THE INTEGRATION OF ARTIFICIAL INTELLIGENCE INTO DATABASE SYSTEMS (AI-DB INTEGRATION REVIEW)

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ABSTRACT

In recent times, it can be deduced that a distributed workforce is the future of work, and the future is now. Therefore, it is essential to know that AI-DB integration is not only for the effective application of Artificial intelligence technology, and the development of database technology, but also for the next generation of computing, which will support future Intelligent Information Systems, and allow work to be more effective and productive. Hence, AI-DB Integration will contribute generally to the infrastructure of science and technology, businesses, and humanitarian applications of computers. With all the potential contributions in play, AI-DB Integration is considerably more important than might be assumed from its contribution to the enhancement of AI and DB technologies alone. In this review, different concepts were discussed by emphasizing some key areas like the design of Intelligent Database Interfaces (IDIs), Learnable databases, and Smart Query. The three fundamental areas geared us to investigate how AI enhances database efficiency by optimizing query performance, automating routine management tasks, and fortifying data security. Also, the paper presents short-term and long-term application areas where AI and databases have converged, providing a comprehensive overview of progress, challenges, and opportunities. The outcome of this review expresses some authors' or experts' opinions on the need for and importance of AI-DB integration and on the future generation of computing.

KEYWORDS

Artificial Intelligence, Database System, IDI, Smart Query, SQL, Machine Learning, NLP, DBMS

1. INTRODUCTION

The recent merger of artificial intelligence (AI) and database systems (DB) has become a disruptive trend with significant ramifications for data management, analytics, and decision-making processes across numerous fields. AI's capabilities in machine learning, natural language processing, and pattern recognition have redefined the traditional paradigms of database systems, ushering in an era of enhanced data processing, intelligence extraction, and automation. This research, herein referred to as the "AI-DB Integration Review," delves into the complex environment for integrating AI technology into database systems, intending to explore the synergistic potential, challenges, and implications of this integration.

Data Integration as revealed by [1] is the process of combining data from different sources into a unified view or format. In the context of AI-DB Integration, it involves harmonizing AI-generated data with existing databases.

Data, in its raw form, lacks context and meaning. Consider the sequence "0, 20, 46, 09" – it's data, but without context, it remains uninformative. To unlock the true value of data, it must transform

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– a process of contextualization, aggregation, and analysis [2]. At the core of any information system lies the task of converting data into meaningful information. This transformation is the fundamental purpose, a meticulously organized repository where data finds logic and relevance. Database systems and applications serve as the conduits that translate raw data into actionable insights. Indeed, what good is data if it cannot be retrieved, analyzed, and employed in decision-making? This fundamental question has driven relentless efforts to refine and expand Database Management Systems (DBMS). While NoSQL databases have gained prominence, SQL databases continue to hold their ground. In this paper, we venture into the empirical investigations and scholarly research undertaken by academia and researchers regarding the integration of Artificial Intelligence (AI) and database systems.

From the perspective of [3], database systems are software systems designed to efficiently store, manage, and retrieve data. They offer a methodical technique to arrange and navigate large volumes of data[3].Database systems form the backbone of AI-DB Integration, providing the foundational infrastructure to store, manage, and retrieve data. They enable effective data access and analysis by facilitating the seamless integration of artificial intelligence techniques.Through this integration, organizations and researchers may use AI to make better decisions, do predictive analytics, and gain real-time insights, promoting innovation and competitiveness in the age of big data.

AI-DB Integration refers to the process of combining Artificial Intelligence techniques with traditional database systems to enhance data processing, analysis, and decision-making capabilities.The integration of Artificial Intelligence into Database Systems (AI-DB Integration) has profound implications for data management and decision-making. It enables advanced data analytics, real-time processing, and predictive capabilities, enhancing the value and efficiency of database systems. This synergy empowers organizations to extract valuable insights from their data, ultimately driving innovation and competitiveness in various domains[4].

AI involves the development of algorithms and statistical models that enable computers to improve their performance on a specific task through learning from data[5]. Machine Learning as a subset of AI is essential to the integration of AI and databases by enabling databases to autonomously adapt and optimize their performance. ML algorithms enhance data management, query optimization, and predictive analytics, making databases smarter and more efficient. This integration revolutionizes data-driven decision-making processes by enabling systems to handle massive volumes of data with higher precision and responsiveness. [6]

Another important part of smart query observed by [7] was Natural Language Processing (NLP), which is a branch of AI that focuses on enabling computers to understand, interpret, and generate human language in a way that is both meaningful and contextually relevant. Natural Language Processing plays a pivotal role in AI-DB Integration by enabling databases to understand and interact with human language. As a result, users are given the ability to query databases using natural language, improving the usability and accessibility of data access. NLP also facilitates sentiment analysis, text mining, and automated content tagging, enhancing the value of databases for various applications.

Neural Networks are also identified as one of the classes of AI algorithms thatare inspired by the structure and function of the human brain. They consist of interconnected nodes (neurons) and are used for tasks like pattern recognition and deep learning. [8]Neural Networks are a critical component of AI-DB Integration, enabling advanced pattern recognition and deep learning within databases. They enhance data analysis, predictive modeling, and anomaly detection, making databases more intelligent and adaptable. The integration of neural networks empowers database systems to handle complex data tasks efficiently. [8]

Data Analytics is the process of examining data to extract meaningful insights, patterns, and trends. AI-DB Integration often leverages advanced analytics techniques to extract valuable information from databases. Data Analytics is instrumental in AI-DB Integration, enabling the extraction of valuable insights from vast datasets. It enhances decision-making, detects trends, and offers predictive capabilities, all within the integrated database systems. The ability to make data-driven decisions and achieve a competitive advantage is enabled by this synergy for enterprises [6].

In a nutshell, Artificial Intelligence refers to the simulation of human intelligence in machines that are programmed to think and learn like humans. It encompasses various techniques such as machine learning, natural language processing, and neural networks [9].Artificial Intelligence is a multidisciplinary field that seeks to imbue machines and computers with human-like intelligence. It encompasses an array of technologies such as machine learning, natural language processing, and computer vision. AI empowers machines to mimic human cognition, execute complex tasks, and continuously improve their performance based on accumulated data [10].The integration of AI into database technologies represents a pivotal moment in the evolution of DBMS. It is the realization that computing systems can attain their full potential only by seamlessly merging with AI and database technology. This synergy between AI and databases promises not just incremental enhancements but paradigm shifts across industries, sectors, and applications.

The "AI-DB Integration Review" strives as a compass in this uncharted terrain, pointing the way to a future where data is empowered to improve the very foundation of our decision-making processes rather than merely being managed. It endeavors to unravel the intricacies of AI-DB integration, providing a comprehensive understanding of its potential to revolutionize industries, sectors, and applications. As we delve into this synthesis of technological marvels, we shall explore the multifaceted dimensions of this integration, from enhancing query performance to pioneering AI-driven data security, ultimately transcending the conventional limits of data management, and unveiling the unprecedented possibilities that emerge when AI and databases converge.

In this paper review, we aimto explore this convergence in depth and identify methods to simplify human-database interactions, making data retrieval and manipulation more intuitive. As a result, we have the following objectives to accomplish.

toinvestigate how AI can enhance database efficiency by optimizing query performance, automating routine management tasks, and fortifying data security through AI-driven threat detection and response mechanisms.

To delve into various domains and application areas where AI and databases have converged, providing a comprehensive overview of progress, challenges, and opportunities.

To illuminate the vast potential that arises when AI and databases collaborate to create intelligent data-driven systems. It's not merely about improving databases with AI; it's about reimagining the possibilities that emerge when these two transformative technologies unite.

2. LITERATURE REVIEW

2.1. Intelligent Database Interface (IDI)

The idea of an Intelligent Database Interface (IDI) is more like the regular system interface, it is an interactive and compactable user interface that is intended to provide efficient access to multiple databases in several remote database management systems (DBMS) that permit Structure query language (SQL). Intelligent Database Interface Language (IDIL) is a unique query language of IDI, which interacts with SQL by translating queries into SQL and then directing the query to the right DBMS. The results from the intelligent database interface are returned as one tuple at a time. Fig. 1 below is the diagram representation of the flow of IDI [10,11,12].

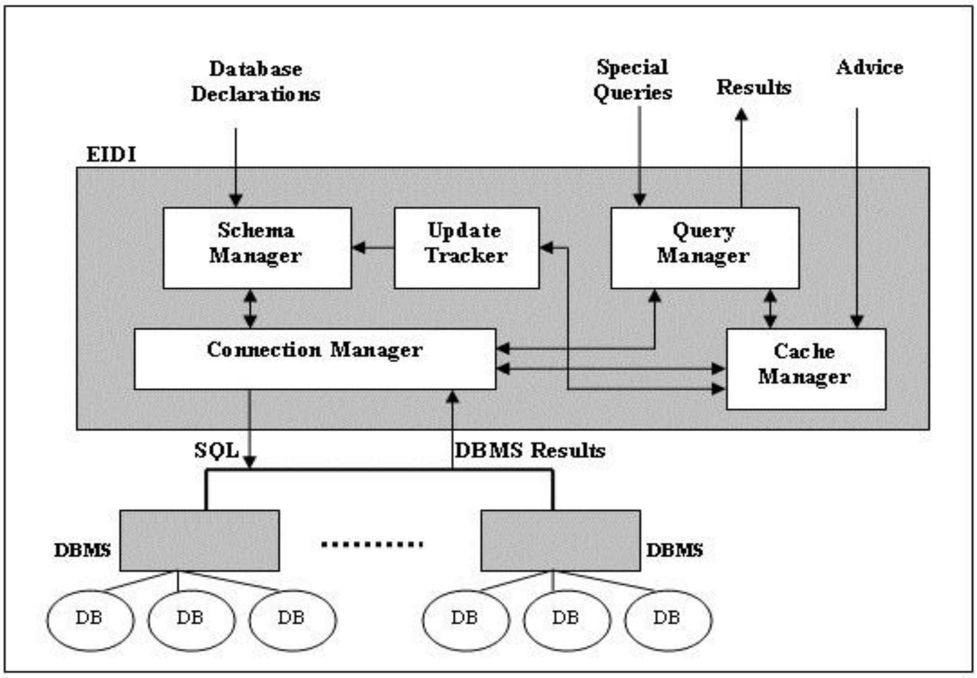

Fig. 1: The IDI Diagram credited to Sheikh Sadid-Al-Hasan, Department of Computer Science & Engineering, BUET, Dhaka, Bangladesh [13].

2.1.1. The Schema Manager (SM)

The information of a declared database is determined by the schema manager. The schema manager also provides information for individual database relations to the query manager. Part of the responsibility of the schema manner is also to process database declarations, access, and store schema information for the declared database, and manage relation name aliases, this occurs when there are identical names in two or more databases containing relations [14, 10].

2.1.2. The DBMS Connection Manager (DCM)

The remote connection of all the databases to DBMS is being managed by the DCM, this comprises processing requests to the close and open database connections in addition to performing all the low-level 1/0 operations related to the connection. In the IDI, each database has at most one connection linked with it and each connection has 0 or more outcome streams [10, 13].

2.1.3. The Query Manager (QM)

The QM hosts and manages the IDIL queries and their results. Another function of the QM is returning a generator for the result relation if the query is successfully executed by the DBMS, this happens when IDIL queries are processed by translating them into SQL with the help of the DCM. A generator as used above is an abstract data type used to denote the outcome of IDIL [10].

2.1.4. The Cache Manager

The result of the cache of the query is the responsibility of the cache manager. This comprises identifying IDIL queries for which the outcome exists in the cache [10].

This is used when dealing with the active database to validate the cache at regular time intervals. Since the CM manages a part of DB that is frequently been accessed, when DB is changed immediately cache is updated, there becomes a problem, and that is where the UT comes in, it helps to make the connection with the CM regularly, to determine if the part of the relation in the cache is the present one. In the process of forcing the CM to update, it also updates the QM [14, 12].

IDI is an ongoing project, and several pieces of research are still being carried out in development. However, the progress made so far will provide a firm basis for creating a modern interface for the current DBMS we have today. The key features of IDI are [14, 10, 11];

1. Provision of seamless and efficient access to remote DBMS.
2. Provision of a wide range of interference between different DBMS with little or no modification, and this is possible because SQL is still being used to communicate with the remote DBMS.
3. It enables various connections with different or the same DBMSs (Database Management Systems) at the same time and all the connections involving several queries are active at the same time.
4. IDI can access schema information automatically; the system is not obliged to hold up-to-date schema information for IDI. This drastically lowers the possibility of errors brought about by old schema activities or manually entered data.

2.2. Learnable Database

With the progress that has been made in machine learning, some of these are speech recognition, etc. Reinforcement learning is an aspect of ML that comprises the general outline of learning, decision-making, and prediction. Reinforcement learning can provide solutions such as optimization of the strategy of the manual design and automation if the issue being faced can be converted into a repeated decision-making challenge [10, 15].

What is special about ML is the ability to learn from historical data, which most DBs are unable to do, but lately, there has been a rise in the methods that use artificial intelligence to power conventional databases. Learnable DB will make databases more intelligent and adaptive, having the ability to instinctively improve according to old data or records and present query workload [10, 15].

A learnable database can also depict various features of data with machine learning and pick the most efficient model that will improve the DBMS. Though ML will continue to create a massive impact on database development, the bottleneck faced by experts is the lack of harmony in the descriptions and ambiguous categorization from an ML viewpoint.

We will look at some areas or aspects of learnable DB that some work has been done and how it improves the performance of database systems.

2.2.1. Configuration of Database Parameter

The amount of load on databases is increasing rapidly due to the explosion of big data, and queries. As mentioned earlier, machine learning learns from old data to be able to predict, and it also helps learnable database applications organize the parameters under separate capacities to form the most efficient plan that best lowers query cost and time.Learnable database configuration aims to utilize AI techniques to automatedatabase configurations and functionality and improve performance and efficiency, and some of the ways this has been done are as follows.

- **Analysis of Workload**

Online Transaction Processing (OLTP) databases can analyze the workload of a database and readjust the available resource configuration before the process gets to its peak. The ML uses a time series model based on dynamic programming to reconfigure the database, which then decides the limit of each different application and thereby lowers the configuration database. Note that this is different from the use of dynamic allocation to calculate workload adjustment, which ended up adding more burden to the system.

- **Tuning Plan**

The turning plan is controlled by the amount of cached data and the buffer pool size in the database. The effectiveness of the turning can help improve the system's performance by avoiding the cache that will negatively impact it.

- **SQL rewriter**

Logic query performance can be considerably improved by removing unnecessary or ineffective operators using SQL rewriter. Traditional empirical questions may be restated in a predetermined order, top-down, and may result in suboptimal questions, whereas reinforcement learning may be used to carefully choose the right rules and apply them in the right order, this is where AI meets DB [16].

- **Database Partition**

The conventional approach cannot strike a balance between load balancing and access efficiency since it heuristically chooses columns (often single columns) as partition keys. To calculate the advantages of a partition, a reinforcement learning model investigates various partition keys and employs a fully connected neural network [16].

The assessment of the learnable database configuration of the parameter model is broken into the analysis of workload and turning plan. Bayesian optimization, deep Q-learning, and neural networks are the ML models used in the analysis of workload. The input elements are code vectors and workload, and the outcome of the model is action deployment, response time, scheduling strategy, and performance configuration.

Turning plans use Gaussian and reinforcement learning ML models. The input elements are the turning plan and the model's outcome are the parameter of configuration and optimal configuration, respectively.

Therefore, we can conclude that the intelligent data configuration of the parameter can calculate the workload and find the optimal optimization plan. This will improve the performance of the query, and database storage management, and equip the database for the era of big data adaptability.

2.2.2. Database Storage Management

Data is more valuable than ever before, and a database has proven to be the most common way to manage and store data by using any of the available DBMS. Storage manager equipped with AI features uses modern analytics to speed up data retrieval and analysis.

2.2.3. Database Query Optimization

Applying machine learning to query optimization can help increase the efficiency of how a query runs. Since ML can learn from historical data, this feature can change the traditional query optimization method and suggest the best path for the query, and this follows the neural network pattern, to learn from experience.

To buttress this point, a cost Optimizer looking at three tables may join two of the tables first, and then, join the last table with the result of the first operation. ML might learn that this is the best way and instead, join all three tables together at once. “According to IBM internal testing, it has been found that ML query optimization has resulted in some queries being completed 10 times faster than the conventional querying method.

Query plan estimation, query scope, query cost estimation, etc. are some of the headiest in which query optimization can be measured.

2.2.4. Query Interface

The query interface uses methods that turn spoken words into query language. It has characteristics such as a query plan and template, its unique feature is the training of a long short-term memory (LSTM) neural network to the advised query trajectory which is then used to denote the analysis and contextual nature of the query. This will be discussed extensively in the next chapters [10].

2.3. Smart Query

There has been tremendous development and advancement in databases. Smart query and intelligent databases are emerging technologies that will have a drastic impact on the way humans interact with databases. Over the years and even in a few years to come, before there is an eventual breakthrough in technology, there will continue to be high demand for non-expert users to be able to query conventional relational databases in more natural ways. The ability to speak to a machine in a natural language, i.e., plain English continues to drive the progress of human-computer interaction.

This desire and quest for a breakthrough in this aspect of advancement of databases and smart query have led to the development of a branch of natural language processing (NLP) called natural language interface to databases (NLIDB), which permits users to formulate queries in a natural language, accessing the information stored in the database without the knowledge of programming. NLP is a beautiful concept that attempts to create an easy and friendly environment for a computer user to be able to interact seamlessly with core knowledge of programming.

It is worth knowing that in as much as this technology seems to make life easy for nonexperts, it is still very experimental, and limited in scope in terms of operation. When the amount of information involved is large, the system fails due to the inability to combine information into parse statements.

This is still an open problem for the research communities. We will however mention some of the outlines or methods because of the several types of research carried out thus far on the subject [17,18, 19,20,21].

1. The smart query employs speech recognition techniques to convert spoken language input into text.
2. Then a semantic matching technique is employed in converting natural language queries to SQL words [20].
3. Complemented by using a dictionary and a set of production rules. The dictionary consists of semantics sets for columns and tables.

2.4. Autonomous Databases

The number of installed DB instances increases drastically with the digitalization of society and industry. All this creates a bad reputation for the databases: they are claimed to be overly complex products that need expensive personal and expensive hardware to be used. This is a big challenge not only for the consumers but also for the producers of the databases. One way to reconcile this problem is the cloud services. With cloud services, the care for infrastructure, installation, support, and running of the DBs and applications is delegated to the provider. However, the provider has its problems – there are too many database instances on the Cloud and too few experienced personnel and time to support the farms with the databases. So, the industry slowly goes to the idea of "autonomous" databases. This means that the maintenance, update, upgrade, and security of the installed and running databases will be done automatically. Even more – the complex performance tuning will be automated.

2.4.1. Oracle 18c – Limited Steps to an Autonomous DB

The next release of Oracle DB (12.2.0.2) is named Oracle 18. This release coincides with the new trend of hosting every kind of software – Cloud Services. The Cloud gives the unseen possibility for enterprises (also middle and small) to host their software in the Cloud Services providers. This triggers a new problem – the huge amount of this software (particularly databases) needs support efforts – patching, updating, upgrading, bug fixing, performance tuning, problems fixing, backup and recovery, and many other activities which are the contents of the DBA job – extremely expensive because of the need for big amount of knowledge, experience, passion, and talent. There are not enough people to meet these requirements. So, for good or bad these activities should be automated as much as possible. The autonomous Oracle database will be available for now only in the Oracle Cloud environment. The No Oracle Cloud installations so far are not able to be autonomous. The main expectation is that the Oracle Autonomous Database Cloud offers total automation based on machine learning and eliminates human labor, human error, and manual tuning. The primary features are: [26]

1. No Human Labor: Database automatically upgrades, patches, and tunes itself while running; automates security updates with no downtime window required.
2. No Human Error: SLA guarantees 99.995% reliability and availability, which minimizes costly planned and unplanned downtime to less than 30 minutes a year.

3. No Manual Performance Tuning: Database consumes less computer and storage because of machine learning and automatic compression. Combined with lower manual admin costs, Oracle offers even bigger cost savings.

These unprecedented targets at this point of the development of the software sound like pure fantasy for every DBA. This will be possible only in Oracle Cloud because of the uniformity of the installation, the usage of Oracle Exadata Appliance in these Cloud Computing Centers, and the total control of Oracle engineers over the installations. But this is not possible with the other kind of installation – the so-called on-premises installations due to the unpredictable parameters of the hardware, operating systems, and other installation components. The biggest obstacle is that the autonomous DB (as declared above) needs permanent bidirectional access from and to Oracle domains in the WEB. Few companies will agree to grant such access to their productive DB installations due to many reasons – an open door for hacking, confidentiality of the productive data, law restrictions, and many other security reasons. In most cases, the Oracle databases run deep behind firewalls and have no access to public Web services. Another interesting question is how the users of the Oracle Cloud Services will agree to grant almost unlimited access to their data to Oracle personnel and how this will harm the confidentiality agreements of the deployment. There will be other ways to ensure the autonomy of the databases on-premises e.g., manually delivering the patch sets, patch bundles, update sets, and bug fixes to the DB and giving the DB the possibility to decide on what to apply. But the problem with the downtime still exists and it is an arduous task to solve it.

3. RECENT OUTLOOK OF AI-DB

The performance of databases is changing because of AI-powered query optimization. Utilizing machine learning algorithms, databases may examine query trends and suggest the best execution strategies. The speed and responsiveness of the database are increased overall thanks to this automation's significant reduction in query processing times. This method is covered in several articles that have been published, underscoring how the database management landscape is changing [22,23,24].

AI-powered query optimization relies heavily on machine learning algorithms. As a result, databases can make wise judgments about query execution plans by learning from previous query data and user habits. These algorithms incorporate several methods, including deep reinforcement learning, neural networks, and decision trees, which collectively enable databases to continuously improve their performance depending on actual usage.[23]

Automated query tweaking is a key benefit of AI-powered query optimization. Databases can autonomously identify performance bottlenecks and suggest real-time improvements by utilizing machine learning and AI algorithms, negating the need for manual intervention from database administrators. In the end, this improves the efficiency and responsiveness of database systems by not only streamlining query performance but also ensuring that databases dynamically adjust to shifting workloads and data patterns. [24].

4. TABLE AI-POWERED DB OVER CONVENTIONAL DB

Aspect	Traditional DB	AI-Powered DB
Data Storage and Retrieval	Data storage and retrieval based on schemas and structured queries.	Supports unstructured data and uses natural language processing (NLP) for querying.
Query Optimization	Traditional query optimization techniques are used.	Utilizes machine learning for query optimization, improving performance.
Real-time Insights	Real-time data processing capabilities are limited.	Enables real-time data processing and provides instant insights.
Scalability	Scaling can be complex and may require manual intervention.	Offers automatic scalability to handle growing data loads efficiently.
Natural Language Interfaces	Typically lacks natural language interfaces.	Incorporates NLP for intuitive querying using everyday language.

5. FUTURE OF AI AND DB INTEGRATION

Intelligent Database Interface (IDI): AI-driven interfaces will become more user-friendly and intuitive, enabling natural language interactions with databases, and increasing non-technical users' ability to access and manipulate data.

Learnable Databases: Databases will become more adaptive because of user queries and usage trends, optimizing data organization, indexing on their own, and enhancing query performance.
Smart Queries: AI algorithms will improve query optimization, providing more effective and context-aware query processing, resulting in faster insights and less query complexity.

Autonomous databases: In the future, we'll see fully autonomous databases that can self-monitor, self-tune, and self-repair, minimizing downtime and manual database maintenance activities, increasing reliability, and lowering operating costs.

6. CONCLUSION

In this comprehensive review, we have examined various avenues of development in the convergence of AI and DB systems, shedding light on their potential impact from different authors of similar research publications. We cannot but agree with some important highlights information by [10], which emphasizes more on some key integrations like Intelligent Database Interfaces (IDIs), Learnable Databases, and Smart Queries as the major driving forces for an intelligent DB system. Across all the journals considered for this review, we were able to deduce major ingredients and components that allow seamless integrations with an effective user experience.

Finally, the integration of AI with database systems offers the potential to transform how organizations operate, make decisions, and interact with customers. However, it also comes with challenges related to data privacy, ethics, and the need for skilled AI professionals to manage and interpret the results. Organizations that successfully leverage AI-DB integration can gain a competitive advantage and drive innovation in their respective industries.The three approaches; speech conversion to text, semantic matching, and dictionary-based rules—offer promising avenues for further research and development. However, it is essential to recognize that these approaches are in progress and require further refinement and implementation [12,25].

As we look to the future, the integration of AI and DB systems holds immense potential for revolutionizing how we interact with data. While challenges and complexities remain, the relentless pursuit of innovation in this field promises a future where databases are not only intelligent but also seamlessly accessible and adaptable to a wide range of users and applications. Continued research and development will be instrumental in realizing this vision, creating a more efficient and user-friendly data-driven world [11].

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