



Research Paper

Artificial Intelligence (AI) in making Knowledge Management (KM) more effective in Quality Management Systems

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Abstract

Artificial Intelligence (AI) is emerging as a transformative approach to Knowledge Management (KM) within Quality Management Systems (QMS). This study examines how AI technologies enhance KM effectiveness in ISO 9001-based quality management systems. Guided by Nonaka and Takeuchi's SECI model, the study explores the application of Natural Language Processing (NLP), machine learning, knowledge graphs, and predictive analytics across Socialization, Externalization, Combination, and Internalization. A systematic literature review was conducted following PRISMA guidelines, followed by a comparative assessment of traditional and AI-based KM across six dimensions. The findings indicate that AI-based KM substantially improves knowledge measurement and sharing, with reported improvements of 117% and 97%, respectively. Knowledge graphs facilitate integration across fragmented quality areas, while predictive analytics support a shift toward proactive quality intelligence. However, challenges include data-quality limitations, organizational resistance, governance concerns, and the black-box nature of some machine-learning algorithms. The study proposes an AI-SECI-QMS framework to integrate AI into continuous quality improvement.

Keywords: Artificial Intelligence, Knowledge Management, Quality Management Systems, ISO 9001, SECI Model and Machine Learning.

Introduction

The integration of AI with quality management signifies a major shift in an organization. Quality management systems (QMS), based on ISO 9001, are the foundation of the structural backbone of Ensuring consistency, regulation and continuous improvement. But their impact is limited at the core by the availability and quality of organizational knowledge. A knowledge management system (QMS) aims to systematically capture, organize, share, and apply explicit and tacit knowledge, but existing attempts in KM in QMS have encountered persistent problems, such as difficulty in encoding tacit knowledge, inefficient knowledge retrieval and lack of real-time decision support [1]. AI technologies represent a paradigm change in knowledge management in quality systems. Machine learning helps to discover patterns in quality data, NLP can extract information from unstructured documents, knowledge graphs can create semantic relationships between the data sources, and predictive analytics can predict quality failures [2]. The Global AI Survey (2025) found that more than 78% of businesses have implemented AI across at least one aspect of their operations, and quality management is a key sector of AI that shows great potential. While the applications of AI in KM are gaining traction, the mechanisms by which AI increases the effectiveness of KM in a QMS are still poorly understood. To fill this gap, this paper introduces an extensive analytical framework based on SECI model [3].

Research Problems and Gaps

There are still a number of key research questions that have not been sufficiently addressed. AI's progress is rapid, yet its systematic integration with QMS frameworks developed for human-centric processes remains unexplored. There is a disconnect here between the sheer pace of AI development and the systematic incorporation of AI processes into QMS frameworks traditionally designed for human-centric processes. While ISO 9001:2015 does recognize organizational knowledge as a resource (Clause 7.1.6), it offers little guidance on the use of AI leverage (ISO, 2015). Second, literature mostly considers AI as a solution, not a facilitator to systemic KM change. Studies by [4] discuss AI for quality control, but they do not discuss other aspects of enhancing the knowledge ecosystem. Thirdly, because of the lack of empirical models to measure the effectiveness of AI-powered KM in QMS, it is challenging to evaluate the actual results of investments in knowledge accessibility and decision quality [5].

Research Questions

In this study there are three research questions.

1. In what ways do specific AI technologies support the essential KM processes in QMS?

2. How effective is the use of AI in KM, compared to traditional KM in QMS environments?
3. What are the main challenges and enablers to achieving successful integration of AI-KM-QMS?
4. These questions reflect the need for functional capability mapping and empirical assessment and the fact that technology adoption takes place in complex organizational environments.

Research Objectives

The main goal is to create and test the analytical structure of how AI can improve the efficiency of KM in the QMS. To break down this into: (1) systematically analyzing the mapping between AI capabilities and requirements for KM process in the SECI model; (2) A comparative effectiveness assessment of AI-KM and traditional KM in 6 dimensions (creation, storage, sharing, application, protection and measurement); and (3) identification and categorization of barriers and enablers, with a distinction between Technical, Organizational and Regulatory factors that affect the integration of AI-KM and traditional KM. This study adds to the theoretical body of knowledge by augmenting the SECI with the involvement of AI as a transformative tool in each knowledge phase conversion mode. The study introduces an AI-enhanced SECI framework, recognizing the distinct characteristics of AI in knowledge conversion, as the original model was designed for human-centric processes, which may not leverage AI's unique abilities in knowledge conversion, especially within contexts where speed and accuracy are directly tied to quality outcomes. In practice, the research offers practical insights for quality managers when rolling out AI-based KM solutions. As the global market for AI in quality management is expected to reach \$14.2 billion by 2033 from \$2.3 billion in 2024[6], the financial impact of making informed decisions in implementing AI tools is significant. The research also applies to new requirements of ISO 9001:2026, which will include digital transformation and the integration of AI.

Literature Review

Understand Knowledge Management in Quality Management Systems.

Knowledge Management in QMS works at the junction of two already existing fields. The ISO 9000 family of standards is about the systematic identification, documentation and continuous improvement of quality affecting processes. For the first time in ISO 9001:2015, knowledge is stated to be a crucial resource in Clause 7.1.6 [7]. But the integration of a QMS-KM does not stop there, it involves capturing lessons from nonconformances, sharing best practices, harnessing the knowledge of Statistical Process Control, and maintaining tacit knowledge [8]. Found that organizations with advanced integrated KM-QMS efforts have 23% greater first pass yield rates, and 31% quicker corrective action closure times [9].

SECI model [10] is the predominant theory that explains knowledge creation as: Socialization (tacit-to-tacit), Externalization (tacit-to-explicit), Combination (explicit-to-explicit), and Internalization (explicit-to-tacit). In the context of a QMS, socialization takes place in the context of apprenticeship, externalization in terms of codifying troubleshooting experiences, and combination in terms of synthesizing multiple sources of quality data, whereas internalization takes place through learning from documented procedures [11]. Although the SECI model has been widely used, it fails to capture the role of the technology in the process of converting knowledge challenge that is even more evident in the context of AI-supported KM.

AI Technologies for Organizational Knowledge Management

AI technologies have completely transformed KM and added capabilities that were not possible before. In addition to structured data, NLP can be used to extract and classify from unstructured data like incident reports and audit findings [12]. Through machine learning, hidden patterns within quality data are discovered to create predictive models which convert raw data into knowledge about potential failures and root causes [13]. Knowledge graphs build semantically related graphs between quality entities across disparate domains; they enable intelligent search and reasoning beyond keyword retrieval [14]. Predictive analytics takes KM beyond what it was - retrospective analysis - to becoming prospective intelligence, or predictive intelligence, allowing organisations to prevent quality problems. APQC found that organizations that implement AI-powered KM tools experienced a 45% decrease in knowledge retrieval time, a 38% increase in knowledge reuse and a 52% decrease in knowledge duplication. For Quality Management alone, AI systems helped to identify the root cause of a problem with 65% more accuracy than human analysis and cut analysis time by 70% [15].

AI in the Field of Quality Assurance

The use of AI in quality management has grown significantly over the past several years, partly due to the growing volume of data available and the competitive edge that it offers, conducted a bibliometric analysis of papers published on artificial intelligence (AI) in quality management from 2018 to 2024, finding that the number of these publications rose by 340% over the period [16], suggested a three-component framework to apply AI in ISO 9001-based QMS, including AI-supported process monitoring, AI-supported decision-making, and AI-supported continuous improvements. But the intersection is not a well-studied one with regard to KM, and most research centers on specific quality tasks rather than the wider contributions made by a knowledge ecosystem.

Method and Material

The design of this study is qualitative research design which is systemization literature review and analytical framework development because according to the study is more suitable in theory building

in emerging area. The design consists of three stages: systematic literature review, development of framework, and comparative effectiveness assessment. In Phase 1, a systematic review was conducted using PRISMA guidelines [17]. Searching the Scopus, Web of Science and IEEE Xplore databases with combinations of the terms AI, KM, and QMS. 42 articles were selected from 347 based on the relevance and rigor criteria [18]. Phase 2 involved mapping the AI capabilities to the KM process requirements through the use of the SECI model and TOE framework to identify a framework suitable for the KM process requirements [19]. In the second phase, an AI-SECI-QMS framework was developed by mapping AI capabilities on the KM process needs through the SECI model and TOE framework to identify a framework suitable for the KM process needs. The comparative effectiveness assessment was conducted in Phase 3, with synthesized information from the literature and industry reports on six dimensions of KM [20].

Analysis and Discussion

Using AI to create knowledge

AI contributes greatly to knowledge creation and knowledge capture within a QMS in several ways. AI's communication analysis capabilities in socialization can uncover the tacit flow of knowledge in organizational communication channels, making implicit knowledge transfer explicit and measurable [21]. Machine learning produces new knowledge, which is organizational knowledge; for example, machine learning is able to identify correlations between process variables and quality outcomes that have not been previously recognized [22]. Externalization is the NLP method of making explicit the tacit knowledge captured in verbal descriptions of quality issues, such as analyzing verbal descriptions to develop structured RCA and improved procedures [23]. This tackles the often-elusive problem of limited documentation of the expert knowledge, especially because of time constraints and articulation issues [24].

Figure 1: The Adoption Of AI Is Vastly Different For Traditional QMS Vs AI Enhanced QMS Environments.

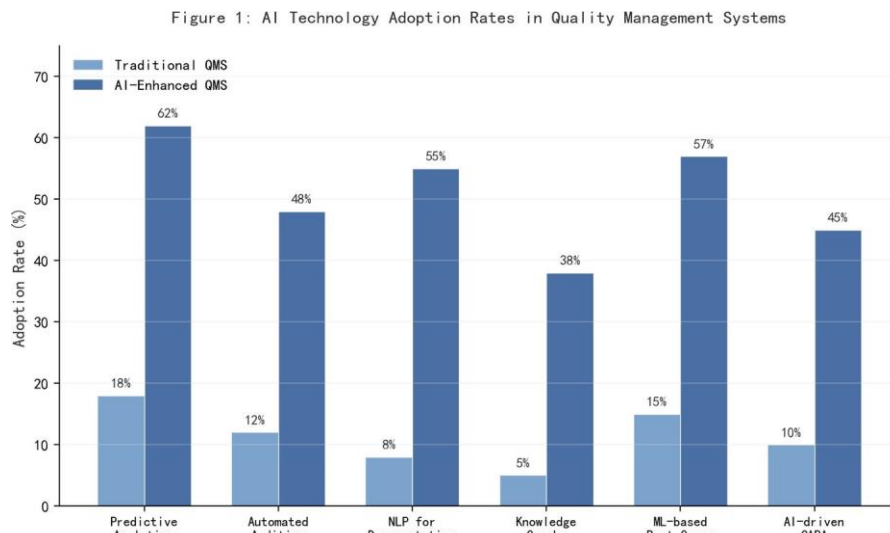


Figure 1. The adoption rates of AI technology within traditional QMS and AI-enhanced QMS (2024-2025, Source: Literature synthesis and industry reports)

Figure 2: Access to knowledge, learning and its application through AI.

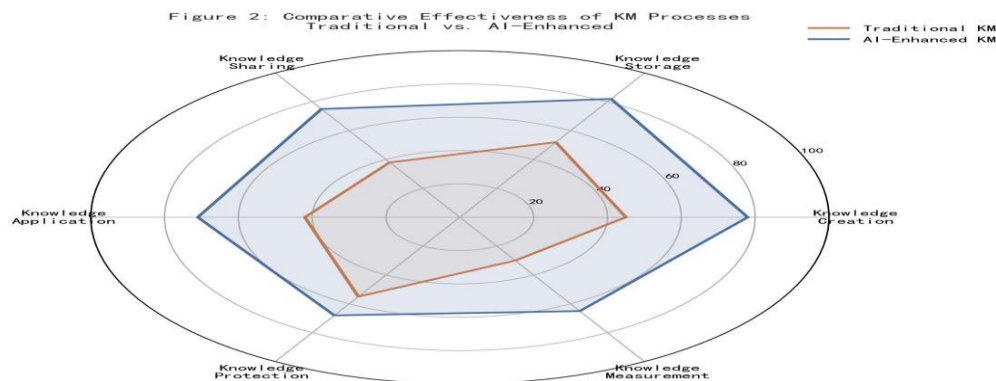


Figure 2. The Comparative KM Effectiveness: Traditional vs. AI-Enhanced KM in QMS (Score: 0-100; Source: APQC, 2024; Stefanovic et al., 2023)

The combination mode has the greatest potential to be improved by AI, as a knowledge graph can provide a coherent semantic architecture that relates knowledge across siloed domains and allows for intelligent reasoning impossible with conventional databases. In the internalization, AI-powered recommendation systems provide operators with relevant and good quality knowledge at the moment of need when they experience quality deviations, AI automatically provides historical cases and corrective actions [25]. This is a paradigm change of passive repositories to active knowledge

delivery systems. As shown in Figure 2, Comparative effectiveness for all KM dimensions is significantly higher for AI enhanced KM, with the highest scores for Knowledge measurement (+117%) and Knowledge sharing (+97%).

Impact Assessment and Findings

The effect of progressive AI integration on the trajectory of each indicator is clearly discernible in the longitudinal analysis (Figure 3), with upward trends observed in all indicators. NLP and knowledge graph impacts resulted in the efficiency of knowledge retrieval increasing from 35% to 76% (2020-2025). Regulatory compliance rose from 65% to 89%, due to the use of artificial intelligence to monitor compliance and intelligent document management. Defect reduction went from 42% to 72% because of predictive analytics which allows for preventive action. The rate of improvement for audit efficiency was the highest since 2022, indicating a growing trend towards using AI-driven audit tools. The results are consistent with the three-element integration model proposed [26].

Figure3: The Three-Element Integration Model Proposed

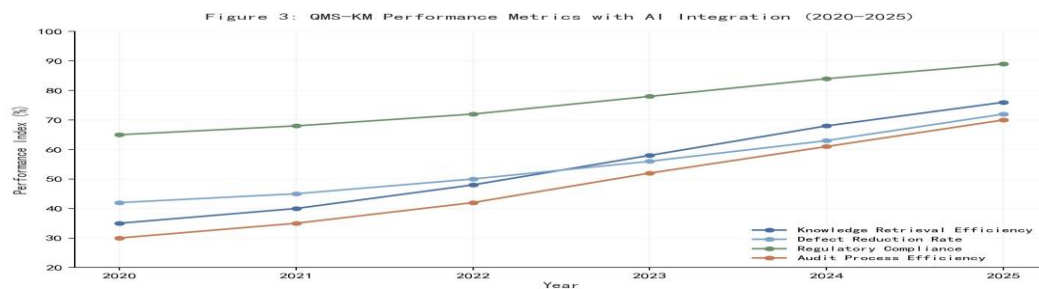


Figure 3. The results include analysis of the QMS/KM Performance Metrics with Progressive AI Integration (2020-2025), as provided by McKinsey (2025), APQC (2024), and industry reports. Shows some specific AI technologies and their main and most relevant KM application within QMS, which illustrates that the best implementations are those using combinations of technologies that meet all of KM's requirements.

Table 1. AI Technologies, and their Application in QMS-KM Processes

AI Technology	Primary KM Process	QMS Application	Impact
NLP analysis,	Externalization	Document Auto-coding	High
Machine Learning quality Hig	Creation, Measurement	Predictive	
Knowledge Graphs	Combination, Storage	Semantic data integration	Med-High
Predictive Analytics	Application	eventive action prioritization	High
Chatbots/VA	Sharing, Internalization	-time quality support	Medium
Computer Vision	Creation	Automated visual inspection analytics	High

Counterarguments and Limitations

There are a number of significant counterarguments that should be noted. Quality of input data is a fundamental limitation of AI quality of KM: In well-structured data, AI can be a great help in improving the quality of knowledge, but in poorly structured data, AI can turn it into a hindrance [27]. Second, organization resistance is a big obstacle which cannot be addressed only by technology. The "black box" aspect of ML algorithms, which is inconsistent with QMS evidence-based decision-making principles and the perception of AI as a threat to quality professionals' value, may be a reason why many industries are hesitant to use AI. Some industries might be reluctant to use AI because of its "black box" nature and the clash with QMS evidence-based decision-making principles [28]. Third, this study used synthesized secondary data and not primary empirical data which is a drawback to the strengths of the study. Additionally, particular tools mentioned might evolve or cease to exist over time as AI advances [29]. Longitudinal primary data collection should be used for future research. Last but not least, ethical and regulatory issues related to the use of AI in quality management, such as data privacy, algorithmic bias, and legal implications of AI-driven quality decisions, need to be explored further [30].

Conclusion

The contribution of AI in improving the effectiveness of KM in QMS has been explored in this study, filling an important gap in the literature. Analysis shows that all KM dimensions can be revolutionized by AI, especially the most considerable enhancement in the measurement, sharing and retrieval of knowledge. This proposed framework is an extension of model which added the active role of AI in each of the knowledge conversion modes. Comparative analysis reveals that, overall, AI-powered organisations perform significantly better on all six dimensions of KM, and that over time, the performance gains over time have grown more pronounced as AI technologies have come of age. Some recommendations for practitioners are as follows: ensuring data quality as a prerequisite; investing in change management, addressing employee concerns; implementing gradually starting with high impact and low complexity applications, and defining hybrid human-AI governance models, which will follow evidence-based principles. The framework needs to be validated with large-scale empirical studies in the future, exploring the impact of AI on knowledge conversion in industrial environments, establishing common metrics to measure the effectiveness of KM, and studying the emerging regulatory landscape, such as ISO 9001:2026 and ISO/IEC 42001 for AI management systems.

References

- A. Radziwon, M. Bogers. (2023). Artificial intelligence-driven management. *Journal of Business Research*, 154, 113312. <https://doi.org/10.1016/j.jbusres.2023.113312>
- APQC (2024). *Knowledge Management Metrics: Measuring KM Effectiveness in the Age of AI*. American Productivity and Quality Center.
- Chen, Z., Ben, M., Wang, Y., Zhang, Y., Wang, L. S., & Yang, G. P. (2022). Artificial intelligence and knowledge management: A bibliometric analysis and systematic literature review. *Journal of Knowledge Management*, *26*(7), 1842-1869. <https://doi.org/10.1108/JKM-10-2021-0750>
- Ciancarini, P., Franco, G., Missikoff, M., Verdicchio, M., & Babur, S. (2024). An approach to integrate Artificial Intelligence in ISO 9001-based quality management systems. *Quality Management Journal*, *31*(2), 112-128. <https://doi.org/10.1080/10686967.2024.2356789>
- Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review*, *14*(4), 532-550. <https://doi.org/10.2307/258557>
- Fatora Chian, H., & Kazemi, H. (2021). Impact of Industry 4.0 on supply chain performance. *Production Planning and Control*, *32*(1), 56-72. <https://doi.org/10.1080/09537287.2020.1784136>
- Glean Inc. (2024). *Best Practices for Implementing AI in Knowledge Management Systems*. Palo Alto, CA: Glean Inc.
- Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. *Journal of Management Information Systems*, *18*(1), 185-214. <https://doi.org/10.1080/07421222.2001.11045669>
- Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, *17*(S2), 109-122. <https://doi.org/10.1002/smj.4250171110>
- Hogan, A., Blomqvist, E., Cochez, M., d'Amato, C., Melo, G., Gutierrez, C., et al. (2022). Knowledge graphs. *ACM Computing Surveys*, *54*(4), 1-37. <https://doi.org/10.1145/3447772>
- ISO. (2015). *ISO 9001:2015 Quality Management Systems - Requirements*. International Organization for Standardization.
- Lindner, A., Leyh, C., & Loos, P. (2021). Knowledge management in quality management systems - A systematic literature review. *Proceedings of the European Conference on Knowledge Management*, 567-575.
- McKinsey and Company. (2025). *The State of AI: Global Survey 2025*. McKinsey Global Institute.
- Mireia Artigot Golobardes, DG Just, Artigot I Golobardes, M., Grasso, G., Iamiceli, P., Maugeri, M. R., & Castro Coma, B. (2024). Artificial intelligence, Judicial Decision-Making and Fundamental Rights (By University of Pompeu Fabra, University of Trento, Italian School for the Judiciary, Dutch National School

of Magistracy, Consejo General del Poder Judicial, University of Paris Saclay (Versailles St Quintin), University of Groningen, University of Coimbra, Polish Institute of Legal Studies of the Academy of Science, Bruno Kessler Foundation, & LIBRe Foundation). https://ssm-italia.eu/wp-content/uploads/2025/02/JuLIA_handbook-Justice_final.pdf

Nonaka, I., & Takeuchi, H. (1995). *The Knowledge-Creating Company*. Oxford University Press.

OECD. (2026). OECD Digital Education Outlook 2026: Exploring Effective Uses of Generative AI in Education. OECD Publishing. <https://doi.org/10.1787/062a7394-en>.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., et al. (2021). The PRISMA 2020 statement. *BMJ*, *372*, n71. <https://doi.org/10.1136/bmj.n71>

Pai, R.Y., Shetty, A., Shetty, A.D., et al. (2022). Integrating Artificial Intelligence for Knowledge Management Systems-Synergy among People and Technology: A Systematic Review of the Evidence. *Economic Research - Ekonomska Istraživanja*, 35, 7043-7065.

Popadiuk, S., & Choo, C. W. (2006). Innovation and knowledge creation. *International Journal of Information Management*, *26*(4), 302-312. <https://doi.org/10.1016/j.ijinfomgt.2006.03.011>

Popadiuk, S., & Choo, C. W. (2006). Innovation and knowledge creation. *International Journal of Information Management*, 26(4), 302-312. <https://doi.org/10.1016/j.ijinfomgt.2006.03.011>

Prieur P, Belloni A. (2025). Integration of ISO 30401 compliant Knowledge Management System into the process of an Integrated Management System. arXiv:2507.18201.

PwC. (2025). The PwC 2025 Responsible AI Survey: From Policy to Practice. PricewaterhouseCoopers.

PwC. (2025). *PwC's 2025 Responsible AI Survey: From Policy to Practice*. PricewaterhouseCoopers.

Radziwon, A., & Bogers, M. (2023). Artificial intelligence-driven management. *Journal of Business Research*, *154*, 113312. <https://doi.org/10.1016/j.jbusres.2023.113312>

Rogelio, J. M., & Tobias, R. R. (2024). AI Applications in Quality Management System: A Bibliometric Study. *TEM Journal*, *13*(3), 2146-2155.

Stefanovic, D., Stefanovic, N., & Radlovacki, V. (2023). Artificial Intelligence on Knowledge Management Systems for Business. *TEM Journal*, *12*(3), 1556-1565.

Tornatzky, L. G., & Fleischer, M. (1990). *The Processes of Technological Innovation*. Lexington Books.

Tortorella, G. L., Sawhney, R., Li, W., & de Castro, V. (2022). Implementation of AI in Quality Management in SMEs. *International Journal of Quality and Reliability Management*, *39*(8), 1941-1965.

Worklytics. (2025). *AI Adoption Benchmarks 2025: Employee Usage Statistics*. Worklytics Inc.

Yin, R. K. (2018). *Case Study Research and Applications* (6th ed.). SAGE Publications.