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FACTORS INFLUENCING ORGANIZATIONAL LEARNING AND PERFORMANCE: ASSESSING THE MODERATING ROLE OF KNOWLEDGE DIGITIZATION

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ABSTRACT

The purpose of this study was to investigate how knowledge digitization affects the connection between organizational performance and learning across several industries. The study model was developed and validated using a structured questionnaire, expert evaluation, regression analysis, and systematic scientific literature analysis. A standardized questionnaire was used to gather data from specialists employed by businesses. Under the moderating influence of knowledge digitization, the research findings confirmed the hypotheses that organizational learning has a favorable impact on organizational performance. The possible integration of AI and machine learning technologies, virtual and augmented reality, and more advanced analytics and reporting tools were among the topics covered in the discussion about the future extent of digitization in businesses. The importance of evaluating the current workforce and progressively accelerating digitization with appropriate management and employee support is emphasized in the paper's conclusion.

Keywords: Level of Automation, Data and Content, Level of AI adoption, Economic Outcome, Knowledge Stock, Organizational learning, Organizational performance, Knowledge Digitization

1. INTRODUCTION

The rapid pace of technological change has reshaped how organizations work together, requiring us to more closely examine how knowledge is shared across different industries(Mahdiraji et al., 2021). The increasing complexity and specialization involved in modern work has made organizations pursue collaborations; in these situations, the sharing of knowledge is incredibly valuable for both innovation and staying ahead of the competition. Knowledge digitization, or the conversion of knowledge into a digital format, is key in making communication and understanding between organizations more effective(Cardoso et al., 2023) . The ability to share knowledge seamlessly, regardless of where organizations are located, is crucial for collaborative problem-solving and aligning strategies in this era of ongoing digital innovation (Massa et al., 2023). Digitization not only means converting information to digital formats but also encompasses how this information is stored, accessed, and shared, thus boosting collaboration efficiency (Porath, 2023).

Studies show that organizations that make good use of digital platforms for knowledge sharing tend to see positive outcomes, such as greater creativity, improved innovation, and quicker responses to market changes(Cardoso et al., 2023). The role of knowledge digitization helps us better understand what affects knowledge sharing between organizations, highlighting the mechanisms that can either support or hinder collaboration(Massa et al., 2023).

However, as inter-organizational collaboration changes, we must also acknowledge the challenges in sharing knowledge. Issues like data misinterpretation and the digital divide can complicate knowledge transfer strategies(Arduin & Ziam, 2024). It is therefore essential to develop comprehensive strategies that focus on both the technological elements of digitization and the human and organizational factors that influence knowledge sharing behaviors(Massa et al., 2023). Empirical research indicates that organizations that foster supportive leadership, build a culture of trust, and ensure aligned objectives generally experience more favorable results from their knowledge sharing efforts(Cormican et al., 2021).

Given these insights, a strong grasp of the complex relationship between knowledge digitization and inter-organizational collaboration is crucial for organizations seeking success in today's digital world. Organizations can create synergistic relationships that boost innovation and efficiency by effectively navigating the complexities of knowledge sharing through digital channels(Elgargouh et al., 2024). In addition, shared knowledge enhances learning and helps organizations collectively grow and adapt to new challenges(Li & Herd, 2017). Consequently, identifying the key leverage points within inter-organizational frameworks can offer valuable insights into the best practices for knowledge sharing in this digital age.

As discussions about knowledge sharing continue, future research should explore the specific conditions under which knowledge digitization either facilitates or impedes effective inter-organizational collaboration. Understanding these subtleties is necessary for creating practical initiatives that aim to improve knowledge-sharing activities across different organizational settings. Exploring this relationship will not only add to the theoretical knowledge of knowledge management but also provide actionable insights for practitioners aiming to maximize the benefits from inter-organizational collaborations in the age of digital innovation(Vaio et al., 2020). Ultimately, as organizations move forward in maximizing the potential of knowledge sharing, integrating digitization strategies is not only a necessity but also a foundation for maintaining a competitive edge in an increasingly connected world(Riadi et al., 2023).

2. LITERATURE REVIEW

The realm of knowledge sharing, especially across different organizations, is drawing considerable academic interest as organizations grapple with ever-evolving technological environments. Digitizing knowledge is a key element in making this exchange easier(Yao et al., 2023). Looking at what's already out there in terms of research, we see that knowledge sharing hinges not only on technology but also on the culture of an organization and the relationships between entities. Studies have shown that using digital tools can really change how knowledge is managed, suggesting that digitizing things can make information flow better between organizations(Mahfodh & Obeidat, 2020; Malik et al., 2024). It's important to understand how digital platforms can help spread knowledge, and some researchers have pointed out that organizations with good digital infrastructures are in a better spot to work together and break down traditional barriers(He et al., 2024; Malik et al., 2024; Massa et al., 2023).

In addition, trust matters big time when it comes to relationships; it's what gets organizations to share their secret information. A lot of research tells us that when organizations trust each other, they're less worried about the risks of sharing knowledge, which leads to better cooperation and more innovation(Khassawneh et al., 2022; Mayer et al., 1995; Rossoni et al., 2024). Digital platforms can boost trust by making things more transparent, letting everyone see the processes and rules that guide how they interact, as seen in recent studies(Khan et al., 2023). On the flip side, a lack of trust can really get in the way, which means we need to think about the relationship side of things along with the technology if we want knowledge sharing to work well.

2.1 Organizational learning (OL) and Level of Automation (LOA)

The Level of Automation (LOA) becomes a key factor in how well an organization learns (OL), especially as organizational structures depend more and more on automated processes. Automation improves processes, but it also changes how knowledge is acquired and spread among everyone involved. Some studies suggest that organizations that use automation more effectively process and analyze data more efficiently. This in turn encourages a better environment for sharing information and learning(Dogan et al., 2023). This is especially true today, as adaptability and innovation are necessary to maintain a competitive advantage. Automation helps to provide real-time insights, which organizations can use to improve operations and refine strategies(Liu, 2023).

Besides building an environment conducive to learning, LOA moves the focus to using digital tools to manage knowledge. Automated systems frequently have strong knowledge management features that can greatly improve learning. These systems are designed to capture feedback loops and spread learning throughout the organization, building a culture of ongoing improvement(Tanpoco & Cordova, 2023). Transparent learning environments are facilitated by the systematic incorporation of these tools into daily operations. Insights are easily available, and action can be taken(Schilling et al., 2011).

H1: Organizational learning (OL) is positively impacted by Level of Automation (LOA)

2.2 Organizational learning (OL) and deficient Data and Content (DAC)

The relationship between DAC and OL matters, especially now that things change so quickly and organizations need to learn and unlearn fast. Some suggest that organizations with ineffective information systems may struggle to build a culture of continuous learning and progress(Lee & Lee, 2023). Staff might focus on their own local knowledge instead of understanding the organization’s goals as a whole. Because of this disconnect, best practices aren’t shared, and different teams waste resources and lower overall productivity by duplicating efforts(Bento et al., 2020; Waal et al., 2019). All in all, DAC can get in the way of achieving what an organization wants, because it stops the effective spreading of knowledge needed for making good decisions and innovating.

Several studies show that DAC and OL are related. They emphasize that organizations that put money into good information systems often report better learning abilities and more innovative results (Arias & Solana, 2013; Farzaneh et al., 2020). Methods that value the quality of knowledge more than its amount create settings where people feel they can share thoughts and work together effectively. Because of this, they add more to the organization’s knowledge base(Yeboah, 2023). But, if data and content aren’t managed with integrity, it can lead to people doubting shared knowledge. This greatly lowers the desire to participate in organizational learning activities

H2: Organizational learning (OL) is negatively impacted by deficient Data and Content (DAC)

2.3 Organizational learning (OL) and Level of AI adoption (LOAI)

Organizations are increasingly weaving digital tech into their daily grind, which really amps up the stakes for how they learn and adapt, especially with AI barging onto the scene. AI doesn't just make things run smoother; it's also shaking up how knowledge gets made, passed around, and actually put to use between different organizations. Turns out, the more an organization embraces AI, the better they seem to get at soaking up and using new knowledge, almost like AI is giving them a learning superpower (Li et al., 2022). With AI tools in tow, companies can sift through oceans of data in a snap, pulling out the golden nuggets that help them make smarter calls. This knack for analysis really beefs up a company's "memory," making it easier to remember and share the lessons they've picked up from both their own experiences and what's happening outside their walls.

organizations that are big on AI tend to have learning systems that are quick on their feet, with feedback loops that pump up learning outcomes. When AI-driven systems are in place, people get feedback that's both timely and on point, which is key for sharpening their skills and getting them in sync with what the organization is shooting for (Lhakard, 2024). This quick feedback lets employees change gears fast, throwing new knowledge into their day-to-day. This back-and-forth learning cycle that AI fosters means that organizational learning is anything but set in stone; it's a living, breathing thing that keeps evolving as organizations chew on new data and insights.

H3: Organizational learning (OL) is positively impacted by Level of AI adoption (LOAI)

2.4 Organizational learning (OL) and Economic Outcome (ECO)

Following up on the examination of how knowledge digitization affects learning between organizations, it's really important to look at how these things affect bigger ideas like Economic Outcome (ECO) and Organizational Learning (OL). The way these variables relate shows that better knowledge sharing and digital innovation can lead to better economic results, which then helps organizations learn. Research suggests that companies that use smart ways to manage knowledge to get good economic results usually see their ability to learn improve(Subrahmanyam et al., 2024). This mainly happens because when things go well, resources are available to put back into the learning process, making a continuous cycle of improvement (Paliwal et al., 2024).

H4: Organizational learning (OL) is positively impacted by Economic Outcome (ECO)

2.5 Organizational learning (OL) and Knowledge Stock (KNS)

The connection between what an organization knows (Knowledge Stock or KNS) and how well it learns is super important for doing better overall, especially when it comes to using new digital tools. As businesses deal with changes happening faster and faster, building up KNS becomes crucial. It's not just about staying ahead of the competition but also about encouraging everyone to keep learning. Basically, if an organization can bring together, create, and use knowledge well, and if it has a solid stock of knowledge to work with, that really helps. Research has shown that a good KNS can really open up more learning possibilities within the organization. Employees can get to lots of different sources of info, which helps them solve problems better(Olan et al., 2023). This is especially true when you think about digital tools, which help spread KNS around the organization even more.

There's research that backs up the idea that KNS and good organizational learning go hand in hand. For example, organizations that put money into knowledge management systems tend to be better at taking in and using knowledge. This leads to new ideas and better results(Qadri et al., 2021). Also, when KNS is part of everyday work, it helps create an environment where people want to learn. Employees feel like they can share what they know and work together to solve problems(Danko & Crhová, 2024). This not only makes the organization's knowledge base richer but also strengthens relationships between employees, creating a sense of community and shared goals.

H5: Organizational learning (OL) is positively impacted by Knowledge Stock (KNS)

2.6 Organizational learning (OL) and Knowledge Digitization (KD)

KD helps by allowing focused learning efforts. With data analysis and AI, businesses can spot what skills and knowledge are missing, allowing them to make custom learning plans for both individuals and groups(Stachová et al., 2020). This smart way to learn not only boosts individual skills but also makes the company's overall knowledge stronger, showing how KD and OL are

linked(Qadri et al., 2021). Indeed, businesses that focus on digitizing knowledge see better operations and create a place where learning is part of the company's life.
H6: Organizational learning (OL) is positively impacted by Knowledge Digitization (KD)

2.7 Knowledge Digitization (KD), Level of Automation (LOA) , Organizational learning (OL) and Organizational performance

Organizations find transformative opportunities in the combination of automation tech and knowledge digitization. The influence of automation levels (LOA) on organizational learning (OL) grows especially important as more organizations use these technologies, creating a relationship that calls for deeper analysis. Knowledge digitization, or changing analog info into digital, acts as a key facilitator between LOA and OL. It helps organizations make information flow better and changes unspoken knowledge into easily shared forms on digital platforms(Bennet & Tomblin, 2006; Lu & Taghipour, 2025). Making data accessible helps create a learning environment where workers can use data, get insights, and improve.
These implications go beyond to overall organizational performance. Better OL results in innovation and quick response to market changes, boosting competitive advantage. Learning and adapting, sped up by digitization, helps organizations stay competitive in fast-changing markets(Awad & Martín-Rojas, 2024). This fits with theories that say effective OL encourages adaptability and proactive behavior(Setia et al., 2024). Knowledge digitization makes it easier for organizations to align automation with digitization, improving performance.
H7: Knowledge Digitization (KD) moderates the relationship between Level of Automation (LOA) and Organizational learning (OL), impacting Organizational performance

2.8 Knowledge Digitization (KD), deficient Data and Content (DAC) ,Organizational learning (OL), and Organizational performance

Research also shows that digitized knowledge helps businesses collaborate, enriching their learning culture. Digitized platforms make it easier to share insights between organizations, supporting collective learning and innovation(Cardoso et al., 2023). So, LOA and OL should not be viewed separately. Knowledge digitization is critical, suggesting that high-performing organizations need to recognize the synergy of these variables.
Empirical studies support the idea that organizations with high LOA and robust digitization practices outperform those with less-developed systems(Gao et al., 2023; Grijalba et al., 2024; Ruiz et al., 2024). Knowledge digitization improves organizational learning, ensuring automation is not just for efficiency but also for systemic learning(Thakuri et al., 2024). Organizations wanting to maximize automation investments must prioritize both LOA and OL through effective digitization
H8: Knowledge Digitization (KD) moderates the relationship between deficient Data and Content (DAC) and Organizational learning (OL), impacting Organizational performance

2.9 Knowledge Digitization (KD), Level of AI adoption (LOAI) ,Organizational learning (OL), and Organizational performance

Organizational performance, organizational learning (OL), and the level of AI adoption (LOAI) are intertwined in a complex way, and knowledge digitization (KD) acts as a crucial mediator in this relationship. As organizations integrate new technologies, their ability to learn and internalize data becomes vital for competitive advantage and innovation. Research indicates that increasing AI adoption can significantly improve OL, providing access to large datasets that inform strategic planning and decision-making(Najana et al., 2024). Knowledge digitization, in this situation, acts as more than just a facilitator of information sharing; it transforms how knowledge is created, curated, and used(Ayestarán et al., 2022). Firms can go beyond conventional operational limits by digitizing knowledge effectively, which encourages collaborative environments that support ongoing learning and adaptation(Li et al., 2025).
H9: Knowledge Digitization (KD) moderates the relationship between Level of AI adoption (LOAI) and Organizational learning (OL), impacting Organizational performance

2.10 Knowledge Digitization (KD), Economic Outcome (ECO) , Organizational learning (OL), and Organizational performance

Economic Outcome (ECO) and Organizational Learning (OL) are becoming ever more intertwined, especially with the rise of Knowledge Digitization (KD) as part of digital innovation. Organizations aiming to improve often find KD acts as a pivotal moderator, helping them not only absorb knowledge but also get more out of their organizational learning. OL, in this context, means how organizations change and grow by using insights and experiences, potentially leading to better metrics like profitability and efficiency(Chughtai et al., 2023). By making knowledge readily accessible and easily shared, KD bolsters these processes and encourages teamwork that boosts learning and growth.
Evidence highlights the need to include Knowledge Digitization in strategic planning to enhance economic outcomes and organizational learning. This helps to improve organizational performance, and shows how technology is integral to organizational knowledge systems
H10: Knowledge Digitization (KD) moderates the relationship between Economic Outcome (ECO) and Organizational learning (OL), impacting Organizational performance

2.11 Knowledge Digitization (KD), Knowledge Stock (KNS) , Organizational learning (OL), and Organizational performance

Organizational performance often hinges on the effective sharing of knowledge between different parts of a company. So, it's important to consider how knowledge digitization affects the connection between a company's knowledge base and how well it learns. A company's knowledge base—all the information and understanding it possesses—forms the basis for learning and gaining an edge in the market(Grant, 1996). However, just having knowledge isn't enough; it needs to be used well and turned into practical learning. This is where knowledge digitization comes in. It helps in two ways: it makes things easier and boosts the relationship between what a company knows and how it learns. By changing information into digital formats, companies can make access simpler, lower sharing barriers, and encourage teamwork that supports ongoing learning.

The idea that knowledge digitization shapes the relationship between knowledge and organizational learning emphasizes that companies need to pair their knowledge resources with strong digitization skills. By doing this, they not only make it easier to share knowledge but also improve their overall performance(Cheng et al., 2023). The resulting combination of these things creates an environment where learning can flourish, new ideas can grow, and competitive advantages can last. So, effectively adding knowledge digitization into organizational practices isn't just useful but crucial for unlocking the full potential of inter-organizational knowledge sharing(Abdalla et al., 2020).

H11: Knowledge Digitization (KD) moderates the relationship between Knowledge Stock (KNS) and Organizational learning (OL), impacting Organizational performance

2.12 Organizational learning (OL) and Organizational Performance (OP)

The theoretical basis for this relationship can be traced back to the ideas of absorptive capacity and the knowledge-based view. These ideas suggest that the ability to assimilate and use new knowledge—a key part of organizational learning—directly impacts an organization's ability to improve its performance(Bouguerra et al., 2021; Lane & Lubatkin, 1998). Organizations that actively engage in OL are generally better positioned to handle challenges and take advantage of new opportunities, which leads to measurable improvements in responsiveness, productivity, and innovation quality(Liu et al., 2022; Qadri et al., 2021). For instance, organizations that adopt learning-oriented strategies can translate insights from their environment into tailored responses that align with evolving consumer needs and market dynamics, thus gaining a competitive edge(Alzadjali et al., 2023). Investing in OL not only results in short-term improvements but also fosters long-term sustainability by developing a knowledgeable workforce that can adeptly respond to industry changes.

H12: Organizational learning (OL) has significant positive impact on Organizational Performance (OP)

3. MATERIALS AND METHODS

3.1 *Research Model*

The influencing and dependent factors included in the proposed model (Figure 1) include Level of Automation, Data and Content, Level of AI adoption, Economic Outcome, Knowledge Stock, Organizational learning, Organizational performance, Knowledge Digitization

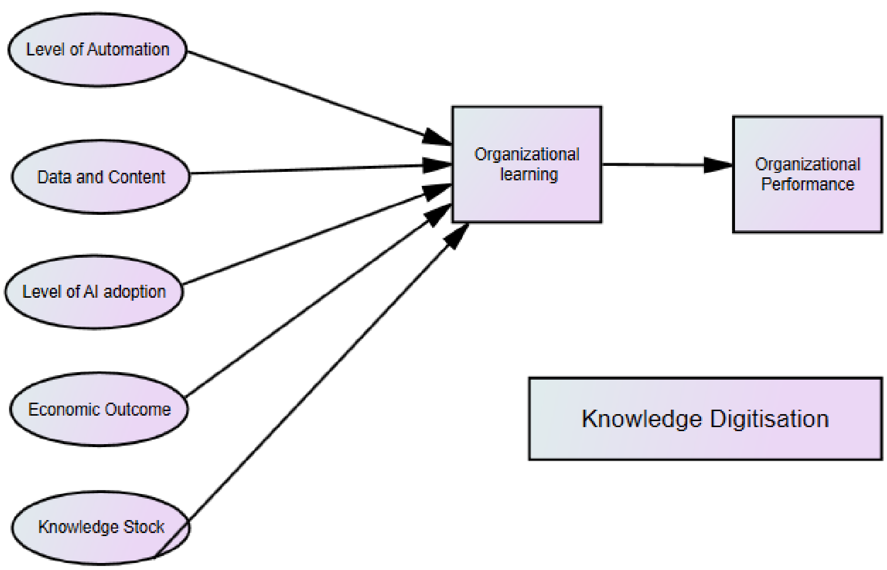

Figure 1: Proposed model showing the relationship between influencing and dependent factors

3.2 *Sample and Data Collection*

We measured every component using the standards that were part of this study. Although it would seem logical to infer that all of the variables are connected, this study also investigates that connection. Using a quantitative research approach, this descriptive study collects data appropriate for analyzing the relationships between independent and dependent variables. Using deliberate sampling, this study produced a sample that was thought to be fairly representative of the population. The core data will be collected from different businesses using Google Docs, which is the most recent data collecting tool and an effective way to collect data with limited time and resources. The entrepreneurs and businesses in the study's sample have prior work experience. As part of the field study, interviews were conducted using a semi-structured script that included conversation themes. In order to gather data, we asked group administrators for their consent before providing them a link to a questionnaire and requesting them to share it with their groups. Of the approximately 550 replies received, 456 were selected for the representative samples.

3.3 *Measures*

In the study, "strongly disagree" was represented by a number 1 and "strongly agree" by a number 5 on a Likert index scale questionnaire. Both direct and mediated hypotheses were examined in the analytical investigation. The profile of the respondents has been determined through the use of descriptive statistics. For our research, we used IBM SPSS Statistics version 20. We used Cronbach's alpha, factor analysis, regression analysis, and test hypotheses to assess the reliability of the proposed model and the validity of the concept statements.

5. Results

1. Demographic profile

To evaluate the respondent's demographic attributes, descriptive demographic statistics were employed. Data was gathered between July 2024 and July 2025 using a systematic questionnaire. Out of the 550 surveys distributed to participants, 456 were deemed to be fully completed and error-free. 82.90% of the responses are regarded as excellent quality after more inspection. Table 1 shows each person's socio-demographic information. Of the 456 responders, there were significantly more men (289, 63.40%) than women (167, 36.60%); the majority of them (130, 28.50%) were between the ages of 30 and 39; 191 (41.90%) possessed a Professional Education degree, with work experience of 11 to 20 years (237, 52%) and an income of more than 30,000 rupees (166, 36.4%).

Table 1. Descriptive Statistics of Demographic Profile

		Frequency	Valid %
Gender profile	Male	289	63.4
	Female	167	36.6
Age profile	20-29 years	63	13.8
	30-39 years	130	28.5
	40-49 years	87	19.1
	50-59 years	106	23.2
	60 years and older	70	15.4
Highest education level	Bachelor degree	59	12.9
	Master degree	116	25.4
	Professional Education	191	41.9
	Other	90	19.7
Working experience in years (total)	Less than 10	132	28.9
	11 to 20	237	52
	21 to 30	79	17.3
	31 to 40	8	1.8
Income	10,000- 20,000	103	22.6
	20,001- 30,000	157	34.4
	30,001- 40,000	166	36.4
	More than 40,000	30	6.6

2. Exploratory Factor Analysis

The PCA approach was used to do the exploratory factor analysis (EFA) for conforming components. A threshold of 0.50 has been established for factor loading in the current investigation. Table 2 displays the factor analysis results. The KMO relevance of the factor analysis for the data is typically represented by values between 0.5 and 1.0. The Bartlett sphericity test indicates how highly correlated the items are with the variable. The significance level of the test results is shown. When the values are less than 0.05, it means that the variables are strongly correlated. Factor analysis may not be suitable for the data if the number is more than or equal to 0.10. Based on the information gathered, test results show that factor analysis is appropriate. After four of the items with loadings less than 0.5 were eliminated, it was eventually determined that all of the items were valid for the final study.

Table 2. Results of Exploratory Factor Analysis

	Statement	Factor loadings	KMO Measure of Sample Adequacy (>0.5)	Bartlett's Test of Sphericity		Items confirmed	Items dropped	Cum % of loading
				Chi Square	Sig. (<.10)			
Level of Automation (LOA)	LOA-1	0.207	0.846	2066.654	0.000	4	1	71.424
	LOA-2	0.930						
	LOA-3	0.945						
	LOA-4	0.955						
	LOA-5	0.927						
Data and Content (DAC)	DAC-1	0.879	0.826	1515.509	0.000	5	0	70.685
	DAC-2	0.901						
	DAC-3	0.894						
	DAC-4	0.796						
	DAC-5	0.720						
Level of AI adoption (LOAI)	LOAI-1	0.666	0.699	1138.523	0.000	4	0	70.155
	LOAI-2	0.888						
	LOAI-3	0.942						
	LOAI-4	0.828						
Economic Outcome (ECO)	ECO-1	0.223	0.853	2071.404	0.000	4	1	71.512
	ECO-2	0.933						
	ECO-3	0.945						
	ECO-4	0.958						
	ECO-5	0.919						
Knowledge Stock (KNS)	KNS-1	0.630	0.720	350.036	0.000	4	1	43.449
	KNS-2	0.793						
	KNS-3	0.782						
	KNS-4	0.186						
	KNS-5	0.708						
Organizational learning (OL)	OL-1	0.227	0.853	2099.522	0.000	4	1	71.828
	OL-2	0.933						
	OL-3	0.947						
	OL-4	0.955						
	OL-5	0.928						
Organizational performance (OP)	OP-1	0.882	0.830	1539.769	0.000	5	0	71.210
	OP-2	0.903						
	OP-3	0.895						
	OP-4	0.800						
	OP-5	0.726						
Knowledge Digitization (KD)	KD-1	0.825	0.708	1078.951	0.000	4	0	70.089
	KD-2	0.935						
	KD-3	0.885						
	KD-4	0.682						

3. Reliability Analysis

The reliability assessment has been made possible by the use of Chronbach Alpha to calculate the internal consistency of the questionnaire. On updated scales, alpha values ought to be at least 0.60. If not, an established scale with internal consistency and an alpha value of 0.70 is applied. A cutoff value of more than 0.7 was used for the inquiry since Cronbach's alpha was found to be within a suitable range. The survey in Table 3 shows an Cronbach's alpha scores, which suggests that the research instrument has a decent degree of reliability.

Table 3 : Results of Reliability test

Variable	Cronbach alpha
Level of Automation (LOA)	0.956
Data and Content (DAC)	0.896
Level of AI adoption (LOAI)	0.857
Economic Outcome (ECO)	0.956
Knowledge Stock (KNS)	0.711
Organizational learning (OL)	0.958
Organizational performance (OP)	0.898
Knowledge Digitization (KD)	0.856

4. Correlatıon Analysis
The findings of the independent variable correlation study indicate that there seems to be a high association between each and every variable. There is a significant association between the dependent and independent variables when all factors are taken into account (Table 4). The variables assessing Knowledge Stock (KNS) and Knowledge Digitization (KD) had the lowest connection (0.719), whereas the variables measuring Level of Automation (LOA) and Economic Outcome (ECO) had the highest correlation (0.998).

Table 4: Correlations

	LOA	DAC	LOAI	ECO	KNS	OL	OP	KD
LOA	1							
DAC	.929**	1						
LOAI	.911**	.875**	1					
ECO	.998**	.924**	.913**	1				
KNS	.796**	.773**	.735**	.802**	1			
OL	.989**	.910**	.906**	.989**	.818**	1		
OP	.925**	.983**	.882**	.925**	.809**	.933**	1	
KD	.832**	.799**	.922**	.836**	.719**	.849**	.831**	1

**. Correlation is significant at the 0.01 level (2-tailed).

5. Regression Analysis
Stepwise regression analysis was used to determine the link between the independent and dependent variables. Tables below showed that Organizational learning and Organizational performance are significantly predicted by the parameters under consideration using step-wise regression analysis.

5.1 Organizational learning (OL) as dependent variable: The predictor-criterion relationship between the independent and dependent variables was found using stepwise regression analysis. Tables 5a and 5b, which used step-wise regression analysis, showed that the variables under investigation are highly significant predictors of the development of Organizational learning. Table 5a shows that these traits account for 98.2% of Organizational learning, with a R square of 0.982. Table 5b displays the regression model's ANOVA values, which demonstrate validation at a 95% confidence level. The beta value of all the components are .731 and 0.237, which accurately reflects their influence on the development of Organizational learning, according to the coefficient summary in Table 5c.

Table 5a: Regression analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.991[a]	.982	.982	.13461

a. Predictors: (Constant), KNS, LOAI, DAC, ECO, LOA

Table 5b: ANOVA analysis

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	441.615	5	88.323	4874.354	.000[b]
	Residual	8.154	450	.018		
	Total	449.769	455			

a. Dependent Variable: OL
b. Predictors: (Constant), KNS, LOAI, DAC, ECO, LOA

Table 5c: Regression coefficients table for dependent variables

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.097	.027		-3.518	.000
	LOA	.739	.097	.731	7.585	.000
	DAC	-.096	.020	-.084	-4.696	.000
	LOAI	.039	.018	.034	2.150	.032
	ECO	.239	.096	.237	2.478	.014
	KNS	.115	.015	.086	7.945	.000

a. Dependent Variable: OL

5.2 Impact of Knowledge Digitization (KD) on Organizational learning (OL): The predictor-criterion relationship between the independent and dependent variables was found using stepwise regression analysis. Knowledge Digitization is important predictor of the development of Organizational learning, as shown by Tables 5d and 5e. Table 5d shows that these factors explain 72.1% of the development of social entrepreneurship, with a R square of 0.721. Table 5e displays the regression model's ANOVA values, which demonstrate validation at a 95% confidence level. The beta value of 0.849, accurately reflects its influence on the development of Organizational learning, according to the coefficient summary in Table 5f.

Table 5d: Regression analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.849[a]	.721	.721	.52543

a. Predictors: (Constant), KD

Table 5e: ANOVA analysis

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	324.431	1	324.431	1175.156	.000[b]
	Residual	125.338	454	.276		
	Total	449.769	455			

a. Dependent Variable: OL
b. Predictors: (Constant), KD

Table 5f: Regression coefficients table for dependent variables

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.197	.079		2.481	.013
	KD	.930	.027	.849	34.281	.000

a. Dependent Variable: OL

5.3 Moderating impact of Knowledge Digitization (KD) between selected influencing variables and Organizational learning (OL): The Zscore values for each variable were developed to examine the relationship between Knowledge Digitization and the development of Organizational learning. Next, by calculating the interaction between all independent factors and Knowledge Digitization, new variables are formed, which are represented as interactions IA1 through IA5.

The dependent variable (OL) and the additional interacting independent variables (IA1 through IA5) were used in a regression analysis. Based on the outcomes of step-wise regression analysis, Tables 5g and 5h show how these interacting traits are a strong predictor of Organizational learning. The R square value of 0.883 in Table 5g indicates that these variables are responsible for 88.3% of the success of Organizational learning. Table 6h displays the regression model's ANOVA values, which demonstrate validation at a 95% confidence level. According to Table 6i's coefficient summary, the beta values are, respectively, 0.706 and 0.110. These ideals fairly reflect the ways in which they influence the Organizational learning.

Table 5g: Regression analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.939[a]	.883	.881	.34246

a. Predictors: (Constant), IA5, IA3, IA2, IA4, IA1

Table 5h: ANOVA analysis

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	396.993	5	79.399	677.002	.000[b]
	Residual	52.776	450	.117		
	Total	449.769	455			

a. Dependent Variable: OL
b. Predictors: (Constant), IA5, IA3, IA2, IA4, IA1

Table 5i: Regression coefficients table for dependent variables

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	2.568	.017		155.061	.000
IA1	.210	.057	.706	3.660	.000
IA2	-.024	.013	-.081	-1.827	.068
IA3	.034	.013	.110	2.622	.009
IA4	.037	.057	.126	.660	.510
IA5	.030	.009	.096	3.184	.002

a. Dependent Variable: OL

5.4 Impact of Organizational learning (OL) on Organizational performance (OP): The dependent variable (OL) and the independent variable (OP) were used in a regression analysis. Based on the outcomes of step-wise regression analysis, Tables 5j and 5k show how these interacting traits are a strong predictor of Organizational performance. Table 5j's R square value of 0.871 indicates that 87.1% of the success of Organizational performance may be attributed to these factors. Table 5k displays the regression model's ANOVA values, which demonstrate validation at a 95% confidence level. According to Table 5l's coefficient summary, the beta value is 0.933, fairly reflect the ways in which they influence the Organizational performance.

Table 5j: Regression analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.933[a]	.871	.871	.31442

a. Predictors: (Constant), OL

Table 5k: ANOVA analysis

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	303.203	1	303.203	3067.033	.000[b]
	Residual	44.882	454	.099		
	Total	348.085	455			

a. Dependent Variable: OP
b. Predictors: (Constant), OL

Table 5l: Regression coefficients table for dependent variables

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.432	.044		9.860	.000
	OL	.821	.015	.933	55.381	.000

a. Dependent Variable: OP

6. Results of Hypotheses Testing

Table 6 displays the 12 initial hypotheses that were put forth in the conceptual research framework, all of which have been accepted, except two (H8 and H10).

Table 6: Summary of Hypotheses Testing

Hy. No.	Independent Variables	Dependent Variables	R-Square	Beta Coefficient	t-value	Sig Value	Status of Hypotheses
H1	Level of Automation	Organizational learning	0.982	.731	7.585	.000	Accepted
H2	Data and Content	Organizational learning	0.982	-.084	-4.696	.000	Accepted
H3	Level of AI adoption	Organizational learning	0.982	.034	2.150	.032	Accepted
H4	Economic Outcome	Organizational learning	0.982	.237	2.478	.014	Accepted
H5	Knowledge Stock	Organizational learning	0.982	.086	7.945	.000	Accepted
H6	Knowledge Digitization	Organizational learning	0.721	.849	34.281	.000	Accepted
H7	IA1	Organizational learning	0.883	.706	3.660	.000	Accepted
H8	IA2	Organizational learning	0.883	-.081	-1.827	.068	Rejected
H9	IA3	Organizational learning	0.883	.110	2.622	.009	Accepted
H10	IA4	Organizational learning	0.883	.126	.660	.510	Rejected
H11	IA5	Organizational learning	0.883	.096	3.184	.002	Accepted
H12	Organizational learning	Organizational performance	0.871	.933	55.381	.000	Accepted

DISCUSSION

According to research findings, Level of Automation has a noteworthy impact on Organizational performance when moderated by Knowledge Digitization (H7, Beta Coefficient = 0.706) and a significant positive relationship with Organizational learning (H1, Beta Coefficient = 0.731). It is clear from the analysis's results that Level of Automation has the strongest positive correlation and a strong relationship with organizational learning (Younis & Adel, 2020). According to Joshi and Masih (2023), knowledge digitization is in the front of change, transforming workplaces and reshaping the nature of work in the future. The importance of knowledge digitization has been emphasized in earlier research by George et al. (2023), Adel (2022), and Aly (2020), which examined the key elements influencing the expansion and productivity of industry organizations. These studies identified a number of important components, including automation, data utilization, work quality, digital transformation, and AI adoption.

Although knowledge digitization did not have a moderating effect, the empirical analysis of hypothesis (H2, Beta Coefficient = -0.084) showed a strong association between inadequate data and content and organizational learning (H8, Beta Coefficient = -0.081; p value = 0.068). Researchers like Chander et al. (2022) and Ahmed et al. (2022) investigated the complex effects of knowledge digitization, pointing out both advantages and disadvantages. They also raised issues about inadequate data and content as well as how organizational learning affects organizational performance. The study examined how knowledge digitization affects inadequate data and content, highlighting the drawbacks of conventional human-centered processes (Ambati et al., 2020). According to Bhardwaj et al. (2020), knowledge digitization helps overcome information processing errors and limitations and introduces a more systematic approach to data and content management. Additionally, using knowledge digitization to centralize company data in the cloud aids in the prediction of important business performance indicators without the need for a data scientist's intervention.

A significant positive correlation between the constructs was found by independent investigation of the relationship between organizational learning and the level of AI deployment. Despite the moderating effect of knowledge digitization (H9, beta coefficient = 0.110), these results are in line with Hypothesis 3 (beta coefficient = 0.034). Increased Knowledge Digitization and AI adoption levels in official tasks are positively correlated with increased work productivity, time and cost savings, and ultimately an organization's overall potential and capacity, according to a study by Reddy et al. (2021) (Sakka et al., 2022).

Economic Outcome has a favorable and significant impact on organizational learning, as demonstrated by the results of hypothesis 4 (beta coefficient = 0.237). However, this effect is not mitigated by knowledge digitization (H10, beta coefficient = 0.126; p value = 0.510). Khatri et al. (2020) assert that the Economic Outcome has a cumulative effect on the learning and growth of industry organizations, which eventually leads to increased economic returns and better work productivity (Berhil et al., 2020; Chowdhury et al., 2023). However, the effects of knowledge digitization do not produce the same results.

Although Knowledge Digitization had a moderating effect (H11, Beta Coefficient = 0.096), a significant positive relationship between Knowledge Stock and Organizational Learning was found in the empirical analysis of hypothesis 5 (Beta Coefficient = 0.086). This element highlights the importance of knowledgeable stock and a constant learning mindset among organization employees in boosting overall work productivity, according to Younis & Adel (2020). According to the findings, knowledge digitization offers a more methodical approach to innovation management by utilizing machine learning algorithms to find new opportunities and get around restrictions on information processing (Zarifhonarvar, 2023). A few elements, such as the Qualitative Transformation Solution, AI-Automation Potential Impact, Innovative Data Outcome, and Team Knowledge, were discovered to work in concert to propel the expansion and efficiency of industry organizations (Liu et al., 2023).

The results of the study show a strong positive correlation between organizational learning and knowledge digitization (H6, Beta Coefficient = 0.849). Effective knowledge digitization helps those organizations by lowering infrastructure and human costs and increasing operational innovation, efficiency, and effectiveness, which results in long-term organizational success (Raudeliuniene et al., 2020; Antunes, 2022). According to Shahzad et al. (2020), knowledge digitization improves an organization's competences to acquire the knowledge that would improve decision-making and problem-solving processes, as well as operational business processes to attain the required performance. According to Antunes and Pinheiro (2020), this procedure would boost the organization's leadership, creativity, and distinctiveness while also improving overall performance. It makes it possible to apply business processes, operations, and activities and enhance organizational outcomes by fusing newly developed and acquired knowledge with the resources at hand (Bilan et al., 2020). Applying necessary knowledge to the organization's operations and procedures in order to accomplish knowledge strategy and long-term organizational performance is known as knowledge application (Balasubramanian et al., 2020; Mittelmann, 2022).

The results of the study for hypothesis 12 (beta coefficient = 0.993) show a strong positive correlation between organizational performance and organizational learning. The business processes and knowledge flows that boost innovation and enhance overall organizational performance and leadership are impacted by organizational learning (Adomako et al., 2021). Furthermore, these successful implementation procedures have a favorable impact on long-term organizational performance, according to the findings of earlier studies (Abbas, 2020). People can acquire pertinent social, professional, and personal skills and experiences through organizational learning (Kusa et al., 2023). This capability enables them to react to environmental changes more effectively, provide value to the firm, increase the efficacy and efficiency of its operations, and achieve sustainable organizational performance (Arslan et al., 2021). A collection of knowledge management procedures known as organizational learning make it easier for people and groups at all organizational levels to create, acquire, store, share, and use knowledge (Ashari et al., 2023). Additionally, it improves staff competencies for effective problem solving and decision making, knowledge strategy achievement, and local and global leadership, all of which have a favorable impact on sustainable organizational performance (Ciampi et al., 2022).

CONCLUSION

The purpose of this study was to investigate how knowledge digitalization has affected the connection between organizational performance and learning in information-intensive industries. According to study findings, managers of businesses can improve organizational performance across a range of industries by implementing knowledge digitization procedures to foster organizational learning. A key component of this change is knowledge digitalization, which makes organizations more efficient and compassionate. In addition to increasing efficiency, knowledge digitization technologies open up new career paths, freeing up staff members to concentrate on other human-centered facets of their jobs, such engagement, customer service, and workplace culture.

The investigation of knowledge digitalization through integration with five knowledge management processes is what makes this study valuable and unique. Additionally, an expert survey and organizational learning contribution regarding the full knowledge management cycle and organizational performance in intense knowledge-based businesses in developing nations served as the foundation for this study. Through an in-depth knowledge-based field, the study's findings will enhance the viewpoints of scientists and business practitioners by providing insight into how organizational learning through the digitization of all knowledge adds to organizational performance.

Future prospects

The findings demonstrate how organizational learning and knowledge digitalization improve organizational effectiveness. It appears that the impact on the companies' knowledge creation is less significant, indicating that developing economies lack the resources necessary to invest in organizational learning for the creation of new knowledge. This illustrates the analysis of the distinctions between local and multinational corporations. These results of the current study should be taken into consideration while conducting related research in the future. Additionally, it is a chance for researchers who wish to embrace other aspects and expand this research using their resources in other places. These can be leveraged well in exploring new routes for particular studies like this.

Practical Implications

This study has practical significance for the knowledge-based economy in developing nations, where knowledge digitization techniques may help grow and enhance the performance of firms operating in various sectors. The study's findings suggest that knowledge-based industries should promote organizational learning to build employees' competencies—the knowledge, skills, and abilities needed to apply knowledge management techniques and sustain organizational performance.

Limitations

Nevertheless, earlier studies had certain drawbacks. For example, in the intensive knowledge-based economy, only a small portion of the knowledge digitization processes were examined in previous investigations. This aspect has made it more difficult to investigate how knowledge digitalization influences the relationship between organizational learning and performance. One of the drawbacks of this study is that the structured questionnaire (expert evaluation) was only used in a specific knowledge-based industry and geographic area. This limited the generalizability of the results because the survey was conducted in a distinct sector. Other knowledge-based industries in various geographic locations with similar cultural and economic backgrounds could be the subject of future investigation.

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