



Examining the mediating role of knowledge management processes between information literacy self-efficacy and user satisfaction with information systems

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Abstract

Introduction. This study examines the impact of information literacy self-efficacy on shaping knowledge management processes and user satisfaction with information systems among agricultural knowledge workers in Punjab, Pakistan. Although information literacy and knowledge management have been widely examined, limited research has modelled them as multidimensional higher-order constructs within agricultural research organisations.

Method. Data were collected from 415 agricultural knowledge workers using stratified proportionate sampling: a survey instrument measured information literacy self-efficacy, knowledge management processes, and user satisfaction with information systems.

Analysis. The data were analysed using SmartPLS 4. A disjoint two-stage approach was employed to estimate higher-order measurement and structural models. Reliability and validity of both lower- and higher-order constructs were assessed before hypothesis testing.

Results. The results indicated that information literacy self-efficacy had a significant positive effect on knowledge management processes and user satisfaction with information systems. Knowledge management processes also significantly mediated the relationship between information literacy self-efficacy and user satisfaction.

Conclusion. The findings demonstrate that strengthening agricultural knowledge workers' information literacy self-efficacy enhances knowledge acquisition, sharing and utilisation, which in turn improves satisfaction with organisational information systems. The study extends the application of higher-order modelling in the agricultural research context.

Introduction

The rapid advancement of artificial intelligence (AI) has fundamentally transformed the landscape of information systems, reshaping how knowledge is accessed, processed, and utilised across research-intensive environments. AI-driven technologies—such as machine learning algorithms, intelligent information retrieval systems, and predictive analytics—are increasingly embedded within organisational information infrastructures, enabling users to manage vast amounts of data (Davenport & Ronanki, 2018; Jarrahi, 2018). But to gain actionable insights from this vast amount of data requires information literacy self-efficacy. This skill is crucial to navigate the AI-driven information systems in research organisations.

In the era of knowledge-intensive economies, information literacy self-efficacy has emerged as a cornerstone for information system effectiveness and organisational performance (Shahzad et al., 2022; Shonfeld et al., 2022; Wu, 2018). Research organisations, especially those in the agricultural sector, understand that the ability of knowledge workers to efficiently identify, evaluate, and utilize information resources directly influences the generation, dissemination, and application of new knowledge (Batool et al., 2023; Lopez, 2020). Agricultural research institutes in Punjab, Pakistan, play a pivotal role in addressing challenges of food security, climate resilience, and rural development (Shahzad et al., 2023). Within such settings, knowledge workers are expected to possess technical expertise in machine learning algorithms, intelligent information retrieval systems, and predictive analytics (Assefa, 2011). Their capacity to demonstrate confidence in their ability to handle diverse AI-augmented information environments is commonly referred to as information literacy self-efficacy (Naveed & Mahmood, 2021).

Self-efficacy determines how much effort people will expend, how long they will persevere when facing obstacles, and how resilient they are to setbacks (Atikuzzaman & Ahmed, 2023). Building on Bandura's (1999) social cognitive theory, Serap Kurbanoglu et al. (2006) introduced the concept of information literacy self-efficacy as the degree to which individuals believe they are competent to perform information tasks successfully. Information literacy self-efficacy has been conceptualised as an individual's belief in their competence to effectively search, access, analyse, and synthesise information in AI-enabled environments (Pinto et al., 2013). Higher levels of self-efficacy enhance an individual's motivation to engage with information tasks, machine learning algorithms, intelligent information retrieval systems, and predictive analytics (Naveed & Mahmood, 2021; Spisak, 2022). However, information skills alone are not sufficient (Akhtar et al., 2023). In organisational contexts, information must be transformed into actionable knowledge through structured knowledge management processes, such as acquisition, sharing, and utilisation (Gold et al., 2001; Lee & Choi, 2003). For agricultural knowledge workers, the interplay between information literacy self-efficacy and knowledge management processes is particularly salient because they frequently engage in collaborative research (Akhtar et al., 2023; Shahzad et al., 2023) and collaborative AI platforms.

At the organisational level, effective knowledge management processes contribute to improved decision-making, innovation, and ultimately to higher user satisfaction with information systems (Bhattacharjee, 2001; DeLone & McLean, 2003). With the growing integration of AI in information science, these processes automate knowledge acquisition, enhance information retrieval, and support data-driven decision-making (Novalin et al., 2024). AI-driven technologies, such as machine learning algorithms and intelligent information retrieval systems, further strengthen the efficiency and effectiveness of organisational information systems (Davenport & Ronanki, 2018; Wamba et al., 2017). User satisfaction with these information systems reflects the extent to which individuals perceive information systems, particularly AI-enabled systems, as meeting their professional needs, providing timely access to relevant knowledge, and supporting task performance (Ibrahim, Zin, Aman-Ullah, & Ghazi, 2023). Understanding the pathways through which information literacy self-efficacy enhances user satisfaction with information systems—

directly and indirectly via knowledge management processes—is thus critical for designing supportive organisational environments in agricultural research. Thus, this study develops and tests a mediation model linking information literacy self-efficacy, knowledge management processes, and user satisfaction with information systems among agricultural knowledge workers in Punjab, Pakistan.

This study makes several important contributions to the existing body of literature. First, it extends research on information literacy self-efficacy by examining its role not only as an individual competence but also as a driver of organisational knowledge management processes in the context of agricultural research institutes in Punjab, Pakistan. This context has been underrepresented in prior studies. Second, it conceptualises both information literacy self-efficacy and knowledge management processes as higher-order latent constructs, advancing measurement practices and providing a more refined understanding of their multidimensional nature. Third, by empirically testing the mediating role of knowledge management processes, the study clarifies how individual information capabilities are translated into user satisfaction with information systems. Thus, the relationship between information literacy self-efficacy bridges micro-level and macro-level perspectives in knowledge research. Fourth, it contributes to information systems success models by positioning user satisfaction as a dependent outcome shaped by both information literacy self-efficacy and knowledge management processes. This enriches the explanatory power of information system evaluation frameworks. Fifth, this study contributes to AI in information science by showing that the effectiveness of AI-enabled information systems depends on users' information literacy self-efficacy and knowledge management processes. Thus, the study highlights the importance of human competencies in realising AI value. Finally, the study offers context-specific insights for agricultural knowledge workers in developing economies, where effective use of information systems is critical for addressing food security, climate resilience, and rural development challenges. The study also broadens the global relevance and applicability of information literacy and knowledge management processes research.

Literature review

Previous studies have shown that information literacy self-efficacy positively influences learning outcomes (Aharony & Gazit, 2019; Bacarrisas, 2023), research productivity (Batoool et al., 2023; Shahzad et al., 2023), collaborative engagement (Zhao, 2024), and interaction with collaborative AI platforms (Sidra & Mason, 2026). In AI-driven information environments, information literacy self-efficacy enables knowledge workers to effectively engage with intelligent information systems, including machine learning-based retrieval tools and data analytics platforms (Alon & Malinoff, 2026; Bećirović et al., 2025). This suggests that information literacy self-efficacy is increasingly essential for navigating AI-augmented information systems and extracting meaningful insights from algorithmically generated outputs. For knowledge workers in agricultural research institutes, high information literacy self-efficacy is critical because their daily tasks require accessing a broad range of print and digital sources, including AI-enabled databases, and interpreting statistical or visual data (Abbas, 2016). It is also important because agricultural knowledge workers prepare research outputs such as technical reports, scientific articles, and extension manuals (Eastwood et al., 2012). These research outputs are developed using AI-assisted tools for data analysis, writing, and knowledge synthesis, making strong information literacy capabilities indispensable.

Information literacy self-efficacy and knowledge management processes

Prior research indicates that individuals with higher information literacy self-efficacy are more confident in their ability to search diverse sources, synthesise information, and apply it to their work (Pinto et al., 2013; Wu, 2018). Individuals with higher information literacy self-efficacy are more likely to effectively engage with AI technologies and utilise advanced intelligent information systems. Although information literacy self-efficacy is an individual-level construct, it has significant implications for knowledge management processes (Al-Emran et al., 2018). Workers

with strong information literacy self-efficacy are more likely to actively engage in knowledge acquisition by consulting diverse sources, including scientific data systems, AI-enabled databases and machine learning-driven information retrieval systems, field surveys, and stakeholder feedback (Ali & Warraich, 2020; Alzahrani & Seth, 2021). They are also more inclined to participate in knowledge sharing because confidence in information handling reduces fear of judgment and enhances willingness to exchange insights with colleagues (Budiardjo et al., 2017; Choi & Song, 2020; Dong et al., 2016). Similarly, high information literacy self-efficacy facilitates knowledge utilisation, as individuals who believe in their competence are more likely to apply information to practical problem-solving (Jasin et al., 2024; Karlinsky-Shichor & Zviran, 2016).

Empirical studies provide support for these links. For example, Tsai and Tsai (2003) found that internet self-efficacy positively influenced students' ability to acquire relevant information online. Information literacy students were more effective in collaborative knowledge sharing (Hwang et al., 2018; Rohma & Khoirunnisa, 2024; Zamir & Kim, 2022). Safdar, Batool, and Mahmood (2020) demonstrated that confidence in information skills predicted knowledge-sharing behaviour. Drawing on these findings, we propose the first hypothesis:

H₁: Information literacy self-efficacy positively impacts knowledge management processes.

Knowledge management processes and user satisfaction with information systems

User satisfaction with information systems is widely recognised as a key measure of system success (Bhattacharjee, 2001; DeLone & McLean, 2003). User satisfaction with information systems reflects the extent to which users perceive that an information system meets their needs, supports their tasks, and provides value (Al-Emran et al., 2018). AI-driven information systems enhance user experiences by enabling intelligent data processing and personalised information retrieval. Machine learning algorithms improve the accuracy and relevance of information provided to users. These AI capabilities increase system responsiveness and support more effective decision-making in research environments (Jarrahi, 2018; Wilson & Daugherty, 2018). In agricultural research contexts, user satisfaction with the information systems is crucial because researchers depend on these systems for accessing global agricultural databases, analysing field data, and disseminating research outputs (Lopez et al., 2020; Shahzad et al., 2023).

The effectiveness of knowledge management processes is closely tied to user satisfaction with information systems. When knowledge acquisition mechanisms are AI-augmented and intelligent, workers perceive information systems as providing relevant and timely resources. When sharing practices are encouraged, systems are seen as supportive of collaboration and collective learning (Alhendawi, 2019; Laily et al., 2024). When utilisation is emphasised, workers find that information systems contribute directly to solving problems and enhancing productivity (Shahzad et al., 2023). Empirical studies suggest that well-functioning knowledge management processes enhance trust in information systems, reduce redundancy, and increase perceived system usefulness (Gold et al., 2001; Lee & Choi, 2003). Accordingly, we hypothesise:

H₂: Knowledge management processes positively impact user satisfaction with information systems.

Information literacy self-efficacy and user satisfaction with information systems

Several lines of evidence suggest that information literacy self-efficacy directly shapes user satisfaction with information systems (Ibrahim et al., 2019; Ibrahim et al., 2023; Naveed & Mahmood, 2021; Tsai & Tsai, 2003). Users leverage AI-enabled information systems more effectively when they possess strong information literacy self-efficacy. They critically evaluate machine learning-generated outputs and integrate them into their research tasks with greater confidence (Alon & Malinoff, 2026; Ng, 2012; Siddiq et al., 2016). Confident information users are more capable of managing complex search interfaces, AI-driven databases, interpreting data

outputs, and managing bibliographic references (Al-Abyadh & Azeem, 2022). These competencies reduce frustration and enhance the perceived ease of use and usefulness of information systems—two key determinants of user satisfaction with information systems (Zamir & Kim, 2022). Bacarrisas (2023) found that individuals with higher information literacy skills were more satisfied with digital library systems. Similarly, Atikuzzaman and Ahmed (2023) reported that self-assessed competence in information tasks was strongly associated with satisfaction in academic settings.

In the context of agricultural knowledge workers, higher information literacy self-efficacy is likely to enhance satisfaction with systems used for accessing scientific journals, agricultural statistics, and policy documents (Assefa et al., 2011). Workers with high information literacy self-efficacy are better able to independently navigate and utilise AI-enabled information systems, including machine learning-driven functionalities, leading to higher user satisfaction with information systems. Therefore, we hypothesise.

H₃: Information literacy self-efficacy positively impacts user satisfaction with information systems.

The mediating role of knowledge management processes

Information literacy self-efficacy is consistently linked to better personal knowledge and information management practices, which are foundational to effective knowledge management processes in organisations (Burchard & Myers, 2019; Calaguas & Consunji, 2022; Shahzad et al., 2023). Studies show that knowledge management processes significantly affect user satisfaction with information systems and organisational performance, and that user information literacy self-efficacy is a key factor in successful knowledge management system adoption and satisfaction (Sahibzada et al., 2019). AI-driven tools support these processes by automating data organisation and retrieval. Machine learning algorithms analyse large agricultural datasets to guide knowledge sharing and utilisation. Researchers leverage AI-enabled platforms to integrate and synthesise information across disciplines efficiently (von Krogh, 2018; Wolfert et al., 2017). While direct studies on the mediation model are scarce, research supports that self-efficacy enhances knowledge management practices and user satisfaction (Batool et al., 2023; Sahibzada et al., 2019; Shahzad et al., 2023). In agricultural research organisations, where multidisciplinary collaboration is essential, information literacy self-efficacy is likely to enhance user satisfaction with information systems, primarily when it contributes to effective knowledge management processes that improve decision-making and innovation. Therefore, we hypothesise.

H₄: The impact of information literacy self-efficacy on user satisfaction with information systems is mediated by knowledge management processes.

Figure 1 presents the proposed mediation model of the study

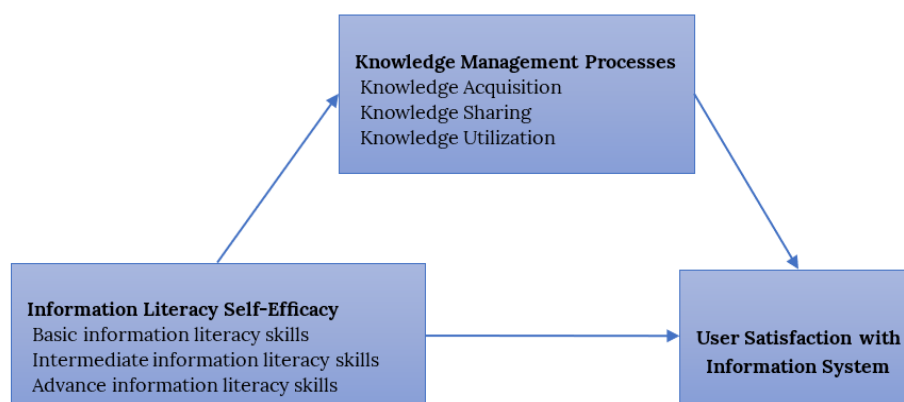


Figure 1. Knowledge management processes mediate the impact of information literacy self-efficacy on user satisfaction with information systems among agricultural knowledge workers

Materials and methods

Sampling and data collection

The study employed a stratified random sampling design with proportionate allocation to ensure that all categories of agricultural research institutes under the research wing of the Punjab Agriculture Department were adequately represented. The sampling frame was obtained from the office of the Chief Information Officer, which provided a complete list of knowledge workers employed in these institutes. From this list, 600 respondents were randomly selected proportionate to the size of each stratum. Data were collected from 600 respondents using a mixed approach that combined online and in-person methods to maximise participation. Specifically, a structured Google Form questionnaire was circulated to the study respondents, and follow-up in-person visits to each institute were conducted to improve response rates and address any queries related to the questionnaire. This approach ensured comprehensive coverage of the target population and minimised the risk of non-response bias. Moreover, 415 surveys were returned giving a response rate of 69%. Out of 415 questionnaires, five had many missing values, four were incomplete due to respondent abandonment, and seven showed respondent misconduct. Finally, 399 surveys were usable for data analysis.

Ethical approval and informed consent statements

The study was conducted in accordance with ethical standards. All participants were informed about the study objectives and procedures. The study participants gave written consent for review and signature before starting the study questionnaire. Confidentiality and anonymity of the study participants' information were strictly maintained throughout the research.

The study measures

All constructs in this study were measured using validated instruments adapted from prior literature. The items were contextualised to reflect the work environment of agricultural knowledge workers in Punjab, Pakistan. Responses for all scales were recorded on a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). Full scales are provided in Appendix A; only illustrative sample items are presented below.

User satisfaction with the information system

User satisfaction with the information system was measured using four items adapted from Bhattacharjee (2001), originally based on Oliver's (1980) satisfaction paradigm. This construct was operationalised as a reflective, single-dimensional variable. A sample item is: Overall, I am satisfied with the agricultural research information system provided by my institute.

Knowledge management processes

Knowledge management processes were measured as a higher-order construct with three reflective-formative dimensions: knowledge acquisition, knowledge sharing, and knowledge utilisation, adapted from Gold et al. (2001). Example items include: *I regularly update my understanding of recent developments in crop, soil, and pest research* (knowledge acquisition), *I freely share my research findings and experiences with colleagues in my institute* (knowledge sharing), and *I apply newly acquired knowledge to design or improve research projects* (knowledge utilisation).

Information literacy self-efficacy

Information literacy self-efficacy was measured as a higher-order construct comprising three reflective-formative dimensions: basic skills, intermediate skills, and advanced skills. The scale was adapted from Serap Kurbanoglu et al. (2006) and contextualised to agricultural research activities. A sample item is: *I feel confident using electronic information sources (online databases, research portals).*

Research strategy

Data analysis was conducted using SmartPLS 4, a variance-based structural equation modelling (SEM) technique suitable for handling complex hierarchical constructs. The evaluation proceeded in multiple stages. At the first stage, the measurement models for the first-order reflective constructs were assessed to establish reliability and validity. The latent variable scores obtained from this step were then saved and incorporated into the dataset. At the second stage, these scores were used to model the second-order formative constructs, following the disjoint two-stage approach, which is considered robust for estimating higher-order constructs. Once both levels of the measurement model were validated, the structural model was tested to examine the hypothesised relationships among information literacy self-efficacy, knowledge management processes, and user satisfaction with information systems. This approach ensured rigorous validation of the hierarchical measurement structure while enabling robust hypothesis testing.

Data analysis

Participants demographics

Figure 2 presents the sociodemographic characteristics of the study sample. In terms of gender, 290 were male (72.5%), while 110 were female (27.5%). Regarding qualifications, 281 held an M.Phil./M.Sc. (Hons.) degree (70.3%), 112 held a PhD (28%), 6 held a Master's degree (1.4%), and 1 held a B.Sc. (Hons.) degree (0.3%). In terms of designation, 210 were Scientific Officers (52.4%), 158 were Senior Scientists (39.4%), 19 were Principal Scientists (4.8%), 10 were Chief Scientists (2.5%), and 3 held other positions (0.8%).

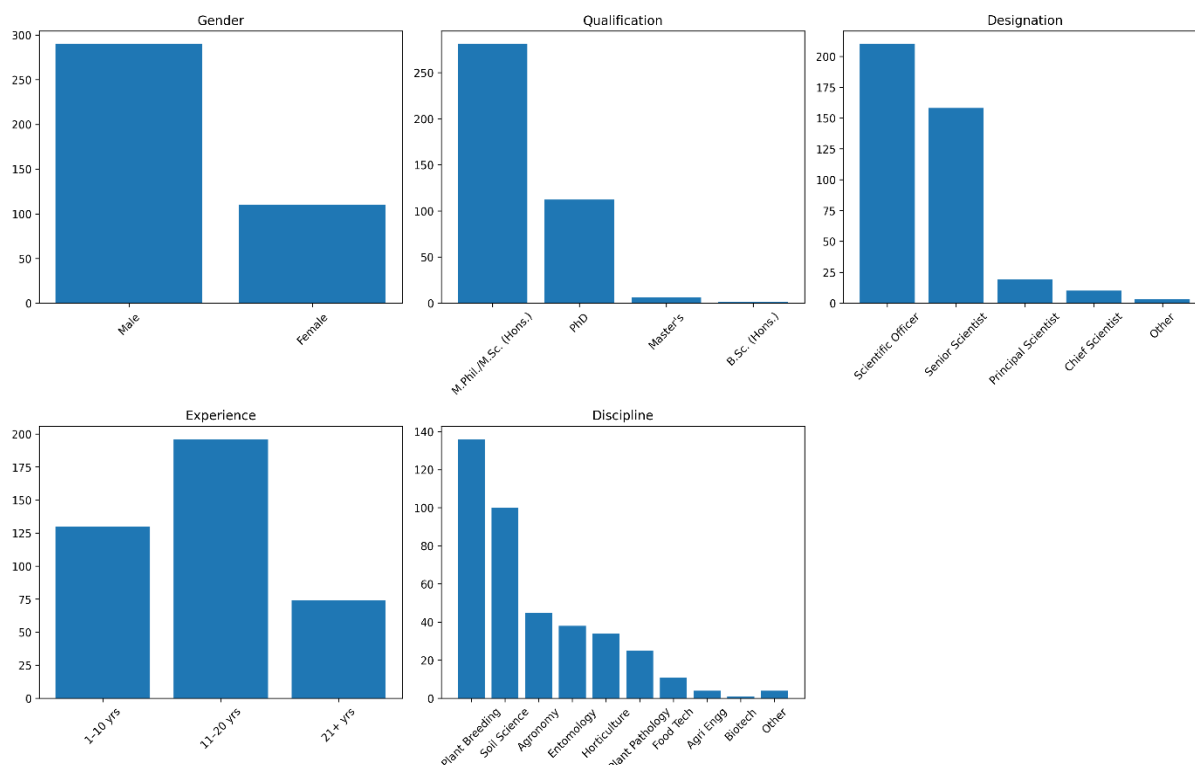


Figure 2. Demographic profile of the sample population, illustrating distributions by gender, academic qualification, job designation, professional experience, and field of specialisation.

With respect to professional experience, 196 were mid-career professionals with 11–20 years of experience (49%), 130 were early-career professionals with 1–10 years of experience (32.6%), and 74 were late-career professionals with 21 years or more (18.4%). Participants represented a wide

range of agricultural disciplines, including Plant Breeding and Genetics with 136 respondents (34%), Soil Science with 100 respondents (24.9%), Agronomy with 45 respondents (11.3%), Entomology with 38 respondents (9.6%), Horticultural Sciences with 34 respondents (8.5%), Plant Pathology with 25 respondents (6.2%), Food Technology with 11 respondents (2.8%), Agricultural Engineering with 4 respondents (1.1%), Biotechnology with 1 respondent (0.3%), and 4 respondents from other fields (1.1%). Overall, the sample was largely composed of mid-career researchers, with Plant Breeding and Soil Science emerging as the most represented areas of specialisation.

The assessment of the measurement model (lower-order constructs)

The study variables	Loadings	Alpha	CR	AVE	VIF
Advance information literacy skills		0.858	0.87	0.704	
A1	0.787				1.781
A2	0.898				2.723
A3	0.786				1.714
A4	0.878				2.418
Basic illiteracy skills		0.833	0.854	0.667	
B1	0.763				1.585
B2	0.894				2.392
B3	0.834				1.919
B4	0.769				1.708
Intermediate information literacy skills		0.925	0.934	0.658	
I1	0.9				3.92
I2	0.702				1.596
I3	0.904				4.041
I4	0.812				2.377
I5	0.739				1.943
I6	0.759				2.044
I7	0.786				2.115
I8	0.865				3.025
Knowledge acquisition		0.891	0.912	0.753	
KA1	0.915				3.213
KA2	0.911				3.02
KA3	0.784				1.915
KA4	0.855				2.296
Knowledge sharing		0.874	0.893	0.726	
KS1	0.778				1.776
KS2	0.887				2.616
KS3	0.913				3.004
KS4	0.825				2.006
Knowledge utilisation		0.871	0.886	0.723	
KU1	0.901				2.839
KU2	0.798				1.866
KU3	0.796				1.781
KU4	0.9				2.816
User satisfaction with the information system		0.855	0.861	0.696	
USIS1	0.814				1.826
USIS2	0.83				1.918
USIS3	0.817				1.896
USIS4	0.876				2.249

Note: CR = Composite reliability, AVE = Average variance extracted, VIF = Variance inflation factor

Table 1. Loadings, reliability, validity, and variance inflation factor values of the lower order constructs

Data analysis began with an assessment of the measurement model for the lower-order constructs, followed by validation of the higher-order constructs, and finally testing of the structural model

to evaluate the proposed hypotheses. Reliability and validity indicators were computed for each construct to ensure the adequacy of the measurement model.

	A	B	I	KA	KS	KU	USIS
A							
B	0.756						
I	0.710	0.671					
KA	0.431	0.360	0.345				
KS	0.425	0.368	0.375	0.775			
KU	0.476	0.417	0.405	0.820	0.850		
USIS	0.481	0.479	0.416	0.533	0.591	0.628	

Note: B = Basic, I = Intermediate, A = Advance, KA = Knowledge acquisition, KS = knowledge sharing, KU = Knowledge utilisation, USIS = User satisfaction with information system

Table 2. Discriminant validity through Heterotrait–Monotrait ratios

Internal consistency reliability was assessed using Cronbach's alpha (α) and composite reliability (CR). Following Hair and Alamer (2022), α and CR values above 0.70 are considered acceptable for social science research. All constructs in the study met or exceeded this threshold, indicating strong internal consistency (Table 1). Convergent validity was examined using average variance extracted (AVE) and item loadings. An AVE of 0.50 or higher is regarded as evidence of convergent validity (Fornell & Larcker, 1981), while standardised loadings above 0.70 indicate adequate indicator reliability (Hair & Alamer, 2022). All constructs in the model exhibited AVE values well above the recommended 0.50 threshold, and most items loaded above 0.70, confirming convergent validity. Multicollinearity among items was assessed using the variance inflation factor values. Variance inflation factor values below 5.0 are generally accepted as indicating no problematic collinearity (Hair & Alamer, 2022). All items in this study met this criterion, showing that the indicators did not exhibit collinearity issues.

	A	B	I	KA	KS	KU	USIS
A	0.839						
B	0.647	0.817					
I	0.640	0.596	0.811				
KA	0.381	0.320	0.329	0.868			
KS	0.375	0.320	0.349	0.691	0.852		
KU	0.417	0.361	0.373	0.734	0.749	0.850	
USIS	0.418	0.412	0.373	0.474	0.518	0.548	0.835

Note: Diagonal values (bold) = Square root of AVE for each construct, Off-diagonal values = Correlations between constructs, B = basic, I = intermediate, A = Advance, KA = Knowledge acquisition, KS = Knowledge sharing, KU = Knowledge utilisation, USIS = User satisfaction with information system

Table 3. Discriminant validity through Fornell and Larcker criteria

Additionally, discriminant validity was assessed using three complementary approaches: the Heterotrait–Monotrait (HTMT) ratios of correlations (Table 2), Fornell–Larcker criterion (Table 3), and cross-loadings (Appendix B). According to the Fornell and Larcker (1981) criterion, the square root of the AVE for each construct should exceed its correlations with other constructs. The results indicated that all constructs met this criterion, as the diagonal values (square roots of AVE) were greater than the off-diagonal correlations. Next, HTMT ratios were examined to ensure that constructs were distinct from one another. Consistent with the guidelines of Henseler et al. (2015) and Hair and Alamer (2022), HTMT values below 0.85 (or more conservatively 0.90) indicate adequate discriminant validity. All HTMT ratios in this study fell below the 0.85 threshold, supporting discriminant validity. Finally, cross-loadings were examined to ensure that each indicator loaded highest on its intended construct compared to all other constructs. These cross-loadings are presented in the Appendix B.

Together, these findings demonstrate that the lower-order constructs achieved satisfactory reliability and construct and discriminant validity according to standard guidelines. Using the disjoint two-stage approach, latent variable scores from the first-stage model were used to estimate the higher-order constructs of Information Literacy Self-Efficacy and Knowledge Management Processes. This two-stage procedure allowed for robust testing of the higher-order model and the subsequent structural model (Sarstedt et al., 2019).

Validating higher-order constructs of knowledge management processes and information literacy self-efficacy (reflective formative)

Higher-order constructs offer several benefits to researchers. They streamline complex models by reducing the number of direct paths between variables, thus improving parsimony (Edwards, 2001; Johnson et al., 2011; Polites et al., 2012). By combining multiple related dimensions into a single overarching construct, researchers can simplify relationships in their models and avoid redundancy between lower-order components and outcomes. Higher-order constructs also address the bandwidth–fidelity dilemma (Cronbach & Gleser, 1957), balancing the breadth of information captured with the depth of measurement accuracy. In addition, they help mitigate collinearity among formative indicators by redistributing items or dimensions across more clearly defined subdimensions of the overall construct (Hair et al., 2023).

HOCs	LOCs	VIF	Outer weights	T statistics	P values	Outer loadings
ILSE	B	2.069	0.508	4.769	0.000	0.918
	I	1.907	0.349	3.132	0.002	0.850
	A	1.882	0.288	2.796	0.005	0.822
KMP	KA	2.404	0.204	1.932	0.053	0.842
	KS	2.526	0.332	3.11	0.002	0.890
	KU	2.858	0.557	5.182	0.000	0.956

Note: ILSE = Information literacy self-efficacy, KMP = Knowledge management processes, B = Basic, I = Intermediate, A = Advance, KA = Knowledge acquisition, KS = knowledge sharing, KU = knowledge utilisation, LOC = Lower-order constructs, AVE = Average variance extracted, HOC = Higher-order constructs

Table 4. Validity of higher-order constructs of knowledge management processes and information literacy self-efficacy

Information literacy self-efficacy and knowledge management processes were higher-order constructs in the study. Information literacy self-efficacy was comprised of basic, intermediate, and advanced information literacy skills as reflective lower-order constructs. Knowledge management processes had knowledge acquisition, knowledge sharing, and knowledge utilisation as reflective lower-order constructs.

Several steps were taken to validate both higher-order constructs. First, multicollinearity was assessed to check the collinearity issues with formative models. Variance inflation factor values were checked for both information literacy self-efficacy and knowledge management processes higher-order constructs. When the Variance inflation factor is higher, multicollinearity is higher. Variance inflation factor values of 5 or higher indicate multicollinearity issues. In the present study, multicollinearity did not pose any serious threat because Variance inflation factor values were less than the recommended cut-off value of 5. Next, the statistical significance and relevance of outer weights were assessed. Outer weights were found to be significant. This further validates the higher-order constructs of information literacy self-efficacy and knowledge management processes. Finally, outer loadings were found to be greater than 5 and significant for each indicator of the formative higher-order constructs, information literacy self-efficacy and knowledge management processes. Since all criteria are met (Table 4), the validity of the higher-order constructs is established.

Structural model assessment

Following the assessment of measurement models, the next step is the evaluation of structural paths for the evaluation of path coefficients (relationships among the study constructs) and their significance.

Direct relationships					
Hypotheses	β	SE	T	P value	Decision
H ₁ : ILSE → KMP	0.464	0.041	11.305	0.000	Supported
H ₂ : KMP → USIS	0.457	0.040	11.332	0.000	Supported
H ₃ : ILSE → USIS	0.253	0.043	5.903	0.000	Supported

Note: ILSE = Information literacy self-efficacy, USIS = User satisfaction with information system, KMP = Knowledge management processes

Table 5. Structural model: Coefficients of direct relationships

H₁ evaluate whether information literacy self-efficacy positively and significantly affects knowledge management processes. The results reveal that information literacy self-efficacy had a significant and positive impact on knowledge management processes ($\beta = .464$, $t = 11.305$, $p < 0.001$). Hence, H₁ is supported. H₂ assess whether knowledge management processes positively and significantly affect user satisfaction with information systems. The findings demonstrate that the knowledge management processes have a positive and significant impact on user satisfaction with information systems ($\beta = 0.457$, $t = 11.332$, $p < 0.001$). Consequently, H₂ is supported. H₃ ascertains whether information literacy self-efficacy positively and significantly impacts user satisfaction with information systems. The results show that information literacy self-efficacy has a positive and significant impact on user satisfaction with information systems ($\beta = 0.253$, $t = 5.903$, $p < 0.001$). Thus, H₃ is supported. The results are presented in Table 5.

H₄ evaluates whether knowledge management processes mediate the relationship between information literacy self-efficacy and user satisfaction with information systems. The results demonstrate that knowledge management processes mediate the relationship between information literacy self-efficacy and user satisfaction with information systems ($b = 0.212$, $t = 7.834$, $p < 0.001$). Therefore, H₄ is supported. Notably, the direct impact of information literacy self-efficacy on user satisfaction with information systems in the presence of the mediator is significant and positive ($\beta = 0.253$, $t = 5.903$, $p < 0.001$). Indirect impact was also found to be significant and positive. Hence, there is partial and complementary mediation in the structural model. The summary of mediation results is presented in Table 6.

Total effect (ILSE -> USIS)		Direct effect (ILSE -> USIS)		Indirect effects of ILSE on USIS				
β	P value	β	P value		β	SE	T value	P value
0.465	.000	0.253	.000	H4: ILSE -> KMP > USIS	0.212	0.027	7.834	0.000

Note: ILSE = Information literacy self-efficacy, USIS = User satisfaction with information system, KMP = knowledge management processes

Table 6. Structural model: Summary of mediation results

Discussion

This study examined how agricultural knowledge workers' information literacy self-efficacy impacts their knowledge management processes and, in turn, their user satisfaction with information systems. By conceptualising information literacy self-efficacy and knowledge management processes as higher-order constructs, the study provides a comprehensive framework linking individual competencies, knowledge management processes, and user satisfaction with information systems within the underexplored context of public-sector agricultural research institutes in Pakistan.

Information literacy self-efficacy positively and significantly impacted knowledge management processes (H₁). This finding suggests that agricultural knowledge workers with stronger information literacy self-efficacy in locating, evaluating, and synthesising information are more likely to acquire, share, and utilise knowledge effectively. A plausible explanation is that individuals confident in their information literacy skills can access diverse data sources (journals, experiments, field data), evaluate the relevance of this information, and apply it to ongoing research tasks, thereby engaging more fully in knowledge processes. This aligns with Bacarrisas (2023), who argues that information literacy is a foundational competence enabling knowledge activities. This finding also corroborates Hwang et al. (2018), who demonstrate that individual competencies drive knowledge management processes. In the agricultural research context of Punjab—where knowledge is dispersed across multiple field stations, crop domains, and extension services—workers with stronger information literacy self-efficacy may also feel more comfortable collaborating and sharing insights with peers, strengthening collective knowledge flows.

Knowledge management processes positively and significantly impacted user satisfaction with information systems (H₂). This finding indicates that workers who actively acquire, share, and utilise knowledge are more satisfied with the institutional systems supporting these activities. A likely explanation is that when workers perceive the information system as a reliable tool to facilitate knowledge processes, they experience fewer barriers to accessing, sharing, and applying research information, which in turn increases user satisfaction with information systems. This result mirrors prior studies in the information system success literature, which show that knowledge management effectiveness improves perceptions of system quality and satisfaction (Al-Emran et al., 2018; Arisman & Fuadah, 2017; Zamir & Kim, 2022). In Punjab's research institutes, where information systems often serve as repositories for experiments, field data, and policy documents, workers who routinely engage in knowledge management processes may develop higher trust in and satisfaction with the system because it demonstrably supports their knowledge tasks.

Information literacy self-efficacy positively and significantly impacted user satisfaction with information systems (H₃). This implies that agricultural knowledge workers' confidence in their own information literacy abilities translates into more positive evaluations of the information system. A possible explanation is that workers with higher information literacy self-efficacy may experience less cognitive strain and fewer technical difficulties when searching digital repositories, catalogues, and datasets (Misra & Stokols, 2012). This leads to smoother interactions

and greater satisfaction. This supports Bhattacharjee's (2001) expectation-confirmation model, which posits that user perceptions of ease and competence drive satisfaction and continuance intentions. In the agricultural research setting, this may be especially salient because much of the work requires integrating new findings with field data and past reports—a task facilitated by strong information literacy skills.

Knowledge management processes mediated the relationship between information literacy self-efficacy and user satisfaction with information systems (H_4). This indicates that part of the effect of information literacy self-efficacy on user satisfaction with information systems operates indirectly through knowledge management processes. This suggests that while individual competencies directly improve user satisfaction with information systems, they also enhance satisfaction by improving knowledge acquisition, sharing, and utilisation practices. A plausible explanation is that high-information literacy self-efficacy workers are not only adept at using systems but also more likely to embed these skills into collaborative and organisational knowledge processes, which then boost satisfaction with system outcomes. In the context of Punjab's agricultural institutes, which rely heavily on collaborative field trials and interdepartmental data sharing, this mediating role of knowledge management processes underscores the importance of linking individual skill development with institutional knowledge management policies.

Contextual contributions to the literature

These findings contribute to the literature in several ways. First, they extend the study of information literacy self-efficacy beyond academic libraries and student populations to public-sector research organisations in a developing country. The findings show that information literacy self-efficacy remains critical for knowledge management processes and user satisfaction with information systems. Second, they validate the disjoint two-stage approach for higher-order constructs in the agricultural research context. The findings also demonstrate a robust methodological path for future studies. Third, they highlight the importance of knowledge management processes as a mediating mechanism between information literacy self-efficacy and user satisfaction with information systems—an area often overlooked in information systems and knowledge management research. Finally, they add geographic and sectoral diversity to the literature, which has traditionally focused on business or educational settings in developed economies.

Practical implications

The results underscore the importance of investing in both individual and organisational capacities. Training programmes to improve information literacy—particularly in digital searching, bibliographic management, and data analysis—may directly enhance user satisfaction and indirectly improve it by strengthening knowledge management processes. At the organisational level, policies encouraging knowledge sharing and utilisation can amplify the benefits of individual skills, leading to more efficient use of information systems. By creating an integrated environment where skilled individuals and supportive systems reinforce each other, research institutes can improve not only satisfaction but also innovation and evidence-based decision-making.

Limitations and future research

As with any cross-sectional study, causality cannot be firmly established. Future longitudinal studies could assess whether improvements in information literacy self-efficacy or knowledge management processes over time predict changes in satisfaction. Additionally, the sample was limited to Punjab's agricultural research institutes, which may restrict generalizability to other regions or sectors. Future research could also test other mediators (e.g., organisational culture, leadership support) or moderators (e.g., digital infrastructure quality) to more fully explain the pathways between information literacy self-efficacy, knowledge management processes, and user satisfaction with information systems.

Conclusion

Overall, this study highlights the centrality of information literacy self-efficacy in enabling effective knowledge management processes and improving user satisfaction with information systems. By demonstrating the partial mediating role of knowledge management processes, the research provides empirical support for the integration of individual skills and organisational processes in understanding information system success in public-sector research contexts.

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Appendix

Appendix A: The study measures and their items

User satisfaction with information system

Overall, I am satisfied with the agricultural research information system provided by my institute.
I am pleased with my experience of using this agricultural research information system.
I am content with my decision to rely on this system for my research activities.
My overall experience with this agricultural research information system has been very satisfying.

Knowledge management processes

Knowledge acquisition

I actively seek new agricultural research knowledge from external sources (journals, conferences, collaborations).
I make use of institutional databases and experimental records to acquire relevant information.
I regularly update my understanding of recent developments in crop, soil, and pest research.
I engage with colleagues and networks to obtain knowledge useful for my research tasks.

Knowledge sharing

I freely share my research findings and experiences with colleagues in my institute.
I provide relevant data, documents, or analyses to colleagues who may benefit from them.
I encourage open discussion of lessons learned from experiments or field studies.
I participate in formal and informal knowledge-sharing sessions (seminars, team meetings).

Knowledge utilization

I apply newly acquired knowledge to design or improve research projects.
I use shared knowledge from colleagues to enhance the quality of my experimental work.
I incorporate lessons from previous studies into current research planning.
I translate research knowledge into recommendations or guidelines for field application.

Information literacy self-efficacy

Basic information literacy skills

I feel confident using different kinds of print sources (books, periodicals, extension bulletins, manuals).
I feel confident using electronic information sources (online databases, research portals).
I can locate information sources in the institute's library or document center.
I can use the library catalogue effectively.
I can locate resources using the library catalogue or digital indexing tools.

Intermediate information literacy skills

I can clearly define the information I need for an agricultural research problem.
I can select the most appropriate for the information need.
I can interpret visual information such as graphs, tables, and diagrams in research reports.
I can write a research paper or technical report based on retrieved information.
I can prepare a bibliography following the required citation styles.
I can create bibliographic records for different materials (books, journal articles, theses, web pages).
I can make in-text citations and use quotations correctly.
I learn from each information-problem-solving experience and improve my information literacy skills.

Advanced information literacy skills

I can synthesize newly gathered information with existing knowledge.
I can determine the content and structure of different parts of a presentation (introduction, methods, and conclusion).
I can create bibliographic records and organize the bibliography systematically.
I can critically evaluate the quality of my information-seeking process and its results.

Appendix B: Discriminant validity through cross loadings

	A	B	I	KA	KS	KU	USIS
A1	0.787	0.482	0.468	0.303	0.278	0.321	0.250
A2	0.898	0.613	0.582	0.324	0.335	0.364	0.431
A3	0.786	0.524	0.510	0.309	0.298	0.291	0.344
A4	0.878	0.545	0.576	0.343	0.340	0.412	0.361
B1	0.461	0.763	0.450	0.250	0.241	0.257	0.298
B2	0.617	0.894	0.550	0.306	0.324	0.360	0.398
B3	0.554	0.834	0.521	0.271	0.254	0.281	0.355
B4	0.460	0.769	0.411	0.205	0.212	0.266	0.278
I1	0.588	0.544	0.900	0.321	0.332	0.344	0.340
I2	0.437	0.407	0.702	0.288	0.297	0.313	0.273
I3	0.608	0.566	0.904	0.307	0.330	0.343	0.343
I4	0.523	0.526	0.812	0.252	0.250	0.293	0.296
I5	0.422	0.424	0.739	0.144	0.199	0.219	0.267
I6	0.459	0.409	0.759	0.188	0.204	0.225	0.261
I7	0.525	0.443	0.786	0.283	0.286	0.312	0.296
I8	0.549	0.520	0.865	0.293	0.320	0.330	0.323
KA1	0.367	0.322	0.341	0.915	0.643	0.691	0.427
KA2	0.374	0.310	0.325	0.911	0.647	0.719	0.469
KA3	0.262	0.192	0.192	0.784	0.519	0.504	0.297
KA4	0.302	0.263	0.256	0.855	0.577	0.599	0.427
KS1	0.239	0.226	0.182	0.508	0.778	0.558	0.374
KS2	0.344	0.310	0.348	0.612	0.887	0.653	0.452
KS3	0.375	0.287	0.313	0.662	0.913	0.720	0.525
KS4	0.299	0.261	0.329	0.558	0.825	0.606	0.397
KU1	0.355	0.293	0.331	0.649	0.686	0.901	0.548
KU2	0.277	0.247	0.245	0.602	0.572	0.798	0.412
KU3	0.366	0.324	0.294	0.530	0.575	0.796	0.396
KU4	0.410	0.358	0.384	0.704	0.700	0.900	0.492
USIS1	0.331	0.325	0.304	0.372	0.421	0.443	0.814
USIS2	0.356	0.338	0.342	0.405	0.422	0.452	0.830
USIS3	0.314	0.294	0.261	0.364	0.394	0.428	0.817
USIS4	0.388	0.408	0.332	0.436	0.486	0.501	0.876

Note: B = Basic, I = Intermediate, A = Advance, KA = Knowledge acquisition, KS = knowledge sharing, KU = knowledge utilisation, USIS = User satisfaction with information system