ARTIFICIAL INTELLIGENCE INTEGRATION INTO DBMS: PERFORMANCE OPTIMIZATION, BENEFITS, AND ASSOCIATED CHALLENGES

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Abstract:
The current digital economy requires database management systems (DBMS) capable of adaptation and autonomy. Increased data volumes and rapid analysis current requirements are not support by the traditional DBMS. The right solution for these limitations is integration of artificial intelligence (AI). Due to AI algorithms, queries can be optimized and anomalies can be automatically identified for increased data security, natural language-based interfaces can be developed, and data management activities, such as archiving, indexing, or data migration, can be improved, too. However, the success of the process of AI integration into organizational DBMS depends on economic and technological factors that influence the final result, and some of them can be initial costs, difficulties during the integration, and the level of data quality. The paper aims to analyze the economic and technological context that forced organizations to decide on the integration of AI into database management. The main technologies as well as common implementation methodologies are presented. Operational and economic benefits are highlighted alongside with organizational, technical, and ethical challenges associated with AI integration into DBMS.

Keywords: *Database Management Systems (DBMS), Artificial intelligence (AI), Optimization*

JEL Classification: *C80, O33*

1. Introduction and Context

Data volumes increase exponentially, and the demands for scalability, real-time processing, and management of the unstructured data already exceed the capacity of traditional databases (Islam, 2024; Achanta, 2025; Alalaq, 2025; Babucea, 2025; Dritsas and Trigka, 2025). Organizations in all areas of the economy are forced to make decisions in much shorter times. Static optimization strategies do not suit the dynamic demand, which increases the analytical workloads.

The increased need for better data management, handling of large amounts of data, and especially the need for real-time analytics is leading an increasing number of organizations to make the decision to incorporate artificial intelligence (AI) into the organizations' DBMS (Nihalani et al., 2009; Unuriode et al., 2023). The integration of AI into databases changes how data is stored, queried, and exploited. AI technologies enable intelligent data classification and organization, which increases management efficiency (Alalaq, 2025). Less manual intervention by automatic configuration tuning and adaptive query optimization results in cost savings (Vijaya et al., 2025). AI allows dynamic performance tuning of the system according to the workload and adaptation to changing requirements without heavy resource investment (Jupudi et al., 2024).

When database architectures embed AI based mechanisms for adapting to activity patterns and operating context, DBMSs are named intelligent systems, i.e., such systems are self-adjusting. Consequently, based on the historical workloads, AI self-optimization routines tune execution schedules, based on the historical usage, e.g., query patterns, peak hours, applications behavior, the machine learning (ML) models forecast what data or queries will be accessed in the future, i.e., DBMS will load such data in the cache before the data are requested. In such scenario, it is evident that the management tasks are transferred from an ad-hoc configuration to an automated policy-driven process, thus reducing the operational costs and the necessity of DBAs.

As such, it should be emphasized that data is a primary asset of this transformation because the faithfulness of an automated model also depends on the quality and provenance of data

(Elouataoui, 2024). Moreover, the massive and diverse datasets involve a large amount of data pre-processing of the clean and transform data, which should be clear, standardized, and repeatable in order to improve the robustness of the system and model (Nandan Prasad, 2024). Data AI governance frameworks are needed in relation to data traceability, accountability, and regulatory compliance. That means the need to identify the track of the data during their processing, starting from their origin; the need to identify who created, modified, or used the data; and, above all, the need to ensure compliance with rules and laws. Data trust can be achieved through access control mechanisms (only the authorized person/systems can view /edit the data), and by transparent lineage of data processing from source to use (clear lineage of data). Current DBMS include different AI technologies, which are described in the following.

2. Artificial Intelligence Techniques for DBMS Optimization

Integrating AI technologies like machine learning (ML), deep learning (DL), or natural language processing (NLP) can optimize many database functions, while data consistency can be improved, with such technologies supporting efficient management of large and heterogeneous datasets. The automated analysis of different data characteristics (type, distributions, missing values, outliers, dependencies) may reveal suspects of errors and anomalies, detect inconsistencies among tables or fields, or apply consistent validation and cleaning rules. Adaptive indexing and workload-aware optimization strategies enhance the performance of a DBMS (Nihalani et al., 2009; Lande and Bhore, 2024; Othman, 2025). Thus, queries run more quickly and the behavior of the system becomes more predictable, even under load.

Utilizing advanced algorithms and models that can be tailored for structured and unstructured data from multiple domains can enhance the precision of complex evaluations of machine learning or deep learning (Chaitrashree et al., 2021; Zhang et al., 2024; Choudhary and Choudhary, 2024; Sravanthi et al., 2024; Khan et al., 2025). These advanced models enable the investigation of meaningful patterns and insights from large volumes of unstructured data such as text, images, and audio. AI techniques offer significant improvements in the accuracy and efficiency of data analysis. The AI/ML algorithms improve results using data-driven logic, such as statistical models or classical algorithms that learn patterns from data. The deep neural networks, AI/DL multi-layered systems, automatically learn complex representations from data, particularly unstructured data, and are used to solve complex problems. Thus, challenges related to computational requirements and model interpretability persist. Thus, their application in unstructured data analysis requires their optimization (Choudhary and Choudhary, 2024). Unlike ML and DL techniques, which are proper to internal DBMS optimization tasks, natural language processing (NLP) is well focused to facilitate user interaction and semantic understanding. The NLP techniques enable expressing information requests in a common language on users' interfaces. These are translated directly into SQL or NoSQL queries. Chaitrashree et al. highlight the NLP techniques that facilitate the extraction of critical information from medical texts for disease diagnosis and research by summarizing and classifying unstructured data.

Data mining processes (DM) are employed to identify hidden patterns and hidden knowledge in meaningful data for the domains of activities for prognostic studies and risk assessments. Data mining is the extraction of hidden trends and reliable forecasts from large organizational data sets by means of advanced algorithms and techniques. For instance, the risk potential for an organization can be identified by the application of data mining techniques for forecasting (DMTF) on historical data. Predictive analytics (PA) produce future forecasts by exploiting past observations (Pandey, 2013). A clustering technique (CM) identifies trends and anomalies by categorizing similar data instances (Khalin et al., 2023). Association rule learning (ARL) discovers associations between variables that facilitate the development of an understanding of how different variables could influence future outcomes (Jha and Hui, 1998). In numerous domains, data mining applications are applied to conduct risk assessments.

Economic risk forecasting (ERF) methods assist the enterprise' decision-making by providing predictive analytics (Khalin et al., 2023). Furthermore, predictive modeling supports the organization to drive innovation and competitive advantage by guiding it towards trends (Jupudi et al., 2024). Specifically, risk assessment in the health domain (HAR) using artificial neural networks (ANN) and clustering can identify the cardiac risk patterns with high classification accuracy, (Almeida et al., 2018). Business risk management (BRM) can target the customer behavior and market trends, which can support targeted marketing and more informed strategic decision-making (Jha and Hui, 1998). However, regardless of the benefit of data mining in prediction and risk assessment, one risk is that models can be overly fit to the historical data, and so can give poor predictions when environments are changing. Balancing between model complexity and generalizability can be a challenge.

In general, the AI methods presented beforehand provide for insight extractions or risk assessments. Generative AI (GenAI), on the other hand, is better suited for database administration, as it automates repetitive tasks like data cleaning, query syntax creation, or index tuning. Automation work-flows, allows data quality and operational efficiency no matter what the data environments are. The main advantages in automation are: lower query latency, early detection of security anomalies, analytical support of strategic decisions and reduction of human errors. GenAI helps to detect anomalies and verify data in real-time, assisting to keep decision-making high quality data sets. Using large language models (LLMs) generative AI allows to simplify data systems interaction building complex queries automatically (Khemka and Priyanshi, 2025).

However, even though the economic benefits of AI integration into DBMSs are significant, organizations still need to be managed with care, as they will concerns about ethical issues, privacy of data, and biases in models. Therefore, integration of AI in DBMSs needs to be handled responsibly as legacy systems often make integration process difficult (Vijaya et al., 2025 Conversely, there may be model bias which can lead to incorrect decisions based on the AI. Thus, integration of AI technologies in DBMS largely depends on the transparency and fairness of their algorithms that are crucial for organizational acceptability.

In addition, computational and energy costs must be considerate. This might be addressed by audit mechanisms, strict policies, and constant monitoring by organizations as a basis for responsible integration of AI technologies in DBMS. Sustainable outcomes may need cooperation between engineers, data scientists and privacy ethic experts.

3. AI-Based Enhancement of Database Management Systems

Integration of AI technologies into organizational DBMS refines their functionalities by improving the efficiency and user experience. Based on recent literature on the subject, the following covers the key AI-enabled SGBD functionalities, organizational benefits, and challenges, as well as their current developments and trends.

3.1. Functional Enhancements in Intelligent Data Management

Functional enhancements in data management are obtained through AI integration. The accelerated evolution of the volume, variety, and speed of data generation has revealed significant limitations of traditional DBMSs.

In this context, one solution is integration of AI into data management processes. Such a strategy can optimize the organizational quality and value of information.

In the table no 1 below are presented the most relevant functional enhancements in intelligent data management. As can be noted, automatic data classification, adaptive learning, and data quality monitoring are the essential functionalities of intelligent data management.

Table no. 1 - *Functional enhancements in intelligent data management through AI integration*

Functionalities	Description/Benefits	References
Automated classification	- AI algorithms automatically organize and label data to enhance integrity and accessibility.	Maddali, (2023); Lande and Bhore (2024).
Adaptive learning	- AI-enabled DBMSs adjust internal configurations based on user activity to improve responsiveness and analytical capabilities.	Lande and Bhore (2024); Tedeschi et. al (2025).
Data quality monitoring	- AI continuously validates, cleans, and enriches data to ensure consistency and reduce noise in Big Data environments.	Shah et al., (2024); Dawale et al., (2025); Othman and Yasin (2025)

Automatic data classification is based on ML and NLP algorithms that allow the identification of semantic and structural patterns in large data sets. Unlike manual classification, automatic data classification eliminates human intervention and so reduces the errors and operational costs. Increased data integrity, improved accessibility and interoperability, and accelerated search and analysis processes are led by AI algorithms that can automatically organize and label data. Where data comes from heterogeneous sources (structured, semi-structured, and unstructured), as in Big Data environments, AI integration is particularly relevant. For example, in large organizations, the document management systems can integrate AI to automatically classify documents based on content and metadata, facilitating compliance with regulations such as GDPR.

Adaptive learning is the ability of an AI-assisted DBMS to change its internal parameters according to user behaviors and usage patterns. This is possible through the use of reinforcement learning (RL) and predictive machine learning (PML). Adaptive systems optimize their frequent queries automatically, dynamically manage resources (memory, storage, and indexing), and, last but not least, greatly enhance response times and analytical performance. The adaptability changes the DBMS from a passive system to a proactive and intelligent one. AI can see the analysts' query patterns and preload or reorganize the relevant financial analysis platform data. This is the sure way to reduce latency in critical decision-making processes. For instance, a business organization (e.g., a multinational retail organization) connects ERP, CRM, e-commerce platforms, and other external vendor data. As a result of the large volume and high frequency of updates, the chances of data errors and inconsistencies become higher.

Businesses can derive substantial economic and operational benefits by leveraging Artificial Intelligence (AI) as a complement to their DBMSs. Artificial intelligence capabilities that can be integrated into the DBMS include automatic data classification, adaptive learning, and continuous data quality monitoring Automatic classification enhances the organization and accessibility of data, reduces the cost of operations, and enhances data analytics. Adaptive learning lowers response time and resource consumption because the system can learn and continuously improve performance by changing the configuration in response to how the system is used. Continuous data quality monitoring of the organization can mitigate the risks from poor data and can help make decisions with confidence by guaranteeing the completeness, consistency, and accuracy of operational and financial data. These AI capabilities enable the organization to turn its data as a strategic asset and achieve improved productivity and trust in analytics and business intelligence.

3.2. Functional Enhancements in Query Optimization

AI techniques integration into DBMS provides advanced features which further improve the performance and flexibility of query optimizers as well.

The main AI-enabled features that facilitate query optimization procedures, improving execution efficiency, flexibility and overall database performance are summarized in the table below. The most significant contributions mentioned in the literature on the topic are reinforcement learning (RL) for selecting optimal query plans, predicting conflicts in OLTP (Online Transaction

Processing) transactions, and predicting the future workload.

Table no.2. - *Functional enhancements in query optimization through AI integration*

Functionalities	Description / Benefits	References
Reinforcement learning (RL)	Based on workload history, the RL models identify optimal query execution plans. Latency and resource consumption are minimized.	Vijaya et al., (2025); Jupudi et al., (2024); Dhanasekaran, (2025); Rella, (2025)
Conflict prediction in Online Transaction Processing (OLTP)	Transaction conflicts in OLTP systems are predicted and mitigated by AI. Deadlocks are reduced, and concurrency management is improved.	Zhang, T., et al., (2018); Vijaya et al., (2025); Zhang, T., et al., (2024);
Workload forecasting	Predictive models estimate future database loads, allowing pre-allocation of resources and improved scalability	Chinta (2025); Jupudi et al., (2024); Jaini, (2024); Madathala et al., (2023)

Query optimization by reinforcement learning means adaptation of RL for query execution planning. The system models query optimization as sequential decision-making task in which each state is a query structure and the system state. Each action is an execution plan. For example, a DBMS detects repeated join queries on large tables. The RL model learns which join order and index usage lead to lower latency under specific workloads. Over time, the model selects plans based on prior outcomes rather than static cost estimates. Some important benefits are obtained, respectively: lower query latency under changing workloads, reduced CPU and memory consumption, automatic adaptation to data growth and schema changes, and better performance than rule-based optimizers in complex workloads.

Conflict prediction in OLTP systems is about anticipating transaction conflicts before execution, and for that, machine learning (ML) models are used. In this respect, the system examines the historical access patterns and lock behavior and, using this information, the AI model predicts the transactions that will contend for the same data items. For example, in a bank's OLTP system, concurrent balance update transactions contending for the same accounts occur during peak hours. The AI model predicts a high probability of conflict and adjusts the transaction scheduling. Some advantages are included here: deadlocks during high concurrency, higher transaction throughput, reduced response time for critical operations, better stability during peak load.

On resource optimization for workload forecasting, predictive models are valuable as they are capable of predicting number of queries in the future but also complex. The system learns from past workload traces and time-based patterns and predictions can be used to provision resources. An example of this is when an enterprise DBMS notices a pattern of spike in analytical queries at the end of month. The forecasting model predicts a spike in CPU and memory usage, so the system provisions the resources during the transition. The main advantages are increased concurrency, predictable performance, seamless performance and reduced operational costs from being able to provision resources accurately, and ability to plan for long term scaling. These AI optimizations bring query optimization from static planning space to continuous learning space. The advantages are called faster queries, increased concurrency and predictable performance in dynamic workloads.

3.3. Enhanced Functionalities of Databases' Security and Maintenance

Integration of AI functionalities in DBMS also enhances database protection mechanisms and supports autonomous maintenance processes for sustained system stability.

Some of them, claimed in the most recent literature on the topic, including cybersecurity, self-healing mechanisms, anomaly detection, and intelligent logging, are described in Table no. 3.

Table no. 3 – *Functional enhancements in improved security and maintenance through AI integration*

Functionalities	Description / Benefits	References
Cybersecurity	Anomalies, intrusions, and malicious access patterns in real time are detected with machine learning (ML) models, so database security layers are strengthening.	Alalaq, (2025); Asokan, (2025)
Self-healing mechanisms	AI-based predictive maintenance early detects the failures and automatically recovers them, ensuring higher system reliability	Zachariah et al., (2024)
Anomaly detection and intelligent logging	Irregularities in log files and user behavior are detected by deep learning models supporting proactive maintenance and agreement auditing.	Maddali, (2023)

AI-based cybersecurity is trained on access patterns and query behavior and system events with the goal of detecting anomalous or malicious behavior in DB activity in real time. For example, a production DBMS may receive thousands of user queries per minute. The trained model can detect if the frequency of queries or the access time or the privilege usage is anomalous. In case of possible intrusion, the session can be alerted and terminated before the data is released. The real value: real-time detection of unauthorized access, mitigation of data breach risk, quicker response to intrusion attempts, and greater security with no manual updates to rules.

Self-healing mechanisms use predictive maintenance models to keep the system healthy. AI watches the metrics such as disk usage, memory errors, query failures, latency trends, etc. The system predicts failures before they happen and can even trigger automated recovery actions. For example, a DBMS may notice a sudden spike in I/O latency and a rise in the number of errors in the logs. The AI model predicts storage failure is imminent. The system migrates workloads and restarts affected services automatically. Real benefits include increased system availability, fewer unplanned outages, reduced manual intervention, and faster recovery from failures.

AI models for large scale log file and user behavior analysis for anomaly detection or intelligences data logging. Deep learning is used to discover irregular sequences and unexpected patterns. It is also used for proactive maintenance and compliance inspections. Log analysis can discover irregular query structures and irregular login patterns outside normal operating hours. The system alerts administrators. Early detection of operational problems, automated recovery and continuous monitoring of the system with AI-based capabilities provides powerful in-database security and maintenance. Good compliance with security policies may be a strong benefit.

4. Challenges Associated with AI integration into DBMS

Literature on the subject frequently highlighted ethical and operational challenges associated with AI integration into DBMS. Some of them are data privacy and bias (Vijaya et al., 2025; Chinta, 2025) as well as transparency and accountability (Othman and Yasin, 2025; Asokan, 2025).

DBMS integration with AI relies on persistence. Because the AI is trained on the data containing query logs, access histories, and their usage patterns, privacy is a direct concern. Therefore, the bias manifests through a historical workload overrepresenting certain users or applications or time periods. For instance, the query scheduling optimization in a database management system (DBMS) might be trained on historical query logs that capture, for instance, user IDs, access times, and query structure. The AI model might then decide to prioritize patterns from dominant departments, such as finance and accounting. If the traffic in the system is high, reporting queries might be prioritized by CPU and memory consumption, which means the transactional workloads from customer applications will take longer. Operationally, that means the dominant workloads will execute faster, and the same repeated workload will be optimized for. That yields a few issues: sensitive user behavior might be exposed through the training data, other workloads might suffer persistent delays, and the biased optimization decisions might be reinforced through re-training.

4.2. Transparency and Responsibility

AI-driven decisions shape access control and logic data recovery. The complexity of the models reduces their interpretability because, without clear audit trails, responsibility for system outcomes becomes unclear.

In other words, an AI model can alter join strategies under peak load, so the queries slow down, and their performance degrades for critical users. On the other hand, the optimization decision logic lacks visibility; thus, there is no clarification for it. The benefits of operational outcomes, like automated adaptation without manual tuning or reduced response time during normal load, came with risks. As can be noted, there is no traceability for optimization decisions, and delayed root cause analysis, or limited ability to justify system behavior during audits.

5. Ethical AI Aovernance

Ethical AI governance in data management: transparency, accountability and sustainability.

Ethical AI governance in data management in data management is based on explicit compliance with transparency, accountability, fairness and sustainability as advocated by European regulations and the IEEE standards. In December 2023, the European AI Act, authorizing European institutions to test AI producers' products in accordance with the standards of respecting fundamental rights, and to operate in a secure, traceable, non-discriminatory and environmentally sustainable manner (Gornet and Maxwell, 2024).

The IEEE Standards Association (IEEE SA) that promotes, develops, and advocates a wide range of global technologies through IEEE standards, defines AI frameworks and encourages safety, transparency, accountability, and bias minimization. In particular, to use AI models in DBMS contexts for the optimization of querying and operational activities, it should be tracked and documented. Thus, all decisions for auto-index reorganization or query plan changes should be logged, and model updates should be tracked and supervised by database administrators and monitored for performance. Finally, to ensure continuous ethical conformance, performance testing on varied datasets and resources usage, and re-evaluated audit policies can be monitored.

6. Conclusion

In recent years, artificial intelligence (AI) technologies have attracted great interest in various fields of computer science. In the area of database (DB) technologies, extensive research has been conducted to improve DBs in order to provide intelligent data management, query optimization, efficient security mechanisms and support for ethical governance. This paper presents an overview of the state-of-the-art of AI technologies in DBMS and identify research challenges and directions for the future. While the integration of AI technologies in DBMS allows for self-adaptive systems with improved performance, scalability and reliability that in turn support better and faster decision making, it also raises several technical, organizational and ethical challenges. Accordingly, the proposed solutions have to be effective, but also comprehensible, transparent, and accountable. Hence, the research should focus on developing standard integration frameworks, more interpretable models and exploring proper governance mechanisms.

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