and alignment with journal requirements (Cheng et al., 2025; Gray, 2026; Yousef et al., 2025).

H4: AI-Assisted Research Capability is positively associated with Perceived Publication Readiness.

Research Self-Efficacy and Perceived Publication Readiness. RSE may be positively associated with PPR because confidence in research planning, analysis, interpretation, revision, and scholarly communication may support persistence through manuscript development. Social Cognitive Theory explains this proposed relationship through the association of efficacy beliefs with effort and resilience; it does not imply that confidence ensures publication readiness or success (Bandura, 1977; Phillips & Russell, 1994; Brown et al., 1996; Mydin et al., 2021). Self-assessments may be over- or under-calibrated, and publication outcomes also depend on methodological quality, mentoring, institutional support, and editorial decisions (H. Zhang et al., 2025; Busse et al., 2022).

H5: Research Self-Efficacy is positively associated with Perceived Publication Readiness.

2.3 Indirect Associations

AIRL may be indirectly associated with AIRC through RSE if understanding AI reduces uncertainty and is accompanied by greater confidence in undertaking AI-supported research. Human Capital Theory frames AIRL as a knowledge resource, while Social Cognitive Theory explains why efficacy beliefs may be associated with engagement and persistence in applying that resource (Bandura, 1977; Becker, 1962). This pathway is plausible but conditional: AI knowledge does not itself establish mastery, and access to practice, task specificity, trust, and supervision may shape whether knowledge is accompanied by confidence and applied capability (Bećirović et al., 2025; Peng et al., 2026; Luo et al., 2026; Zhu & Yang, 2026). Given the study design, the proposed indirect pathway is tested statistically and not as a temporal mechanism.

H6: AI Research Literacy is positively associated with AI-Assisted Research Capability indirectly through Research Self-Efficacy.

AIRL may be indirectly associated with PPR through AIRC when AI-related knowledge is translated into accurate, ethical, and researcher-controlled practice. Human Capital Theory provides the connecting rationale: knowledge may become relevant to publication preparation when expressed as applied capability in research and manuscript tasks. AI-literacy frameworks and higher-education research describe potential support for information processing, writing, feedback, and analysis, while warning that unverified automation can introduce error and weaken accountability (Long & Magerko, 2020; Ng et al., 2021; Kasneci et al., 2023; Bui et al., 2026; Dai & Chan, 2026). The proposed indirect association therefore concerns applied capability, not simple exposure to AI tools, and does not imply objective publication outcomes.

H7: AI Research Literacy is positively associated with Perceived Publication Readiness indirectly through AI-Assisted Research Capability.

RSE may be indirectly associated with PPR through AIRC if confidence is accompanied by sustained engagement in AI-supported research tasks and that engagement is associated with practical capability. Social Cognitive Theory explains the proposed role of efficacy beliefs in effort and persistence, while AIRC represents the applied skill resource relevant to manuscript preparation. Research self-efficacy is associated with research productivity and training experiences, and AI-assisted capability captures task application (Phillips & Russell, 1994; Brown et al., 1996; Zhu & Yang, 2026). Institutional support, prior publication experience, and disciplinary expertise remain plausible alternative explanations for these associations.

H8: Research Self-Efficacy is positively associated with Perceived Publication Readiness indirectly through AI-Assisted Research Capability.

AIRL may be indirectly associated with PPR through RSE when stronger AI-related understanding is accompanied by greater confidence in complex research and publication tasks. Social Cognitive Theory identifies efficacy beliefs as relevant to persistence when tasks become uncertain or demanding; AI literacy may provide informational and evaluative resources relevant to those tasks (Bećirović et al., 2025; Livinți et al., 2021; Peng et al., 2026). This proposed pathway remains distinct from AI-specific self-efficacy, and the outcome remains perceived readiness rather than verified manuscript quality or publication productivity. The cross-sectional test can establish a statistical indirect association but cannot show that confidence transmits an effect over time.

H9: AI Research Literacy is positively associated with Perceived Publication Readiness indirectly through Research Self-Efficacy.

The serial pathway integrates the proposed theoretical roles of knowledge, confidence, and applied capability. Human Capital Theory frames AIRL as a potentially productive knowledge resource and AIRC as applied skill; Social Cognitive Theory explains why RSE may be associated with researchers' engagement in challenging scholarly tasks and the use of those resources. Together, these perspectives motivate examining whether AIRL is statistically associated with PPR through RSE and AIRC, while recognizing that practical AI use requires technical judgment and human oversight (Becker, 1962; Bandura, 1977; Cheng et al., 2025; Vadner et al., 2026). Prior studies cited here more often address separate links than the complete sequence (Bui et al., 2026; Peng et al., 2026; Zhu & Yang, 2026). The proposed sequence is therefore a testable, theory-informed association, not evidence of temporal or causal mediation.

H10: AI Research Literacy is positively associated with Perceived Publication Readiness through the sequential indirect pathway involving Research Self-Efficacy and AI-Assisted Research Capability.

3. Methodology

This study adopted a quantitative cross-sectional survey design to examine the relationships among AI Research Literacy, Research Self-Efficacy, AI-Assisted Research Capability, and Perceived Publication Readiness among research-involved individuals in Mogadishu, Somalia. A cross-sectional design was appropriate for estimating associations among these constructs as measured during one data-collection period; it does not establish temporal ordering or causal relationships (Spector, 2019). The model was estimated to be using partial least squares structural equation modeling (PLS-SEM) in SmartPLS to assess the measurement and structural models and the specified direct and indirect associations (Hair & Alamer, 2022; Hair et al., 2019).

Data were collected from June to September 2026. Purposive sampling recruited research-involved respondents in Mogadishu. The questionnaire recorded participants' reported roles, including student, researcher, and lecturer. Eligibility was based on involvement in research activities, use of an AI tool for at least one research activity, and voluntary informed consent. Accordingly, the study operationalized its

target population as researchers defined by research involvement, rather than by degree level or occupational title.

The questionnaire was administered online through KoboToolbox. For some participants, a questionnaire session was scheduled and assistance was provided; responses were then captured in KoboToolbox. The questionnaire began with an informed-consent question. Participants who selected “Yes” could proceed, while those who selected “No” were asked to stop. A total of 513 response records were received before final screening. The first 10 respondents were used to pilot-test the questionnaire; items that caused confusion or misunderstanding were revised, and pilot responses were excluded. The final analytical sample comprised 455 usable responses, meaning 58 records were not retained. The study records identify 10 pilot responses among these exclusions but do not specify the reasons for the remaining 48.

The questionnaire was administered in English and was not translated because the target respondents were considered able to understand it. The final model measured four constructs with four indicators each: AI Research Literacy, Research Self-Efficacy, AI-Assisted Research Capability, and Perceived Publication Readiness. Participants responded using a five-point scale: 1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, and 5 = strongly agree. The wording of the 16 indicators is provided in Appendix A. The supplied questionnaire does not identify the original validated source scale for each item. Citations in Appendix A therefore identify literature used to ground each construct, not verified sources for the exact item wording.

Data analysis followed a two-stage partial least squares structural equation modeling (PLS-SEM) procedure in SmartPLS. The four constructs were assessed using the reported reflective measurement criteria: outer loadings, Cronbach’s alpha, composite reliability, AVE, Fornell–Larcker comparisons, and HTMT. Structural paths were evaluated using coefficients, two-tailed tests, and the reported 95% confidence intervals. Direct and indirect paths were tested with 5,000 bootstrap resamples. The model specification included the five hypothesized direct paths (H1–H5) and the five hypothesized indirect paths (H6–H10); no direct AIRL → PPR path was estimated. R^2 and f^2 were used to summarize explanatory power and path effect sizes. Predictive assessment used Q^2predict and PLSpredict, with indicator-level prediction errors compared against a linear-model (LM) benchmark where reported (Shmueli et al., 2019; Hair et al., 2019). The archived manuscript and Appendix A do not document the SmartPLS version, algorithm settings, bootstrap confidence-interval method or random seed, PLSpredict folds and repetitions, or the screening decisions for the 48 non-pilot records excluded from the 513 received records. These settings and screening records must be supplied from the analysis project or output for exact independent reproduction; they are not inferred here. Because the data are cross-sectional and self-reported, indirect paths are interpreted as statistical associations rather than causal or temporal mediation.

Ethical approval

was obtained from the relevant institutional research ethics committee before data collection. The study was conducted in accordance with the **Declaration of Helsinki**, as applied by the **Benaadir Research, Consultancy and Evaluation Center (BRCE)**. Before accessing the online questionnaire, participants received an electronic information and consent statement explaining the study's purpose, the voluntary nature of participation, confidentiality measures, and their right to withdraw before submitting their responses. Participants provided electronic consent before proceeding. Participation was voluntary and anonymous, and responses were handled confidentially in accordance with applicable ethical standards for research involving human participants.

4. Results

4.1. Preliminary univariate analysis

4.1.1 Demographic Characteristics of the Respondent

Table 1 summarizes the demographic and professional characteristics of the 455 respondents. All respondents reported using AI (100%). Most were aged 18–24 years (63.30%), and 64.62% were male. Bachelor's degree holders made up the largest educational group (70.55%), and the most reported professional role was student (68.35%), followed by researcher (13.19%) and lecturer (10.11%). Regarding research experience, 51.21% had less than one year of experience, while 14.29% reported none. For AI experience, 34.07% had used AI for less than six months, 21.76% for 6–12 months, and 16.26% reported no accumulated experience. This is compatible with all respondents reporting AI use if the use question captured current use and the experience item captured how long they had been using AI: respondents in the "None" category may have only recently begun using it and not yet accumulated experience. Overall, the sample was predominantly young, and respondents generally reported limited research and AI experience.

Table 1
Demographic and professional characteristics of respondents (N = 455)

Variables	Categories	Frequency (n)	Percentage (%)
Do you use AI?	Yes	455	100
Age	18–24 years	288	63.30
	25–34 years	129	28.35
	35–44 years	27	5.93
	45 years and above	10	2.20
	Prefer not	1	0.22
Gender	Male	294	64.62
	Female	161	35.38
Educational Qualification	Diploma	84	18.46
	Bachelor's degree	321	70.55
	Master's degree	45	9.89
	PhD	5	1.10
Professional Role	Student	311	68.35
	Researcher	60	13.19
	Lecturer	46	10.11
	Early-career professional	38	8.35
Research Experience	None	65	14.29
	Less than 1 year	233	51.21
	1–3 years	121	26.59
	4–6 years	28	6.15
	7 years and above	8	1.76
AI Experience	None	74	16.26
	Less than 6 months	155	34.07
	6–12 months	99	21.76
	1–2 years	86	18.90
	3 years and above	41	9.01
Total respondents		455	100.00

4.1.2 Descriptive Analysis

As shown in Table 2*, the mean scores were relatively high across all four constructs, ranging from 3.603 to 3.676. Perceived Publication Readiness recorded the highest mean (M = 3.676, SD = 0.898), followed by AI-Assisted Research Capability (M = 3.644, SD = 0.880), AI Research Literacy (M = 3.635, SD = 0.876), and Research Self-Efficacy (M = 3.603, SD = 0.916). The standard deviations indicate some variation in respondents' scores. All skewness values were negative, ranging from − 0.998 to − 0.795, indicating that responses tended toward the higher end of the scale. Overall, the findings suggest generally favorable responses across the constructs, assuming that higher scale scores represent more favorable perceptions.*

Table 2
Descriptive statistics of the study constructs (N = 455)

Construct	Mean	SD	Skewness
AI Research Literacy (AIRL)	3.6346	.87622	− .949
Research Self-Efficacy (RSE)	3.6033	.91581	− .795
AI-Assisted Research Capability (AIRC)	3.6440	.87968	− .859
Perceived publication Readiness (PPR)	3.6758	.89840	− .998

4.1.3 Assessment of Multicollinearity

The available collinearity results are reported in Table 3 for predictors of Perceived Publication Readiness. VIF values ranged from 2.277 to 2.816 and tolerance values from 0.355 to 0.439; none exceeded the cited VIF threshold of 5.0 (Hair et al., 2019). These results do not document collinearity checks for every endogenous equation in the structural model, so the inference is limited to the predictor set shown in Table 3.

Table 3
Assessment of multicollinearity

Predictor Construct	Tolerance	VIF
AI Research Literacy (AIRL) →Perceived publication Readiness (PPR)	.422	2.371
Research Self-Efficacy (RSE) →Perceived publication Readiness (PPR)	.355	2.816
AI-Assisted Research Capability (AIRC) →Perceived publication Readiness (PPR)	.439	2.277

4.2 Multivariate analysis

4.2.1 Analysis of measurement model

As shown in Table 4, the measurement model demonstrated acceptable indicator reliability, internal consistency, and convergent validity. Outer loadings ranged from 0.751 to 0.828, exceeding the

recommended threshold of 0.708 and indicating adequate indicator reliability (Hair & Alamer, 2022). Cronbach's alpha values ranged from 0.792 to 0.831, indicating satisfactory internal consistency (Hair & Alamer, 2022). Composite reliability values ranged from **0.795 to 0.832**, supporting construct reliability (Raykov, 1997). AVE values ranged from **0.616 to 0.663**, exceeding 0.50 and confirming adequate convergent validity (Fornell & Larcker, 1981). Overall, the constructs demonstrated sufficient measurement quality for structural-model assessment and hypothesis testing (Hair & Alamer, 2022).

Table 4
Measurement model results

Latent Variables	Items	Factor Loading	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
AI-Assisted Research Capability	AIRC1	0.808	0.792	0.795	0.616
AI-Assisted Research Capability	AIRC2	0.760			
AI-Assisted Research Capability	AIRC3	0.811			
AI-Assisted Research Capability	AIRC4	0.758			
AI Research Literacy	AIRL1	0.819	0.794	0.797	0.618
AI Research Literacy	AIRL2	0.800			
AI Research Literacy	AIRL3	0.774			
AI Research Literacy	AIRL4	0.751			
Perceived Publication Readiness	PPR1	0.823	0.831	0.832	0.663
Perceived Publication Readiness	PPR2	0.795			
Perceived Publication Readiness	PPR3	0.828			
Perceived Publication Readiness	PPR4	0.812			
Research Self-Efficacy	RSE1	0.793	0.811	0.811	0.638
Research Self-Efficacy	RSE2	0.807			
Research Self-Efficacy	RSE3	0.796			

Latent Variables	Items	Factor Loading	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Research Self-Efficacy	RSE4	0.799			

As shown in Table 5, the Fornell–Larcker criterion supports discriminant validity among the four constructs. The diagonal values, representing the square roots of AVE, were **0.785** for AI-Assisted Research Capability, **0.786** for AI Research Literacy, **0.815** for Perceived Publication Readiness, and **0.799** for Research Self-Efficacy. Each diagonal value was higher than its corresponding inter-construct correlations, indicating that each construct shares more variance with its own indicators than with other constructs. Accordingly, the constructs demonstrate adequate empirical distinctiveness and discriminant validity (Fornell & Larcker, 1981; Hair & Alamer, 2022).

Table 5
Fornell–Larcker criterion

Latent variables	AI-Assisted Research Capability	AI Research Literacy	Perceived Publication Readiness	Research Self-Efficacy
AI-Assisted Research Capability	**0.785**			
AI Research Literacy	0.663	**0.786**		
Perceived Publication Readiness	0.701	0.613	**0.815**	
Research Self-Efficacy	0.727	0.740	0.686	**0.799**

As shown in Table 6, the HTMT values ranged from **0.752 to 0.871**. Most values were below the conservative threshold of 0.85, indicating adequate discriminant validity among the constructs. The AI-Assisted Research Capability–Perceived Publication Readiness value (**0.863**) and the AI-Assisted Research Capability–Research Self-Efficacy value (**0.871**) slightly exceeded 0.85 but remained below the more liberal threshold of 0.90. Overall, the results provide acceptable evidence of discriminant validity, although the two borderline relationships should be interpreted cautiously and verified using bootstrapped HTMT confidence intervals (Henseler et al., 2015; Hair & Alamer, 2022).

Table 6
Heterotrait–monotrait ratio (HTMT)

Latent variables	AI-Assisted Research Capability	AI Research Literacy	Perceived Publication Readiness	Research Self-Efficacy
AI-Assisted Research Capability				
AI Research Literacy	0.833			
Perceived Publication Readiness	0.863	0.752		
Research Self-Efficacy	0.871	0.821	0.835	

4.2.2 Structural model analysis and hypothesis testing

As shown in Table 7, all five specified direct associations were positive and statistically significant. AI Research Literacy was positively associated with Research Self-Efficacy (H1: β = .740, t = 21.554, p < .001, 95% CI [.666, .801]) and AI-Assisted Research Capability (H2: β = .277, t = 4.409, p < .001, 95% CI [.153, .400]). Research Self-Efficacy was positively associated with AI-Assisted Research Capability (H3: β = .522, t = 8.506, p < .001, 95% CI [.396, .636]) and Perceived Publication Readiness (H5: β = .374, t = 6.842, p < .001, 95% CI [.270, .485]). AI-Assisted Research Capability was also positively associated with Perceived Publication Readiness (H4: β = .429, t = 7.938, p < .001, 95% CI [.319, .532]). The model did not estimate a direct AIRL → PPR path; these results therefore do not establish a direct AIRL–PPR association. The five specified direct hypotheses were supported. Given the cross-sectional design, the findings represent associations and do not establish causal effects.

Table 7
Direct structural path estimates

Hypothesis	Path	β	t	p	LL	UL	Decision
H1	AI research literacy -> research self-efficacy	0.740	21.554	< .001	0.666	0.801	Significant
H2	AI research literacy -> AI-assisted research capability	0.277	4.409	< .001	0.153	0.400	Significant
H3	Research self-efficacy -> AI-assisted research capability	0.522	8.506	< .001	0.396	0.636	Significant
H4	AI-assisted research capability -> perceived publication readiness	0.429	7.938	< .001	0.319	0.532	Significant
H5	Research self-efficacy -> perceived publication readiness	0.374	6.842	< .001	0.270	0.485	Significant

Note. β = standardized path coefficient; LL and UL are the lower and upper limits of the 95% confidence interval. Two-tailed bootstrap tests used 5,000 resamples. All reported p values are < .001.

4.3 Assessment of the Structural Model Prediction

The structural model was evaluated using the coefficient of determination (R^2), the f^2 effect-size statistic, and predictive assessment. R^2 summarizes explained variance and f^2 summarizes the change in explained variance associated with a predictor. Predictive assessment is reported separately using Q^2predict and PLSpredict; these procedures should not be conflated with the traditional Stone–Geisser Q^2 obtained through blindfolding.

4.3.1 Coefficient of Determination (R^2)

The coefficient of determination (R^2) indicates the proportion of variance in each endogenous construct explained by its predictors. Using commonly applied PLS-SEM guidelines, values of approximately .75, .50, and .25 represent substantial, moderate, and weak explanatory power, respectively (Hair & Alamer, 2022). As shown in Table 8, the model explains 56.3% of the variance in AI-Assisted Research Capability (R^2 = .563), 55.8% in Perceived Publication Readiness (R^2 = .558), and 54.7% in Research Self-Efficacy (R^2 = .547). These values indicate moderate explanatory power. Adjusted R^2 values were close to the corresponding R^2 values (.561, .556, and .546), suggesting stable explanatory estimates after adjustment for the number of predictors. AI Research Literacy and Research Self-Efficacy jointly predict AI-Assisted Research Capability in the specified model, while AI-Assisted Research Capability and Research Self-Efficacy predict Perceived Publication Readiness (Hair & Alamer, 2022; Shmueli et al., 2019).

Table 8
Explained variance in endogenous constructs

Endogenous Construct	R-square	R-square Adjusted	Interpretation
AI-assisted research capability	0.563	0.561	moderate
perceived publication readiness	0.558	0.556	moderate
Research self-efficacy	0.547	0.546	moderate

4.3.2 Effect Size (f^2)

As shown in Table 9, f^2 estimates indicate different contributions of the specified predictors. AI Research Literacy had a large effect on Research Self-Efficacy ($f^2 = 1.209$). Research Self-Efficacy had a medium effect on AI-Assisted Research Capability ($f^2 = .282$), and AI-Assisted Research Capability had a medium effect on Perceived Publication Readiness ($f^2 = .197$). The AI Research Literacy effect on AI-Assisted Research Capability was small ($f^2 = .079$). The Research Self-Efficacy effect on Perceived Publication Readiness was small and close to, but below, the conventional medium-effect threshold ($f^2 = .149$; Hair & Alamer, 2022; Hair et al., 2019).

Table 9
Effect sizes for structural paths

Structural Path	f-square	Effect Size
AI research literacy -> research self-efficacy	1.209	Strong
AI research literacy -> AI-assisted research capability	0.079	Small
Research self-efficacy -> AI-assisted research capability	0.282	Medium
AI-assisted research capability -> perceived publication readiness	0.197	Medium
Research self-efficacy -> perceived publication readiness	0.149	Small (near medium)

4.3.3 Predictive Relevance (Q^2predict)

Table 10 reports positive Q^2predict values for Research Self-Efficacy (.543), AI-Assisted Research Capability (.434), and Perceived Publication Readiness (.370). These values are from the reported Q^2predict/PLSpredict assessment and indicate predictive relevance under that procedure (Shmueli et al., 2019). They are not traditional Stone–Geisser Q^2 values: no blindfolding procedure or Stone–Geisser Q^2 result is documented in the supplied materials. Table 12 provides the indicator-level PLSpredict comparison with the LM benchmark. The construct-level RMSE and MAE summaries in Table 10 should be checked against the final SmartPLS export because the archived materials do not include the underlying analysis project or output.

Table 10
Construct-level Q²predict and prediction-error summary

Endogenous Construct	Q²predict	RMSE	MAE	Assessment
RSE	0.543	0.680	0.494	Q²predict > 0
AIRC	0.434	0.756	0.572	Q²predict > 0
PPR	0.370	0.799	0.600	Q²predict > 0

4.4 Indirect Statistical Association Analysis

Table 11 reports positive indirect associations for all five hypothesized pathways. AI Research Literacy was indirectly associated with AI-Assisted Research Capability through Research Self-Efficacy (H6: β = .386, *t* = 7.574, *p* < .001, 95% CI [.287, .486]). AI Research Literacy was also indirectly associated with Perceived Publication Readiness through AI-Assisted Research Capability (H7: β = .119, *t* = 3.656, *p* < .001, 95% CI [.061, .189]). Research Self-Efficacy was indirectly associated with Perceived Publication Readiness through AI-Assisted Research Capability (H8: β = .224, *t* = 5.942, *p* < .001, 95% CI [.155, .304]). The indirect association between AI Research Literacy and Perceived Publication Readiness through Research Self-Efficacy was also positive and significant (H9: β = .277, *t* = 6.352, *p* < .001, 95% CI [.196, .367]). Finally, the serial indirect association from AI Research Literacy to Perceived Publication Readiness through Research Self-Efficacy and AI-Assisted Research Capability was significant (H10: β = .166, *t* = 5.591, *p* < .001, 95% CI [.113, .229]). All reported confidence intervals excluded zero. These estimates represent indirect paths within the specified model; because no direct path from AI Research Literacy to Perceived Publication Readiness is reported, the findings do not establish whether the indirect pathways account for a total, partial, or full relationship. The cross-sectional design also precludes causal or temporal mediation claims.

Table 11
Indirect path estimates and hypothesis tests

Hypothesis	Indirect path	β	t	p	LL	UL	Decision
H6	AIRL → RSE → AIRC	0.386	7.574	< .001	0.287	0.486	Significant
H7	AIRL → AIRC → PPR	0.119	3.656	< .001	0.061	0.189	Significant
H8	RSE → AIRC → PPR	0.224	5.942	< .001	0.155	0.304	Significant
H9	AIRL → RSE → PPR	0.277	6.352	< .001	0.196	0.367	Significant
H10	AIRL → RSE → AIRC → PPR	0.166	5.591	< .001	0.113	0.229	Significant

Note. β = standardized indirect path coefficient; LL and UL are the lower and upper limits of the 95% confidence interval. Two-tailed bootstrap tests used 5,000 resamples. All reported p values are < .001.

As shown in Table 12, all indicator-level Q^2predict values were positive, ranging from .219 to .372. Under PLSpredict, the PLS-SEM model had lower RMSE than the LM benchmark for 11 of 12 indicators; RSE3 was the exception. PLS-SEM had lower MAE for 8 of 12 indicators, while the LM benchmark had lower MAE for RSE3, PPR1, PPR2, and PPR3. Thus, the internal PLSpredict comparison indicates some predictive advantage over the LM benchmark, but not uniformly across indicators. This is not external validation; replication on independent data is needed before claiming generalizable predictive performance (Shmueli et al., 2019; Hair et al., 2019).

Table 12
Indicator-level PLSpredict results

Indicator	Q²predict	PLS-SEM RMSE	PLS-SEM MAE	LM RMSE	LM MAE
RSE1	0.356	0.899	0.668	0.906	0.672
RSE2	0.372	0.896	0.649	0.906	0.652
RSE3	0.364	0.924	0.689	0.922	0.684
RSE4	0.288	0.998	0.764	1.001	0.777
AIRC1	0.306	0.966	0.721	0.976	0.725
AIRC2	0.228	1.005	0.787	1.013	0.795
AIRC3	0.288	0.920	0.683	0.921	0.688
AIRC4	0.243	0.953	0.731	0.961	0.736
PPR1	0.255	0.959	0.742	0.961	0.737
PPR2	0.255	0.948	0.723	0.954	0.722
PPR3	0.246	0.980	0.742	0.983	0.739
PPR4	0.219	0.951	0.697	0.959	0.705

Note. Q²predict = PLSpredict predictive relevance statistic; LM = linear-model benchmark. Lower RMSE and MAE values indicate better prediction error performance.

5. Discussion

This study examined whether AI Research Literacy (AIRL) was statistically associated with Research Self-Efficacy (RSE), AI-Assisted Research Capability (AIRC), and Perceived Publication Readiness (PPR), including the proposed indirect and serial indirect pathways. All five direct hypotheses (H1–H5) and all five indirect hypotheses (H6–H10) were supported by positive path coefficients and bootstrap confidence intervals that excluded zero. The overall pattern is theoretically coherent, but its interpretation must remain associational: the cross-sectional design captures constructs during one data-collection period and cannot establish temporal ordering, causal transmission, or reciprocal effects (Spector, 2019). Accordingly, the findings support the proposed relational model within this sample rather than demonstrating that AI literacy causes confidence, capability, or publication readiness.

The strongest direct association was between AIRL and RSE (H1: $\beta = 0.740$, 95% CI [0.666, 0.801]; $f^2 = 1.209$). This result is consistent with Social Cognitive Theory, which positions efficacy beliefs as relevant to effort, persistence, and engagement with demanding tasks (Bandura, 1977), and with evidence that research self-efficacy is associated with research-related outcomes across educational and scholarly settings (Livinți et al., 2021). Substantively, researchers who understand how AI systems can be selected, evaluated, verified, and used responsibly may feel more able to approach research tasks

involving AI. Nevertheless, the magnitude should be interpreted cautiously. AIRL and RSE were measured through the same self-report instrument, and both involve respondents' judgments about their own capability. Conceptual proximity and common-source measurement may therefore strengthen the observed covariance. The result supports a close association between knowledge-oriented literacy and perceived research confidence, not an experimentally demonstrated increase in confidence caused by literacy training.

H2 was also supported, but the AIRL–AIRC association was materially weaker (β = 0.277, 95% CI [0.153, 0.400]; f^2 = 0.079) than the AIRL–RSE association. This difference is important because it qualifies a simple assumption that knowing more about AI automatically produces stronger applied capability. AI-literacy frameworks distinguish conceptual understanding and critical evaluation from enacted practice, task-specific judgment, and responsible application (Long & Magerko, 2020; Ng et al., 2021; Chee et al., 2025). The smaller coefficient is therefore theoretically plausible: researchers may understand AI limitations and verification requirements while lacking repeated opportunities, institutional support, or discipline-specific practice through which knowledge becomes operational capability. It is also compatible with evidence that AI-literacy dimensions do not relate uniformly to self-efficacy, output quality, or academic performance (Bećirović et al., 2025). The finding does not contradict H2; rather, it supports the hypothesis in a qualified form and indicates that literacy alone may be insufficient for strong applied performance.

The association between RSE and AIRC was stronger than the direct AIRL–AIRC path (H3: β = 0.522, 95% CI [0.396, 0.636]; f^2 = 0.282). This pattern is consistent with the social-cognitive proposition that perceived capability can shape engagement with difficult tasks and persistence when problems arise (Bandura, 1977). It is also compatible with a human-capital interpretation in which acquired knowledge becomes productive only when individuals are able and willing to mobilize it in practice (Becker, 1962). However, RSE and AIRC remain perceptual constructs, and their relatively strong relationship may partly reflect shared confidence language in the indicators. The result should therefore be read as evidence that research confidence is closely associated with perceived ability to apply AI, not as proof that confidence produces technically competent or independently verified AI use. Future studies should compare self-reports with observed research tasks, audit trails, or evaluated manuscripts.

Both AIRC and RSE were positively associated with PPR, supporting H4 and H5. The AIRC–PPR path was larger (H4: β = 0.429, 95% CI [0.319, 0.532]; f^2 = 0.197) than the RSE–PPR path (H5: β = 0.374, 95% CI [0.270, 0.485]; f^2 = 0.149). The comparatively stronger AIRC association suggests that respondents' perceived ability to use AI in literature review, analysis, writing, referencing, and revision is more proximate to feeling prepared for manuscript submission than confidence alone. This interpretation is consistent with research-lifecycle approaches to AI literacy that emphasize applied judgment, verification, and human responsibility throughout scholarly work (Parker & Becker, 2026). At the same time, the RSE effect remains meaningful because confidence may support persistence through revision, criticism, and methodological difficulty. The f^2 value of 0.149 is just below the conventional 0.15 benchmark; it should therefore be described as small and near-medium rather than medium. Most

importantly, PPR is a self-assessment. The findings do not demonstrate better manuscripts, higher publication rates, or greater journal acceptance.

The indirect results provide additional support for the proposed relational structure. H6 (AIRL → RSE → AIRC) was positive and relatively large among the indirect paths (β = 0.386, 95% CI [0.287, 0.486]), which is consistent with the stronger AIRL–RSE and RSE–AIRC direct associations. H7 (AIRL → AIRC → PPR) was smaller (β = 0.119, 95% CI [0.061, 0.189]), reflecting the weaker direct AIRL–AIRC path. H8 (RSE → AIRC → PPR) was positive (β = 0.224, 95% CI [0.155, 0.304]), indicating that applied capability statistically links research confidence with perceived publication readiness. H9 (AIRL → RSE → PPR) was also positive (β = 0.277, 95% CI [0.196, 0.367]). These differences in magnitude are substantively informative: the results suggest that AI literacy may be more closely connected to readiness when it is accompanied by confidence or translated into applied capability. Nonetheless, each estimate is a product-of-paths statistic. Statistical significance does not establish that the intervening construct transmits an effect over time, and the cross-sectional design cannot distinguish mediation from correlated or reciprocal processes (Spector, 2019).

The serial indirect association specified in H10 was positive and significant (β = .166, 95% CI [.113, .229]). This result is consistent with the proposed relational pattern in which AI-related knowledge, research confidence, applied AI capability, and perceived publication readiness are associated. Human Capital Theory frames knowledge and skills as potentially productive resources, while Social Cognitive Theory helps explain how efficacy beliefs may relate to effort and persistence in scholarly work (Bandura, 1977; Becker, 1962). The serial ordering remains theoretically specified rather than empirically demonstrated. Prior research experience, mentoring, institutional resources, publication history, or general digital competence could influence several constructs simultaneously. Because the model did not estimate a direct AIRL → PPR path, it does not estimate the total AIRL–PPR association and cannot classify the indirect paths as full or partial mediation.

The measurement findings reinforce the need for qualified interpretation. Internal consistency, composite reliability, outer loadings, AVE, and the Fornell–Larcker comparisons were acceptable for the retained indicators. However, HTMT values for AIRC–PPR (0.863) and AIRC–RSE (0.871) exceeded the conservative 0.85 benchmark, although they remained below 0.90. This mixed evidence suggests that the constructs are empirically related and may not be sharply separated in respondents' self-assessments. HTMT is designed to identify problems that the Fornell–Larcker criterion may overlook; therefore, favorable Fornell–Larcker results do not erase the caution raised by the higher HTMT values (Henseler et al., 2015). Because bootstrapped HTMT confidence intervals were not available, the structural paths involving AIRC should not be interpreted as if construct distinctiveness were beyond question. The findings are best understood as evidence of related dimensions of perceived research capability, confidence, and readiness that require further validation with revised items and objective indicators.

The model showed moderate explanatory power for RSE, AIRC, and PPR. The reported Q^2predict values were positive, and the indicator-level PLSpredict comparison showed lower RMSE for 11 of 12 indicators and lower MAE for 8 of 12 indicators relative to the LM benchmark. These findings describe Q^2predict and PLSpredict results; they should not be characterized as traditional Stone–Geisser Q^2 because the supplied report does not document a blindfolding analysis. The prediction comparison is mixed and based on the reported internal procedure, so it supports further validation rather than claims of external predictive validity or readiness for high-stakes decisions (Shmueli et al., 2019).

Taken together, the findings support the hypothesized model while also identifying its boundary conditions. AIRL, RSE, and AIRC appear to be interrelated resources associated with perceived publication readiness among research-involved respondents in Mogadishu, but their relationships should not be generalized to all Somali researchers or interpreted as evidence of verified research competence. The strongest implication is not that AI tools independently make researchers publication-ready; it is that research-focused AI knowledge may be most useful when combined with confidence, supervised practice, critical verification, and institutional support. This interpretation is consistent with researcher-oriented AI-literacy frameworks that emphasize responsible application across the research lifecycle rather than simple tool familiarity (Parker & Becker, 2026). Future research should test the model longitudinally, compare self-report measures with observed performance, examine institutional and disciplinary moderators, and assess whether training interventions improve manuscript quality or publication outcomes rather than perceived readiness alone.

6. Conclusion, Limitations and Policy Recommendations

This study examined the relationships among AI Research Literacy (AIRL), Research Self-Efficacy (RSE), AI-Assisted Research Capability (AIRC), and Perceived Publication Readiness (PPR) among 455 research-involved respondents in Mogadishu, Somalia. All five hypothesized direct associations and all five hypothesized indirect associations were supported using 5,000 bootstrap resamples and 95% confidence intervals. AIRL was strongly associated with RSE, RSE was more strongly associated with AIRC than AIRL was directly associated with AIRC, and both AIRC and RSE were positively associated with PPR. The serial indirect association from AIRL through RSE and AIRC to PPR was also statistically significant. The findings therefore support an integrated interpretation in which research-focused AI knowledge, perceived research confidence, and applied capability operate as related resources in respondents' assessments of publication preparedness. This interpretation is consistent with Social Cognitive Theory, which emphasizes the relevance of efficacy beliefs to engagement and persistence, and with human-capital reasoning, which treats acquired knowledge and skills as potentially productive resources (Bandura, 1977; Becker, 1962). The contribution is nevertheless bound: the study demonstrates statistical association within the observed sample, not causal ordering, verified competence, manuscript quality, publication productivity, or journal acceptance.

Several limitations should guide interpretation. First, the cross-sectional design measured all focal constructs during one data-collection period and therefore cannot establish temporal precedence,

causal mediation, reciprocal effects, or change over time (Spector, 2019). The integrated theoretical model specifies a plausible sequence, but the data cannot confirm that AIRL precedes RSE, RSE precedes AIRC, or AIRC precedes PPR. Second, purposive sampling of research-involved respondents concentrated in Mogadishu, limits representativeness and external validity; the findings should not be generalized to all Somali researchers, institutions, disciplines, or regions. Third, the survey relied on self-reported responses collected through an online KoboToolbox questionnaire, including scheduled researcher-assisted sessions, which may introduce social-desirability effects, recall error, differential assistance, and common-method variance. Fourth, 513 response records were received but only 455 were analyzed: the first 10 respondents were used for pilot testing and excluded after confusing wording was revised, while criterion-specific reasons for the remaining 48 excluded records are not retained in the archived materials. Fifth, the instrument was administered in English without translation; although the target respondents were considered able to understand English research terminology, comprehension was not independently assessed beyond pilot feedback, and a complete item-by-item change log is unavailable. Sixth, the archived questionnaire does not verify the exact administered wording or the original source-scale attribution for every retained indicator, so construct-level citations should not be interpreted as proof of verbatim adoption from validated scales. Seventh, the measurement evidence was acceptable for internal consistency and convergent validity, but two HTMT values exceeded the conservative .85 benchmark, bootstrapped HTMT confidence intervals were unavailable, and the close conceptual relationship among AIRC, RSE, and PPR may inflate structural associations (Henseler et al., 2015). Eighth, the model did not estimate a direct AIRL–PPR path, did not include potentially relevant controls such as prior publication experience, institutional support, discipline, or general digital competence, and used perceived publication readiness rather than objective manuscript or publication outcomes. Finally, positive Q^2 values and generally useful PLSpredict results do not establish external predictive validity; indicator-level predictive performance was mixed and requires replication against independent samples and objective benchmarks (Shmueli et al., 2019).

Universities, research institutes, funders, and professional research centers in Somalia should develop staged AI-in-research programmes that combine AI literacy, research self-efficacy, supervised practice, and explicit safeguards for research integrity. Initial training should address core AI concepts, tool selection, prompt and workflow design, source verification, hallucination and bias detection, privacy and confidential-data protection, transparent disclosure of AI assistance, and the continuing responsibility of the human researcher. Because the AIRL–AIRC association was weaker than the RSE–AIRC association, training should not stop at awareness sessions: institutions should provide repeated discipline-specific exercises, mentoring, feedback on real literature reviews and manuscripts, and access to approved tools so that knowledge can be translated into observable capability. Because PPR is a perception rather than an objective outcome, programme evaluation should combine confidence measures with assessed research tasks, citation accuracy, methodological quality, manuscript-quality indicators, and subsequent submission or publication outcomes. Institutions should also establish screening and documentation procedures for AI-assisted work, including records of tool use, verification steps, data-protection decisions, and authorial responsibility. These recommendations are consistent with researcher-focused

AI-literacy frameworks that place critical judgment and responsible application across the entire research lifecycle (Long & Magerko, 2020; Ng et al., 2021; Parker & Becker, 2026). Implementation should begin with locally piloted, resource-sensitive programmes and be evaluated longitudinally, with attention to unequal connectivity, language accessibility, disciplinary differences, and the risk of treating self-confidence as a substitute for demonstrated scholarly competence.

Declarations

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript. The research was conducted independently without any financial, personal, or institutional relationships that could be perceived as influencing the results or interpretation of the study.

Ethics Approval and Consent to Participate

Applicable.

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Author Contribution

Abdinor Abukar Ahmed: Conceptualization, methodology, data analysis, and first drafting of the manuscript.Mumin Yusuf Mohamed and Osman Abdulrahman Mohamed: Data curation and preparation of the initial written draft.All other authors: Data collection, post-drafting contributions, and review of the manuscript.

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Data Availability

Supplementary Appendix A is provided as a single workbook containing seven sheets: Measurements, Terms, Sampling Procedure, Dataset, Questionnaire, Data Dictionary, and Study Documentation. Together, these sheets document the available English questionnaire items, construct definitions and references, sampling and data-collection procedures, retained respondent-level data, variable coding,

and study and ethics information. The Measurements and Questionnaire sheets reproduce the English item wording available in the archived questionnaire record; exact source-scale attribution and item-level adaptation history were not verified.

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Figures

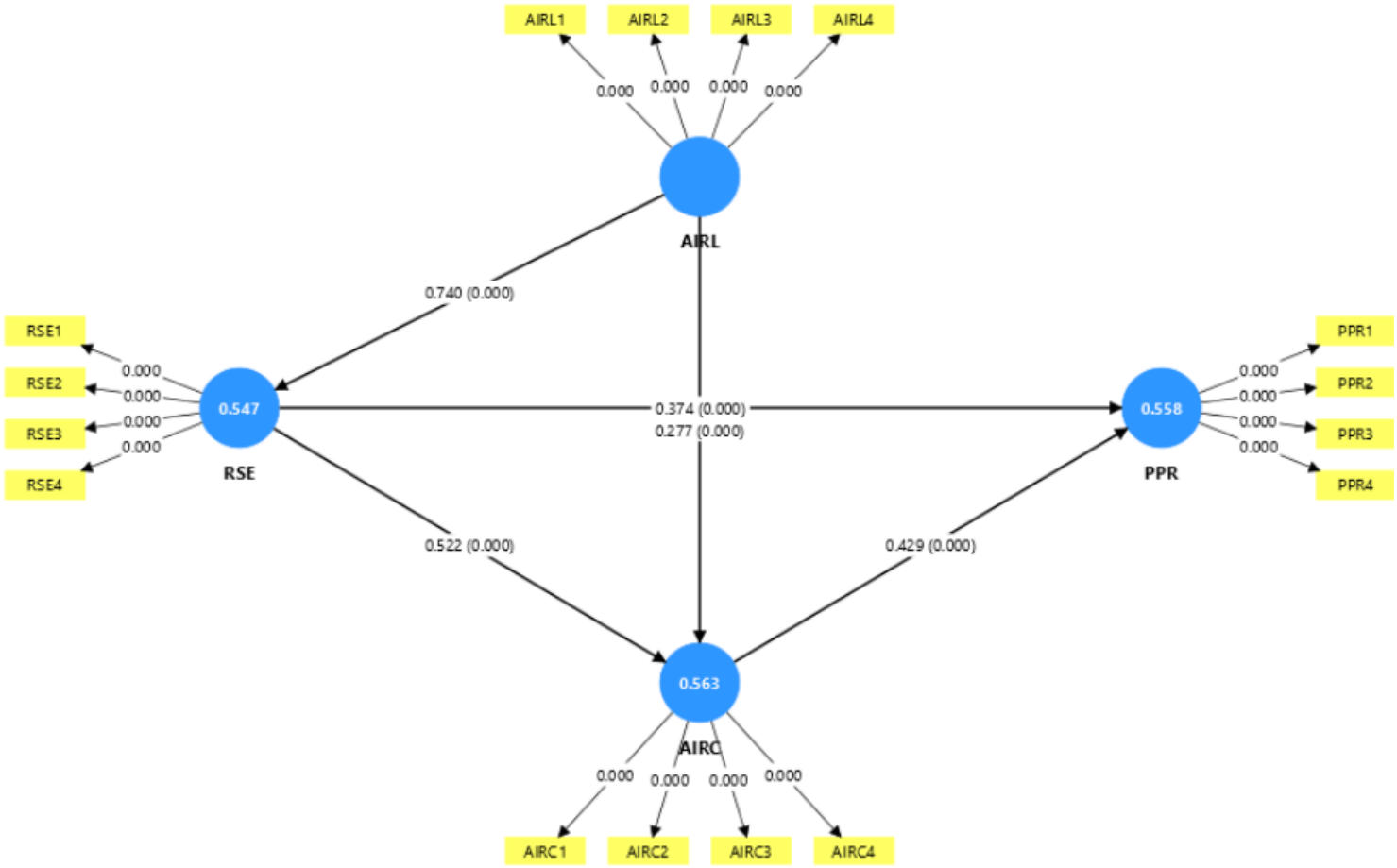


Figure 1

Structural model diagram based on the reconciled final reported paths and indicator loadings.

Supplementary Files

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- AppendixA.xlsx