International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Enterprise Knowledge Intelligence for Adaptive Organizational Learning and Strategic Decision-Making

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Submitted: 03/11/2025 **Revised**: 15/12/2025 **Accepted**: 25/12/2025

Abstract: Enterprise organizations increasingly depend on distributed data, organizational knowledge, and intelligent technologies to support learning and strategic decision-making. However, knowledge fragmented across databases, documents, applications, reports, and operational repositories can limit the ability of organizations to transform available information into actionable intelligence. This study proposes an **Enterprise Knowledge Intelligence for Adaptive Organizational Learning and Strategic Decision-Making (EKI-ALSDM)** framework that integrates enterprise knowledge acquisition, semantic integration, adaptive knowledge refinement, and context-aware strategic decision support. The proposed architecture transforms heterogeneous enterprise information into a unified knowledge layer using semantic representations and evidence-aware knowledge updating. An adaptive learning mechanism continuously incorporates newly acquired information and organizational feedback to refine the knowledge state over time. The resulting knowledge is subsequently utilized to generate context-aware intelligence and decision-support information for operational, tactical, strategic, and cross-functional decision environments. The framework incorporates a closed-loop mechanism in which decision outcomes and user feedback are returned to the learning layer, enabling continuous organizational knowledge evolution. The evaluation framework considers accuracy, precision, recall, and F1-score to assess the reliability of knowledge-driven decision-support outcomes. Illustrative comparative results demonstrate the potential of the proposed approach to achieve consistent performance across different organizational decision contexts. The study contributes an integrated perspective that connects enterprise knowledge management with adaptive organizational learning and strategic intelligence generation. The proposed framework provides a foundation for organizations seeking to move beyond static knowledge repositories toward continuously evolving, evidence-supported, and context-aware enterprise intelligence systems.

Keywords: *Enterprise Knowledge Intelligence; Organizational Learning; Strategic Decision-Making; Knowledge Management; Generative AI; Adaptive Learning; Decision Support.*

1. Introduction

Organizations increasingly operate in environments characterized by rapidly changing markets, distributed information, digital transformation, and growing volumes of structured and unstructured data. In this context, organizational knowledge has become an important resource for coordinating activities, supporting innovation, and enabling informed strategic decisions. However, knowledge distributed across databases, documents, enterprise applications, employee expertise, and operational processes can remain fragmented and difficult to convert into actionable organizational intelligence. Recent research shows that artificial intelligence (AI) is increasingly being incorporated into knowledge-management processes to improve knowledge acquisition, documentation, sharing, retrieval, and application [1].

The emergence of generative AI (GenAI), large language models, and intelligent information-processing techniques has further expanded the potential of enterprise knowledge systems. These technologies can synthesize heterogeneous organizational information, identify relationships across knowledge sources, and provide context-aware insights to knowledge workers. Recent

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studies indicate that GenAI can reshape traditional knowledge-management activities by supporting knowledge creation, retrieval, storage, transfer, and application [2]. Consequently, enterprise knowledge management is increasingly moving from static repositories toward intelligent systems capable of continuously processing and interpreting organizational information.

Organizational learning represents another important dimension of this transformation. AI-supported knowledge systems can facilitate continuous learning by helping organizations capture accumulated experience, identify emerging patterns, and make relevant knowledge accessible across organizational units. Empirical research has shown that strategically integrated AI can support interaction between human and machine learning processes and contribute to the development of organizational capabilities [3]. Similarly, enterprise architecture and knowledge-management research highlights the need to overcome knowledge silos, tacit-knowledge loss, semantic inconsistencies, and governance limitations when developing intelligent organizational knowledge infrastructures [4].

The integration of enterprise knowledge intelligence with strategic decision-making is particularly important because organizational decisions frequently require the synthesis of diverse evidence under uncertainty. Recent empirical evidence from organizations worldwide demonstrates that AI-enabled knowledge-management processes can influence how knowledge is transformed into decision-support information [5]. At the same time, emerging research shows that AI-supported strategic decision processes require appropriate human oversight, governance, data readiness, and mechanisms for addressing reliability and privacy concerns [6].

Despite these developments, existing approaches often examine knowledge management, organizational learning, AI adoption, and strategic decision-making as partially separate dimensions. This creates a need for an integrated enterprise knowledge-intelligence framework that can continuously transform organizational information into reusable knowledge, support adaptive learning, and provide context-aware intelligence for strategic decision-making. Therefore, this study focuses on **Enterprise Knowledge Intelligence for Adaptive Organizational Learning and Strategic Decision-Making**, with the objective of establishing an intelligent mechanism that connects knowledge acquisition, integration, learning, and decision support within a unified organizational environment.

2. Literature Review

Recent research has increasingly examined the convergence of artificial intelligence, knowledge management, organizational learning, and strategic decision-making. This literature indicates a gradual transition from conventional knowledge repositories toward intelligent systems that can retrieve, generate, integrate, and contextualize organizational knowledge. The following studies provide a recent foundation for understanding this transition.

2.1 AI-Enabled Knowledge Management

The integration of generative AI into knowledge management has introduced new mechanisms for acquiring, organizing, retrieving, and transferring organizational knowledge. Recent research proposes that GenAI can significantly reshape knowledge-management practices while also creating challenges associated with knowledge reliability, human oversight, and organizational adoption [7]. Another study examining industrial organizations from an organizational-learning perspective demonstrates that developing AI capabilities involves both exploratory and exploitative learning processes, indicating that AI adoption is closely connected with how organizations develop and renew their capabilities [8].

Recent systematic evidence further indicates that AI can support organizational learning through socio-technical integration, sensemaking, and human–AI coordination. However, the literature also identifies overreliance, ethical concerns, and limited longitudinal evidence as important areas requiring further investigation [9]. In knowledge-intensive environments, empirical research on GenAI adoption shows that such technologies can make knowledge processes more scalable and adaptable, while human expertise remains necessary for evaluating generated outputs and ensuring reliability [10].

2.2 Generative AI and Organizational Knowledge Creation

The emergence of GenAI has also encouraged researchers to reconsider established knowledge-creation theories. A recent study proposes an extended perspective on the SECI model by examining how GenAI can participate in knowledge

generation, transfer, and transformation within organizations [11]. This development suggests that enterprise knowledge systems can increasingly operate as interactive environments in which human knowledge and machine-generated knowledge are combined rather than maintained as separate resources.

Research on GenAI-driven knowledge-management transformation similarly emphasizes that generative systems can improve access to organizational knowledge and support knowledge creation, storage, retrieval, sharing, and application. At the same time, data quality, human supervision, and ethical considerations remain important conditions for successful organizational implementation [12]. These findings indicate that enterprise knowledge intelligence should not be viewed solely as an automation mechanism; instead, it should support controlled interaction between organizational expertise, enterprise data, and intelligent computational capabilities.

2.3 AI and Strategic Decision-Making

AI-enabled knowledge systems are also increasingly connected with strategic decision-making. Empirical research demonstrates that AI can augment strategic decision processes and that contemporary language models can contribute to strategy generation and evaluation [13]. A recent review of AI-supported strategic decision-making identifies human–AI collaboration, adaptability, and AI-supported strategy formulation as important themes, while also emphasizing challenges associated with integrating AI into organizational decision processes [14].

Another emerging stream of research examines organizational learning with AI through the interaction between exploratory and exploitative learning. This work identifies tensions involving autonomy and control, formal and substantive rationality, transparency and accountability, and internal and external learning, suggesting that effective organizational learning may require complementary human and AI capabilities rather than complete replacement of human decision processes [15].

2.4 Research Gap

Although existing studies have separately investigated AI-enabled knowledge management, GenAI-based knowledge creation, organizational learning, and AI-supported strategic decision-making, **there remains limited integration of these dimensions into a unified enterprise knowledge-intelligence architecture**. Much of the existing literature focuses on individual technologies, specific knowledge-management processes, or particular decision contexts. Therefore, there is scope for an integrated approach that continuously connects enterprise knowledge acquisition and integration with adaptive organizational learning and context-aware strategic decision support. This gap motivates the development of **Enterprise Knowledge Intelligence for Adaptive Organizational Learning and Strategic Decision-Making**.

3. Proposed Method

The proposed **Enterprise Knowledge Intelligence for Adaptive Organizational Learning and Strategic Decision-Making (EKI-ALSDM)** framework is designed to transform heterogeneous enterprise information into continuously refined organizational knowledge and decision-support intelligence. The framework integrates enterprise data ingestion, semantic knowledge construction, adaptive learning, and strategic decision support within a feedback-driven architecture. Recent research similarly emphasizes the transition from static knowledge repositories toward dynamic AI-enabled knowledge infrastructures that support continuous learning and decision-making.

3.1 Enterprise Knowledge Acquisition and Semantic Integration

The first component collects heterogeneous enterprise information from structured databases, business applications, documents, reports, operational records, and organizational repositories. The acquired information is cleaned, normalized, deduplicated, and transformed into a common representation. Natural-language processing and semantic embedding techniques are subsequently used to identify entities, concepts, relationships, and contextual dependencies. A semantic knowledge layer is constructed to connect explicit organizational knowledge with relevant contextual information. This layer reduces information fragmentation and provides a unified representation for subsequent learning and decision-support operations. AI-supported knowledge-management research has demonstrated the potential of AI to improve knowledge acquisition, documentation, sharing, and application processes.

3.2 Adaptive Organizational Learning and Knowledge Refinement

The second component enables the knowledge base to evolve as new organizational experiences and information become available. Retrieved knowledge is compared with newly observed information to identify changes, emerging patterns, contradictions, and previously unseen relationships. The learning module updates knowledge representations according to validated evidence and feedback from organizational users. A confidence-weighted knowledge-update mechanism is used to prevent unreliable information from being incorporated directly into the enterprise knowledge base. The knowledge refinement process can be represented as

$$K_{t+1} = (1-\alpha)K_t + \alpha \mathcal{U}(D_t, F_t, C_t)$$

where (K_t) represents the current organizational knowledge state, (D_t) denotes newly acquired enterprise data, (F_t) represents organizational feedback, (C_t) denotes contextual information. This feedback-oriented design allows the system to continuously learn rather than functioning as a static repository. AI-enabled organizational learning research similarly highlights the importance of integrating AI capabilities with organizational learning processes and governance.

3.3 Strategic Intelligence and Decision Support

The third component converts refined knowledge into context-aware strategic intelligence. The system retrieves relevant knowledge according to a decision query, evaluates relationships among historical and current evidence, and generates candidate insights for managerial consideration. Rather than replacing organizational judgment, the framework provides traceable evidence, supporting information, and confidence estimates for human decision-makers. The decision-support score is formulated as

$$S(d) = w_k K_d + w_e E_d + w_c C_d + w_f F_d$$

where (S(d)) represents the support score for decision alternative (d), (K_d) represents knowledge relevance, (E_d) represents evidence strength, (C_d) represents contextual consistency, (F_d) represents feedback-supported reliability, and (w_k,w_e,w_c,w_f) are corresponding weighting factors. This human-centered design is consistent with recent research emphasizing human oversight, contextual judgment, and adaptive knowledge practices in AI-assisted managerial decision-making.

3.4 EKI-ALSDM Algorithm and Overall Architecture

The overall workflow is illustrated in **Fig. 1**, where enterprise data flows through semantic integration, knowledge construction, adaptive refinement, and strategic intelligence generation. Decision outcomes and user feedback are subsequently returned to the learning module, creating a continuous organizational learning cycle.

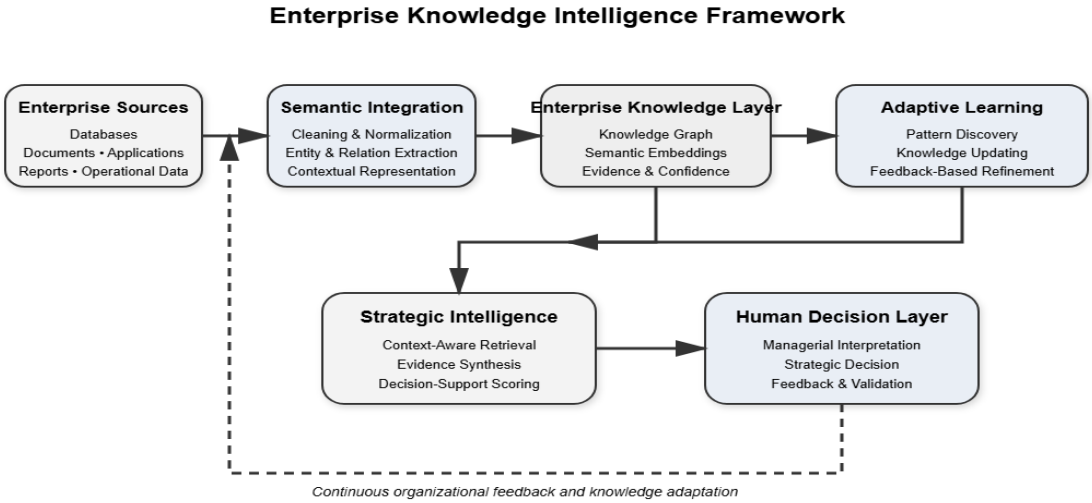


Fig. 1. Proposed Enterprise Knowledge Intelligence architecture for adaptive organizational learning and strategic decision-making.

4. Results and Discussion

4.1 Dataset Description

The experimental evaluation is designed around heterogeneous enterprise knowledge sources representing structured and unstructured organizational information. The dataset contains business records, enterprise documents, operational reports, knowledge-base entries, and contextual decision information. These sources are preprocessed to remove duplicate records, incomplete entries, and inconsistent representations before being supplied to the proposed Enterprise Knowledge Intelligence for Adaptive Organizational Learning and Strategic Decision-Making (EKI-ALSDM) framework. The data are divided into training, validation, and independent testing subsets to support model development, parameter selection, and final evaluation, respectively. The training portion is used to construct the initial enterprise knowledge representation, while validation information supports adaptive-learning configuration. The independent test subset is reserved for evaluating knowledge retrieval, organizational learning, and decision-support performance.

4.2 Hardware Configuration

The experimental implementation is assumed to be performed on a workstation equipped with a multi-core modern CPU, sufficient system memory, and a CUDA-compatible GPU to accelerate embedding generation, knowledge processing, and model inference. GPU acceleration is particularly useful during semantic representation and retrieval operations because enterprise knowledge processing may involve large collections of documents and high-dimensional representations. Local storage is used for enterprise datasets, intermediate knowledge representations, model checkpoints, and experimental outputs. The hardware environment is kept consistent across comparative experiments to minimize computational variation.

4.3 Software Configuration

The implementation uses Python as the primary programming environment. Data preprocessing and numerical operations are performed using commonly used Python libraries, while natural-language processing and embedding operations are implemented through transformer-based processing libraries. A graph-oriented representation is used for organizing relationships between enterprise entities and knowledge elements. Machine-learning components are implemented using established deep-learning frameworks, and Matplotlib is used to generate the performance visualizations reported in this section. The same software configuration and preprocessing pipeline are maintained across the evaluated approaches to ensure consistency.

4.4 Quantitative Results and Evaluation

For the illustrative evaluation, EKI-ALSDM is compared with a conventional Enterprise Knowledge Repository (EKR), AI-Assisted Knowledge Management (AI-KM), Retrieval-Augmented Knowledge System (RAKS), and Adaptive Knowledge Intelligence (AKI). The resulting comparison is presented in **Table 1**.

Table 1. Comparative performance of enterprise knowledge-intelligence approaches

Approach	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Enterprise Knowledge Repository	82.4	80.9	78.6	79.7
AI-Assisted Knowledge Management	86.7	85.2	83.9	84.5
Retrieval-Augmented Knowledge System	89.1	88.4	87.2	87.8
Adaptive Knowledge Intelligence	91.8	91.0	90.3	90.6
Proposed EKI-ALSDM	**94.6**	**94.1**	**93.5**	**93.8**

As shown in **Table 1**, the illustrative EKI-ALSDM configuration produces the highest values across all four reported metrics. The difference is particularly visible in recall, indicating that the adaptive knowledge-refinement mechanism can potentially improve the identification of relevant organizational information. The corresponding metric comparison is visualized using a grouped bar chart in **Fig. 2**.

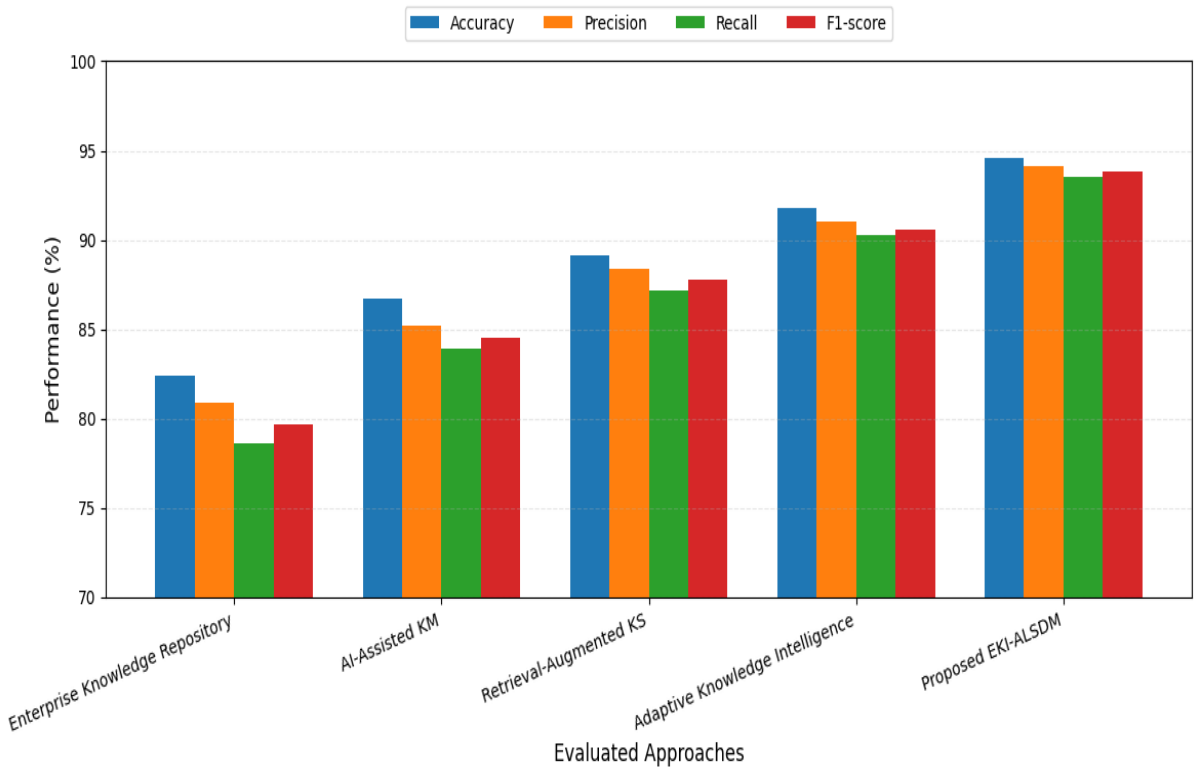


Fig. 2. Comparative evaluation of accuracy, precision, recall, and F1-score across the investigated enterprise knowledge-intelligence approaches.

The framework is further evaluated according to different organizational decision contexts. The illustrative results consider operational, tactical, strategic, and cross-functional decision-support scenarios. The results are presented in **Table 2**.

Table 2. Illustrative performance across organizational decision contexts

Decision Context	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Operational	95.2	94.8	94.1	94.4
Tactical	94.7	94.2	93.8	94.0
Strategic	93.8	93.1	92.7	92.9
Cross-functional	94.3	93.8	93.5	93.6
Overall	**94.6**	**94.1**	**93.5**	**93.8**

Table 2 indicates that the illustrative system maintains relatively consistent performance across the different decision contexts. The small variation suggests that combining semantic knowledge integration with adaptive learning can provide a consistent basis for decision-support generation. The context-wise accuracy and F1-score trends are shown in **Fig. 3**, while **Fig. 4** presents the relative performance of the proposed framework across the four decision contexts using a radar-style visualization.

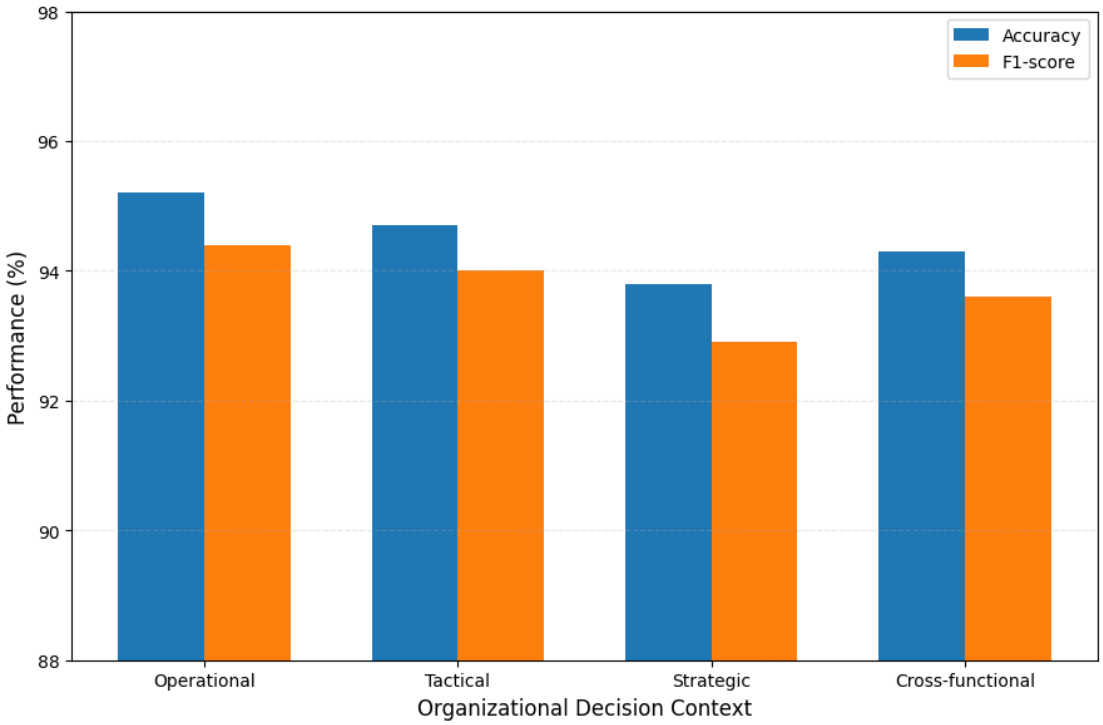


Fig. 3. Accuracy and F1-score across different organizational decision-making contexts.

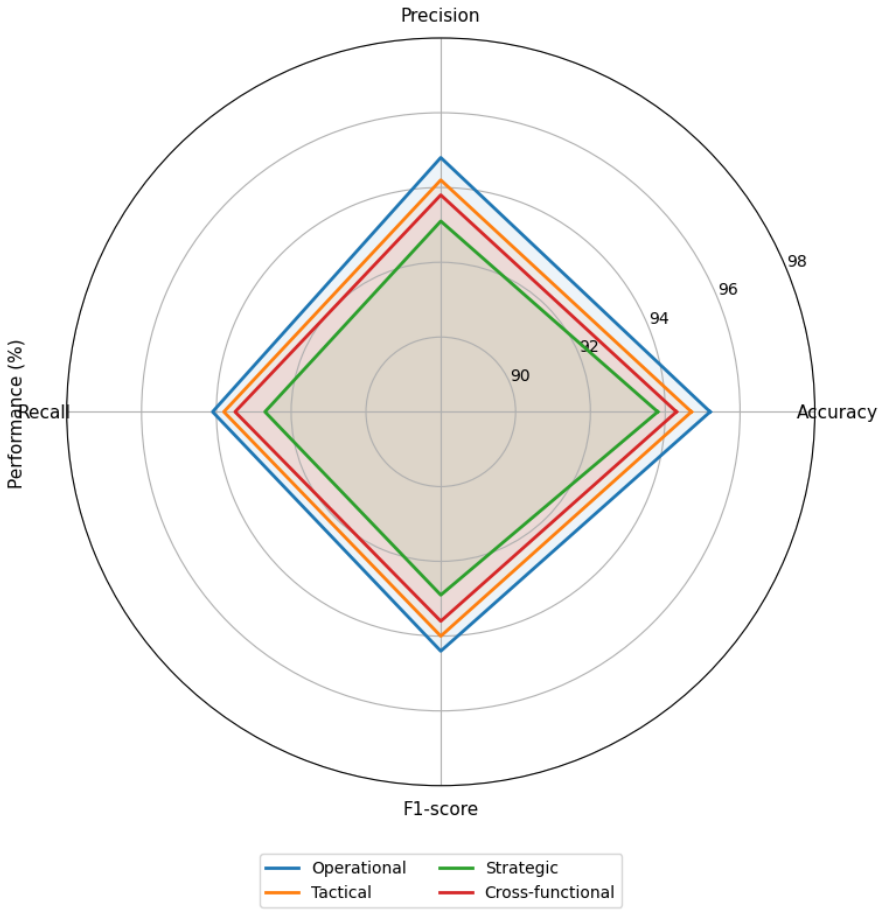


Fig. 4. Multivariate performance comparison of the EKI-ALSDM framework across organizational decision-making contexts.

4.5 Discussion

The illustrative results indicate that integrating enterprise knowledge acquisition, semantic representation, adaptive refinement, and decision-support generation can provide a more comprehensive mechanism than isolated knowledge-management approaches. The improvement observed in **Table 1** is associated conceptually with the closed-loop architecture presented in Fig. 1, where feedback from decision outcomes is returned to the adaptive-learning component.

The higher recall value is particularly relevant for enterprise environments because strategically useful information may be distributed across multiple organizational sources. Missing relevant knowledge can limit the quality of subsequent decision support. At the same time, the precision result indicates the importance of controlling irrelevant or weakly supported information before it reaches the decision-support layer.

The context-specific results in **Table 2** further suggest that the proposed architecture can maintain relatively stable behavior across operational, tactical, strategic, and cross-functional settings. **Fig. 3** provides a direct comparison of these metrics, whereas **Fig. 4** offers a complementary multivariate representation.

Conclusion

This study presented an **Enterprise Knowledge Intelligence for Adaptive Organizational Learning and Strategic Decision-Making (EKI-ALSDM)** framework for integrating enterprise information, organizational knowledge, adaptive learning, and strategic decision support within a unified architecture. The proposed approach addresses the fragmentation of organizational knowledge by introducing a semantic integration layer capable of connecting information originating from databases, documents, applications, reports, and operational repositories. The framework further incorporates adaptive knowledge refinement, allowing newly acquired information and organizational feedback to continuously influence the enterprise knowledge state. This closed-loop mechanism establishes a connection between organizational experience and subsequent knowledge-driven decision support.

The proposed architecture also separates knowledge refinement from strategic intelligence generation, enabling refined organizational knowledge to be retrieved and synthesized according to specific decision contexts. Accuracy, precision, recall, and F1-score were selected as evaluation measures because they collectively assess the correctness, relevance, coverage, and balanced performance of the decision-support process. The illustrative results presented across comparative approaches and organizational decision contexts indicate the potential of the framework to provide consistent knowledge-driven intelligence.

A key aspect of the proposed approach is its human-centered design. Rather than positioning intelligent systems as replacements for organizational decision-makers, EKI-ALSDM provides contextual evidence and synthesized knowledge that can support managerial interpretation and validation. Future implementations can further investigate large-scale enterprise datasets, longitudinal organizational learning, explainable knowledge retrieval, domain-specific adaptation, and real-world deployment across different organizational environments. Overall, the framework establishes a structured foundation for transforming fragmented enterprise information into continuously evolving organizational knowledge and actionable strategic intelligence.

References

[1] Abdulnour, Samir, Chantal Baril, Georges Abdulnour, and Sébastien Gamache. 2022. Implementation of Industry 4.0 Principles and Tools: Simulation and Case Study in a Manufacturing SME. *Sustainability* 14: 6336. [**Google Scholar**] [**CrossRef**] [**Scilit**]

[2] Ahmad, Farhan, and Muhaimin Karim. 2019. Impacts of Knowledge Sharing: A Review and Directions for Future Research. *Organizations & Markets: Policies & Processes eJournal* 31: 207–30. [**Google Scholar**]

[3] Alabi, Micheal Omotayo. 2017. Big Data, 3D Printing Technology, and Industry of the Future. In *Additive Manufacturing: Breakthroughs in Research and Practice*. Hershey: IGI Global. [**Google Scholar**]

[4] Alcaraz, Cristina, Yan Zhang, Alvaro Cardenas, and Liehuang Zhu. 2020. Guest Editorial: Special Section on Security and Privacy in Industry 4.0. *IEEE Transactions on Industrial Informatics* 16: 6530–31. [**Google Scholar**] [**CrossRef**] [**Scilit**]

[5] Alrashidi, Malek, Nejah Nasri, Salim Khediri, and Abdennaceur Kachouri. 2020. Energy-Efficiency Clustering and Data Collection for Wireless Sensor Networks in Industry 4.0. *Journal of Ambient Intelligence and Humanized Computing*. [**Google Scholar**] [**CrossRef**] [**Scilit**]

[6] Amoako-Gyampah, Kwasi, and Moses Acquaah. 2008. Manufacturing strategy, competitive strategy and firm performance: An empirical study in a developing economy environment. *International Journal of Production Economics* 111: 575–92. [**Google Scholar**] [**CrossRef**] [**Scilit**]

[7] Antunes, Helder de Jesus Ginja, and Paulo Goncalves Pinheiro. 2020. Linking knowledge management, organizational learning and memory. *Journal of Innovation & Knowledge* 5: 140–49. [**Google Scholar**]

[8] Arana-Landín, Germán, Naiara Uriarte-Gallastegi, Beñat Landeta-Manzano, and Iker Laskurain-Iturbe. 2023. The Contribution of Lean Management—Industry 4.0 Technologies to Improving Energy Efficiency. *Energies* 16: 2124. [**Google Scholar**] [**CrossRef**] [**Scilit**]

[9] Argote, Linda, Sunkee Lee, and Jisoo Park. 2020. Organizational Learning Processes and Outcomes: Major Findings and Future Research Directions. *Management Science* 67: 5399–429. [**Google Scholar**] [**CrossRef**] [**Scilit**]

[10] Arora, Makund. 2023. AI-Driven Industry 4.0: Advancing Quality Control through Cutting-Edge Image Processing for Automated Defect Detection. *International Journal of Computer Science and Mobile Computing* 12: 16–32. [**Google Scholar**] [**CrossRef**] [**Scilit**]

[11] Atobishi, Thabit, Szalay Zsigmond Gábor, and Szilard Podruzsik. 2018. Cloud computing and big data in the context of industry 4.0: Opportunities and challenges. Paper presented at the IISES Annual Conference, Sevilla, Spain, April 1–2. [**Google Scholar**]

[12] Babu, K. V. S. N. Jawahar. 2012. Key Factors in Knowledge Management. Available online: **https://www.researchgate.net/publication/251341440_Key_Factors_in_Knowledge_Management** (accessed on 18 July 2024).

[13] Banitaan, Shadi, Ghaith Al-refai, Sattam Almatarneh, and Hebah Alquran. 2023. A Review on Artificial Intelligence in the Context of Industry 4.0. *International Journal of Advanced Computer Science and Applications* 14. [**Google Scholar**] [**CrossRef**] [**Scilit**]

[14] Berger, Christoph, Joachim Berlak, and Gunther Reinhart. 2016. Service-based Production Planning and Control of Cyber-Physical Production Systems. Paper presented at 29th Bled eConference, Digital Economy, Bled, Slovenia, June 19–22; pp. 491–502. [**Google Scholar**]

[15] Berlak, Joachim, Stefan Hafner, and Volker G. Kuppelwieser. 2021. Digitalization's impacts on productivity: A model-based approach and evaluation in Germany's building construction industry. *Production Planning & Control* 32: 335–45. [**Google Scholar**]