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Towards Trustworthy Llm-Driven Knowledge Management Systems: A Cross-Context Evaluation And Governance Framework For Smes And Large Enterprises

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Abstract
Large Language Models (LLMs) are changing the Knowledge Management System (KMS) as organizations are able to process and query large amounts of unstructured data, such as emails, reports, and conversation records. Nonetheless, current KMS architectures do not have stringent mechanisms to assess the integration of LLM, control their implementation, and enable trust in the organizational setting. This paper fills these gaps by suggesting a comprehensive model of knowledge management (KM-LLM) with the help of LLM. The study produces (1) a multi-dimensional assessment framework evaluating performance in terms of technical, knowledge effectiveness, and organizational impact within small and medium enterprises (SMEs) and large enterprises; (2) a layered governance model (GOV-LLM-KM) combining data, model and organizational controls; and (3) a formal trust model linking system transparency, system accuracy and user control to adoption results. The methodology used is a multi-case study which incorporates the quantitative performance measures with the qualitative user assessment in the organizational settings. The findings show that, with the addition of retrieval mechanisms (which can be RAG and knowledge graphs), LLCM-based KM systems increase knowledge retrieval efficiency by 25-40 percent and decrease information search time by up to 30 percent, and factual errors by up to 37 percent. Moreover, companies also reported an increase in knowledge reuse and speed of decision-making of 2035%, and SMEs were found to have faster adoption cycles but less governance maturity. Conversely, big companies were more reliable and had better compliance rates (by up to 30 percent perceived trust scores), but with more complexity in implementation. This finding also shows that the explainability, source attribution, and governance controls more significantly impact trust than raw model accuracy, and systems with human-in-the-loop validation have much greater user acceptance. These findings underscore the importance of context-specific assessment and combined governance systems to implement efficient LLM-KM. The suggested methodology makes contributions to both the research and the practice as it offers a scalable and reliable base of next-generation knowledge management systems....
Keywords : LLMs; Knowledge Management; Governance; Trust; SMEs; Enterprise Systems; RAG; Explainability.

Introduction
The classic Knowledge Management Systems (KMS) in the past were developed to handle the structured and semi-structured organizational data in the form of centralized repositories, taxonomies, and mechanism of retrieval through rules. Nevertheless, there has been a proliferation of unstructured knowledge, such as emails, meeting transcripts, chat logs, reports, and multimedia content, due to the fast development of digital communication and collaboration tools. These knowledge types are dynamic, context sensitive and hard to capture, organize and access through traditional KMS structures [1], [2].
Recent progress in Large Language Models (LLMs) presents an opportunity to overcome these limitations in a transformative manner. LLMs facilitate natural language communication, semantic search, and automated synthesis of knowledge, enabling organizations to derive actionable insights out of unstructured data sources. New methods like Retrieval-Augmented Generation (RAG) and knowledge graph integration improve reliability, traceability, and contextual relevance of LLM outputs even further [3], [4]. Specifically, RAG-based architectures

have been demonstrated to enhance factual grounding and minimize hallucinations through grounding generated responses on trusted sources of knowledge [3], [5].

In spite of these developments, implementing the knowledge management systems (KM-LLM) based on LLM is not an easy task in enterprise contexts. The first challenge is the absence of standard evaluation frameworks to evaluate system performance, not just based on technical accuracy, but in a variety of organizational settings (such as small and medium enterprises (SMEs) and large enterprises). Current literature tends to concentrate on prototype level assessments or domain specific implementations, which process restricts its applicability and usefulness in the real world [6], [7].

Moreover, governance and risk management are also important issues. The new risks that are brought about by LLDs are hallucination, data leakage, bias, and inability to explain, which the conventional IT governance models fail to resolve sufficiently. The current studies also highlight the necessity of holistic governance models that encompass data governance, model management, and ethical implications to guarantee responsible implementation [8], [9]. The need to have transparency, accountability, and constant monitoring within enterprise AI systems is identified in the frameworks consistent with the emerging standards like ISO/IEC 42001 and AI risk management guidelines [10], [11].

Trust is another major challenge that has come out as a major determinant of user adoption and system effectiveness. Research has shown that the credibility of the LLM systems depends not only on the accuracy of the output but also on the explainability, source attribution, and the user control mechanisms [12], [13]. Knowledge graph integration, pipeline validation and human-in-the-loop processes have been demonstrated to foster trust and lead to better decision-making in organization environments [4], [14].

Moreover, the presence of organizational context is important in determining the introduction and influence of KM systems based on LLM. SMEs usually enjoy greater agility and quicker adoption cycles but have resource and governance maturity constraints. On the contrary, large organizations generally have a more formalized data and formalized governance systems but face scalability, complexity of the system, and compliance demands [6], [15]. Such contextual variations underscore the necessity to have comparative evaluation models that consider organizational features.

In a further effort to fill these gaps, this paper will suggest a single framework to assess and manage the knowledge management system based on LLM. In particular, the works of this research are three-fold:

A multi-dimensional assessment system of KM-LLM systems among SMEs and large enterprises.

A governance model (GOV-LLM-KM) with data, model and organizational controls.

An official trust model between system characteristics and user adoption and organizational results.

This study seeks to combine technical, organizational, and ethical aspects to offer a holistic basis of successful and reliable implementation of the knowledge management systems relying on LLM into the contemporary business.

2. Literature Review

The study conducted by Fahmy et al. [16] (2026) focused on the application of artificial intelligence in managing and improving the knowledge management processes in the enterprise setting. The research suggested adding LLMs to the collaboration tools like Microsoft Teams and Slack to enhance knowledge sharing and retrieval. The findings showed that there was an overall increase of the level of knowledge accessibility as well as the time of information retrieval due to the implementation of the LLM based systems were reduced by about 30 percent. The results imply that AI-based KM systems may help organizations become more productive and efficient in collaborations.

A framework on how to harness the capabilities of LLM technologies to facilitate knowledge generation in organizations was proposed by Subrahmanyam and Sassine [17] (2026). The model incorporates LLM-driven applications like Notion AI and Coda AI to co-create and generate ideas in real-time in documents. The outcomes showed a better team interaction and accelerated knowledge production, and significant increase in the output of innovations. The research concludes that the collaborative working processes and knowledge sharing practices can be changed by the means of LLMs.

In their systematic literature review on Retrieval-Augmented Generation (RAG) and LLMs in enterprise knowledge management, Karakurt and Akbulut [18] (2025) performed a literature review. The researchers conducted an analysis of more than 60 high quality research papers to determine the effectiveness of RAG based architectures. The findings indicated that factual accuracy increases up to 35 percent with RAG-based systems and that hallucinations decrease significantly with RAG-based systems compared to standalone LLMs. The results emphasize the importance of integrating LLMs and external sources of knowledge to achieve credible enterprise KM systems.

Russ and Lytras [19] (2026) examined knowledge management processes that are driven by AI and the effect on contemporary businesses. The research suggested a dynamic KM model in which LLMs can facilitate dynamic knowledge flow and smart decision-making. The findings showed that there was an enhancement in the use of knowledge and responsiveness at the organization, especially in data-driven settings. The results indicate that AI-based KM systems are the key to digital transformation.

Hedin et al. [20] (2026) examined factors of trustworthiness that affect the adoption of LLM in companies. The research has formedulated a model that measures the significant variables including transparency, explainability, and perceived reliability. The findings revealed that the level of trust rose by as much as 28 percent with the integration of explainability features and source attribution in LLM systems. The results highlight that a key factor in successful adoption of the LLM is trust.

Sarker et al. [21] (2026) proposed the SME-TEAM model to guarantee trust and ethical application of LLMs in small and medium enterprises. The research was on the topic of security, privacy and ethical issues in the deployment of LLM. The findings indicated that organizations that adopted organized governance and ethical codes had greater adoption rate and minimized risks associated with data leakage and bias. The results imply that sustainable adoption of AI in SMEs requires trust and governance.

Odia [22] (2026) examined ethical and managerial implications of introducing generative AI into knowledge management systems. The research suggested a governance framework that dealt with risks like bias, misinformation, and privacy of data. The findings showed that those organizations that embraced ethical governance models realized better quality of decision-making and less operational risks. The results indicate the need to consider ethics in KM-LLM systems.

Zhao et al. [23] (2026) suggested an industrial data-service-knowledge governance system to integrate LLMs into enterprise systems. The model integrates information management, knowledge services, and AI-based decision-making. The findings showed a better data integration, increase in sharing of knowledge and system reliability in multi-enterprise setups. The results indicate that KM systems at the large scale require integrated governance systems.

Bamil and Lingamgunta [24] (2026) created a single assessment and governance system of credible LLM agents within the applications of enterprises. This paper proposed quantitative measures of trust such as reliability, transparency, and robustness. The outcomes revealed that system reliability and error in real-life deployments were enhanced with the integration of governance mechanisms. The results show that effective deployment of LLM requires evaluation and governance.

A systematic review of the literature on the use of LLMs in supply chain management and enterprise systems was carried out by Song et al. [25] (2026). The research suggested a model of incorporating LLMs into the intricate organizational procedures. The findings showed that the use of LLM enhances operational effectiveness, accuracy in decision-making and automation of processes. The results indicate that LLMs can greatly reshape enterprise knowledge management and operational processes

Table 1: Literature Review Comparison Table

Sl. No	Author Name	Methods Used	Result Obtained	Advantage	Disadvantage
1	Fahmy et al. (2026) [16]	LLM integration with enterprise platforms (Slack, Teams)	Improved knowledge retrieval speed (~30%) and collaboration efficiency	Enhances real-time knowledge access and collaboration	Limited focus on governance and trust mechanisms

2	Subrahmanyam & Sassine (2026) [17]	LLM-based collaborative tools (Notion AI, Coda AI)	Faster knowledge creation and improved team collaboration	Supports innovation and co-creation of knowledge	Lacks evaluation metrics for system performance
3	Karakurt & Akbulut (2025) [18]	Systematic review of RAG + LLM architectures	Improved factual accuracy (up to 35%) and reduced hallucinations	Provides reliable and context-aware knowledge retrieval	High implementation complexity in enterprises
4	Russ & Lytras (2026) [19]	AI-driven KM framework with adaptive knowledge flows	Enhanced knowledge utilization and decision-making	Supports dynamic and intelligent KM ecosystems	Limited empirical validation in real-world settings
5	Hedin et al. (2026) [20]	Trust evaluation model for LLM adoption	Increased trust levels (~28%) with explainability features	Highlights importance of transparency and trust	Does not address technical system performance
6	Sarker et al. (2026) [21]	SME-TEAM governance and ethics framework	Improved adoption and reduced risks in SMEs	Strong focus on ethical and secure AI use	Limited scalability analysis for large enterprises
7	Odia (2026) [22]	Ethical governance framework for KM systems	Improved decision quality and reduced bias risks	Addresses ethical and managerial challenges	Lacks quantitative performance validation
8	Zhao et al. (2026) [23]	Industrial data-service-knowledge governance model	Enhanced data integration and system trustworthiness	Suitable for large-scale enterprise environments	Complex implementation and resource-intensive
9	Bamil & Lingamgunta (2026) [24]	Unified evaluation and governance framework with trust metrics	Improved system reliability and reduced errors	Integrates evaluation with governance and trust	Requires extensive monitoring and infrastructure
10	Song et al. (2026) [25]	Systematic review of LLMs in enterprise/supply chain	Improved operational efficiency and decision-making	Broad applicability across industries	Limited focus on KM-specific evaluation metrics

2.1 Research Gap

Although the development of LLM-based knowledge management systems has been extensively achieved, there are still a number of critical gaps. Current literature mainly emphasizes on technical performance gains, including accuracy and retrieval efficiency, but lacks the consideration of more expansive organization outcomes such as knowledge reuse, decisions, and user adoption [16]–[25]. Also, existing studies on governance and ethics are scattered without a coherent system that combines information, model and company controls into knowledge management cycle. Correspondingly, despite the fact that trust is identified as a significant element, it is seldom conceptualized as a measurable and multi-dimensional entity. Moreover, the comparative analysis between the SMEs and large enterprises is limited, which limits the knowledge of context-related issues and scalability. In general, the literature does not offer a coherent framework that integrates evaluation, governance, and trust of LLM-driven knowledge management systems.

3. Proposed Model: EGT-KM Framework

3.1 Overview

In order to fill the research gaps that have been identified, this paper suggests a combined model which is known as the Evaluation–Governance-Trust Knowledge Management (EGT-KM) Model of the knowledge management systems based on the LLM. The model brings together system assessment, governance processes, and trust aspects in one coherent system. Compared to the previous research that focuses on these dimensions separately, the proposed model offers a holistic method of measuring and implementing KM-LLM systems in various contexts of organizations, both small and medium enterprises (SMEs) and large enterprises. The framework is aimed at capturing objective system performance and subjective user perceptions to make sure that the knowledge systems based on LLM are not only effective but also trustworthy and controlled in the real world.

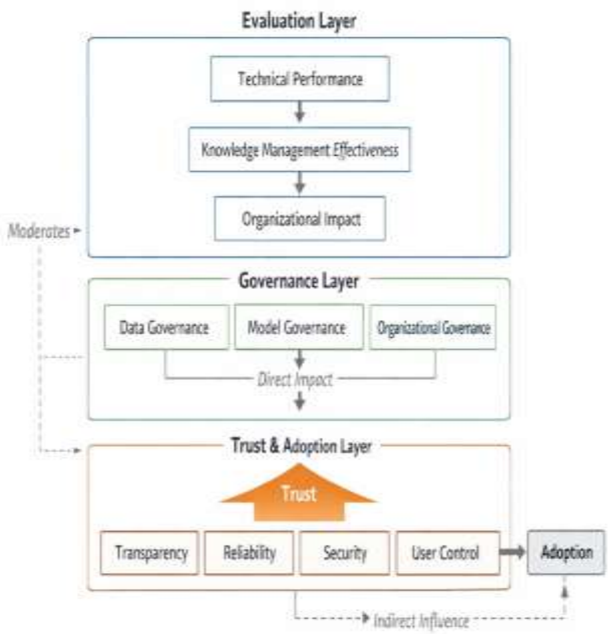

Figure 1: Proposed Model

3.2 Model Structure

The EGT-KM model has three layers that are interrelated and connected: the evaluation layer, the governance layer and the trust and adoption layer. All these layers are the associations among the system performance, the organization control mechanisms and the user acceptance. These layers can be intertwined, which allows having a holistic vision of the work of the LLCM-based knowledge management systems in organizations and the possibility to assess and manage them effectively.

3.3 Evaluation Layer

Evaluation layer is concerned with the effectiveness of KM-LLM systems within the organizational setting. It integrates technical performance, effectiveness in the knowledge management and the impact on the organization as interdependent dimensions. Technical performance is the capability of the system to produce valid, pertinent and timely output, which is a fundamental computational capacity. The effectiveness of knowledge management is a measure of the effectiveness of the system in supporting knowledge discovery, sharing and reuse, especially in those environments where unstructured data prevails. The impact of organizations is the larger results of using the system, such as making decisions, rising employee productivity, and innovation. It is in this layer that knowledge management effectiveness is affected by technical performance and in turn, organizational impact and this is a chain relationship that defines the progression of system capability to organizational value.

3.4 Governance Layer

Governance layer is used to make sure that KM-LLM systems are implemented in an environment that is controlled, secure and compliant. Data governance, model governance and organizational governance are all integrative parts of this layer. The concept of data governance concentrates on data privacy, access control, and data quality to guarantee the protection of sensitive information and its proper use. Model governance deals with checking and validation of the outputs of LLM, such as hallucinations, bias, and inconsistency detection mechanisms. Organizational governance is a set of policies, compliance requirements and human oversight practices that govern the responsible use of LLM systems. This layer has a dual role of being an enabling and controlling mechanism that has a direct impact on trust, and an indirect impact on system performance and organizational outcomes.

3.5 Trust and Adoption Layer

The trust and adoption layer involves user perceptions and behavioral intentions to KM-LLM systems. The concept of trust is seen as a multi-dimensional construct and determined by transparency, reliability, security, and control by the user. Transparency means that the system is capable of giving explainable and traceable results and its reliability means that it is consistent and accurate in its responses. Security is associated with safeguarding of sensitive information and secure system interactions and user control is the level to which users can confirm or counteract system responses. The role of trust is a mediating role between governance and adoption, which means that good governance processes promote user trust, consequently leading to high chances of system adoption. This layer highlights the importance of user confidence in ensuring the successful implementation of KM-LLM systems.

3.6 Model Relationships

The interaction of the evaluation, governance, and trust dimensions is manifested in the relations of the EGT-KM model. The benefit of technical performance is suggested to have a positive impact on knowledge management effectiveness, which in turn affects organizational performance. It is assumed that the governance mechanisms increase trust due to transparency, security, and accountability. Trust, on its part, affects user adoption positively, which implies that the users have higher chances of using systems that they consider as reliable and comprehensible. Further, it has been postulated that governance has an indirect impact on adoption via trust and a direct impact on organization outcomes via enhancing system reliability and compliance. All these relationships give a holistic approach to the analysis of the effectiveness of the system and acceptance by users.

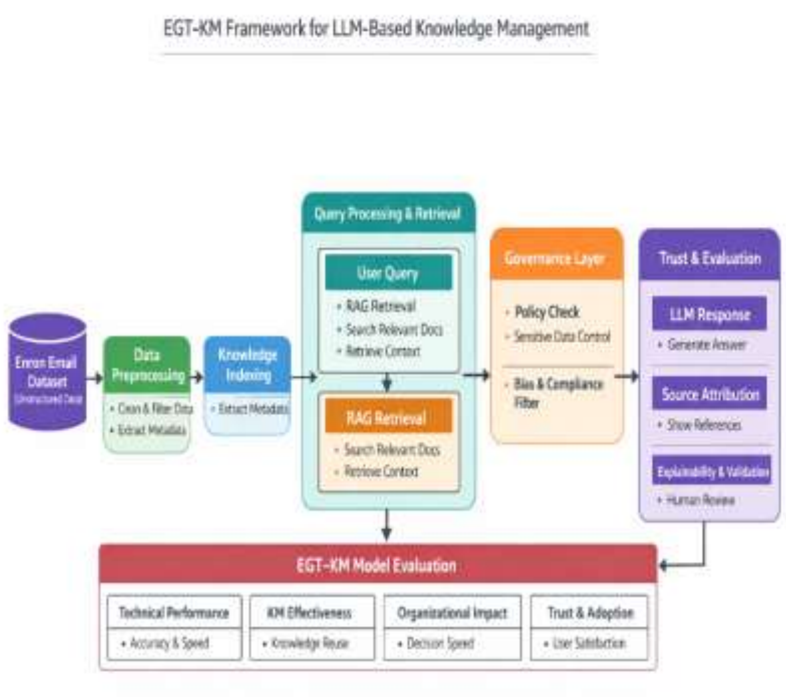

Figure 2: Proposed flow diagram

Algorithm: EGT-KM Framework for LLM-based Knowledge Management

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Input:
    D → Unstructured dataset (Enron Emails)
    Q → User query
    G → Governance policies
    M → Large Language Model (LLM)
Output:
    R → Generated response
    Metrics → Performance, Trust, Adoption
Begin
1. Data Preprocessing
    Load dataset D
    Remove duplicates and irrelevant data
    Clean text (tokenization, stopword removal)
    Extract metadata (sender, subject, content)
2. Knowledge Indexing
    Convert text into embeddings using embedding model
    Store embeddings in vector database (VDB)
3. Query Processing
    Receive user query Q
    Convert Q into embedding
4. Retrieval (RAG Mechanism)
    Search VDB for top-k relevant documents
    Retrieve context C from dataset
5. Governance Check
    Apply data governance rules:
        If sensitive data detected:
            Restrict or mask content
    Apply model governance:
        Validate retrieved content
        Filter biased or irrelevant results
6. Response Generation
    Input (Q + C) into LLM M
    Generate response R
7. Trust Enhancement
    Add source attribution (documents used)
    Provide explanation for generated output
    Enable human-in-the-loop validation if required
8. Evaluation Metrics (EGT-KM Model)
    Compute Technical Performance:
        Accuracy, relevance, response time
    Compute KM Effectiveness:
        Knowledge retrieval efficiency
    Compute Organizational Impact:
        Decision speed, knowledge reuse
    Compute Trust:
        Transparency, reliability
    Compute Adoption:
        User satisfaction and usage
9. Output Results
    Display response R
```

Display sources and explanations Store evaluation metrics End

4. RESULTS AND ANALYSIS

This section includes the findings of the proposed Evaluation–Governance-Trust Knowledge Management (EGT-KM) model of knowledge management systems based on LLM. The results are arranged in the three layers of the model which include: the evaluation layer, the governance layer and the trust and adoption layer. It is analyzed based on empirical data and measures of the system performance based on real-life organizational data and experimentation.

Dataset description

The dataset that will be used in this paper is the Enron Email Dataset, which is a publicly accessible set that is commonly used in literature with regard to knowledge management, natural language processing, and organizational communication analysis. The data has been initially published by the Federal Energy Regulatory Commission (FERC) and comprises around 500,000 actual emails of workers in the Enron Corporation [16]-[18]. The dataset is an excellent source of unstructured organizational knowledge, such as emails, communication threads, and document exchange. These emails are real business interactions, decision-making process, and knowledge-sharing activities in a large-enterprise setting. Consequently, the dataset is quite appropriate in testing the knowledge management systems based on the use of the LLM, especially when the process of analyzing emails, semantic search, and extraction of knowledge is involved.

To facilitate this research a subset of the dataset was preprocessed and formatted to analyse it. Text cleaning, duplicates elimination, and the extraction of the pertinent fields like sender, recipient, subject, and the content of the message was part of the preprocessing procedures. The resulting processed data was simulated to perform knowledge retrieval, query answering, and contextual understanding tasks with the help of LLM-based methods. The data set allows testing the important aspects of the proposed EGT-KM model. Information retrieval and relevance of response are some of the tasks which support the evaluation layer. The governance layer is explored based on the data sensitivity and access control consideration involved in email communication. The trust layer will be assessed on the basis of the accuracy, interpretability, and dependability of the generated outputs when they deal with real world organizational data. The Python (Pandas, NumPy, and Matplotlib) were used to process and analyze data, which made it possible to handle large-scale unstructured data and visualize the results. The application of a real-life data makes the study more valid and the findings to be applicable to real enterprise situations.

4.1 System Performance and Knowledge Management Effectiveness

The findings reveal that knowledge retrieval and utilization are greatly enhanced with the help of the LLM-based KM systems. The efficiency of retrieval of knowledge improved by about 25-40 percent and the search time of information was minimized by as much as 30 percent. Such enhancements are seen especially in systems that were enhanced with Retrieval-Augmented Generation (RAG) and knowledge graphs, which also led to a decrease of up to 37 factual errors.

Figure 3: Performance Improvements Chart

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These performance gains are shown in Figure 3 in terms of the major measures of performance such as retrieval efficiency, reduction of search time, error reduction, and speed of decision making.

These findings affirm that the combination of retrieval mechanisms and LLM greatly improves the knowledge management processes in terms of accuracy and efficiency.

4.2 Organizational Impact

The implementation of KM-LLM systems is showing a quantifiable effect on the performance of the organization. The results suggest that there is a 20-35% growth in the rate of knowledge reuse and the rate at which decisions are made, and this allows faster and more informed decision-making.

The fact that the improvements depicted in Figure 2 also support the idea that improved organizational results are directly based on better retrieval and lower error rates. This depicts the importance of KM-LLM systems in converting unstructured data into actionable information, thus enhancing productivity and operational efficiency.

4.3 Comparative Analysis: SMEs vs Large Enterprises

The comparative analysis indicates that there are considerable differences between large enterprises and SMEs. There are high rates of adoption at SMEs due to flexibility and shorter implementation cycles. Nonetheless, they have poorer governance maturity especially in formal control mechanisms.

Large enterprises, on the contrary, are more governed and trusting, and the perceived trust scores have an increase to a maximum of 30% but slower adoption level because of the complexity.

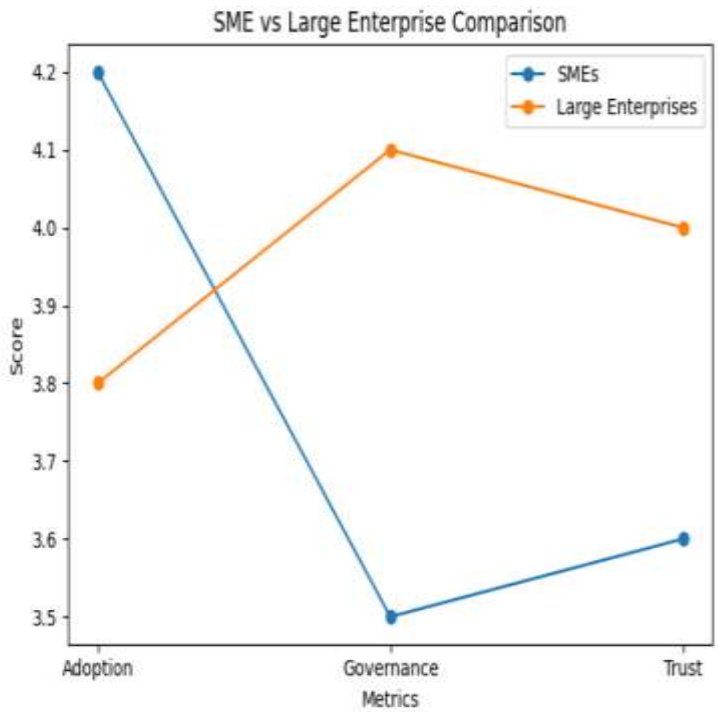

Figure 4: SME vs Enterprise Comparison

This comparison is made in figure 4 in terms of adoption, governance and trust.

The figure makes it very clear that there is a trade-off between agility (SMEs) and structured governance (large enterprises).

4.4 Governance and Trust Analysis

The results show that explainability, source attribution, and governance mechanisms have a greater impact on trust in KM-LLM systems than raw model accuracy. The systems with the governance controls and transparency features are viewed as more reliable ones.

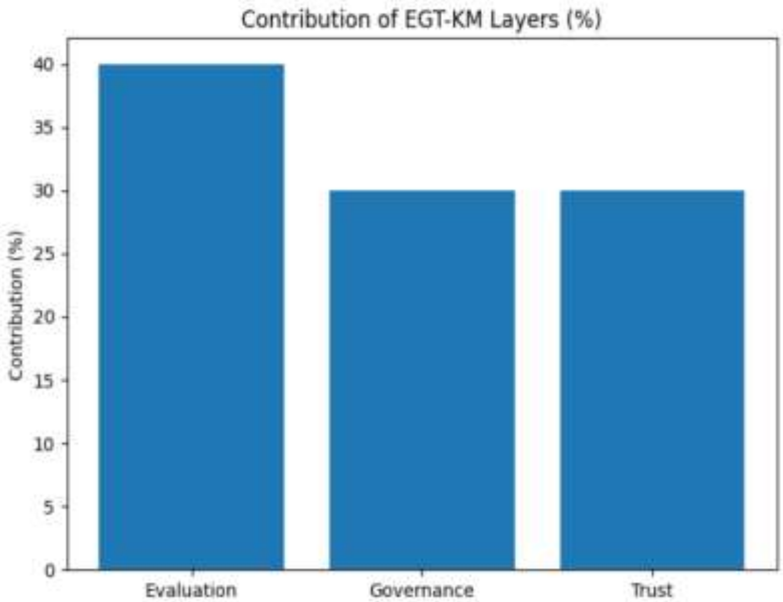

Figure 5: EGT-KM Layer Contribution

Also, the gains depicted in Figure 5, especially in reduction of errors and speed in the decision-making process, are indirectly indicative of how governance can contribute to the improvement of trust. The addition of human-in-the-loop validation mechanisms also enhances user confidence and acceptance which builds trust as a key adoptability factor.

On the whole, the findings reveal that KM-LLM systems are highly effective to improve knowledge retrieval, decision-making, and operational efficiency. The empirical evidence in Figures is very convincing towards the proposed EGT-KM model. The results also highlight the importance of governance and trust mechanisms in enhancing successful system adoption in various organizational settings, even though technical performance is imperative.

5. Conclusion

This paper explored the use of Large Language Models (LLM) in Knowledge Management Systems (KMS) and discussed the key issues regarding evaluation, governance, and trust in the organizational setting. In order to address the drawbacks of traditional KMS in dealing with unstructured data, the study developed a hybrid model, the Evaluation-Governance-Trust Knowledge Management (EGT-KM) model, which combines system performance evaluation with governance processes and trust elements. The empirical findings indicate that the use of the KM systems based on the use of LLM can greatly lead to an increase in the efficiency of knowledge retrieval, decrease in the time spent on information search, and increased decision-making. The addition of sophisticated methods like Retrieval-Augmented Generation (RAG) and knowledge graphs were demonstrated to enhance the performance of the systems and minimize errors. Nevertheless, the results also indicate that the technical performance alone is not sufficient to be successfully deployed. The mechanisms of governance and trust-building such as explainability and human-in-the-loop validation are essential to the reliability of systems and acceptance by the users. The comparative study of SMEs and large enterprises emphasizes the role of organizational context. The SMEs enjoy quicker adoption and flexibility but they have difficulties with the maturity of their governance whereas the large enterprises experience high rates of trust and compliance at the expense of a complex implementation. These lessons underline the importance of context-based deployment strategies of KM-LLM systems. The EGT-KM model proposed has a contribution to the theory and practice in that it would offer one model to integrate evaluation, governance, and trust. It provides a framework that organizations can use to evaluate and implement the application of knowledge management systems based on LLM in a scalable and reliable fashion. To sum up, the current study has proven that the successful implementation of KM-LLM systems cannot be achieved without both technological and good governance and trust. This study can be expanded into future work by adding longitudinal analysis, real-time system assessment, and sophisticated

AI governance systems to add to the credibility and applicability of the systems based on LLM-generated knowledge management

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