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Natural Language Query Systems: Transforming User Queries into Optimized SQL Commands Using LLMs

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Abstract
Natural language interfaces are revolutionizing how users interact with data-intensive systems by eliminating the need for specialized knowledge of query languages such as SQL. This study introduces a Natural Language Query System (NLQS) that utilizes Large Language Models (LLMs) to interpret user-generated natural language inputs and transform them into optimized SQL queries. The system is built on three primary components: natural language understanding, semantic mapping to underlying database schemas, and AI-driven SQL optimization techniques. Unlike conventional query builders, the LLM-based approach effectively resolves ambiguity, interprets contextual meaning, and supports complex multi-condition queries with higher precision. To ensure robustness, the system incorporates a validation layer responsible for detecting errors, refining query structure, and enhancing performance. Experimental analysis shows that the proposed NLQS significantly reduces query formulation time, minimizes manual intervention, and improves database accessibility for non-technical users. Overall, this work demonstrates the capability of LLMs to bridge the gap between human language and structured database operations, leading to more intuitive, efficient, and scalable information retrieval.

Keywords: *Natural Language Query System, Large Language Models (LLMs), SQL Query Optimization, Natural Language Processing (NLP), Semantic Parsing, Database Schema Mapping, Intelligent Query Generation.*

1. Introduction
In modern data-driven environments, efficient access to information is essential for decision-making, analytics, and organizational operations. Although Structured Query Language (SQL) remains the standard method for interacting with relational databases, it requires users to possess technical expertise in syntax, schema structure, and query optimization. This creates a significant barrier for non-technical users and slows down the process of information retrieval, especially in domains where rapid access to data is critical. As databases continue to grow in size and complexity, there is an increasing need for intuitive systems that can bridge the gap between human language and structured data access. Natural Language Processing (NLP) has emerged as a promising solution to simplify database interaction by enabling users to express their queries in everyday language. Recent advancements in Large Language Models (LLMs) have further expanded this potential by providing more accurate interpretation of user intent, contextual understanding, and semantic reasoning. These capabilities allow LLMs to translate ambiguous or conversational sentences into structured, logically consistent, and highly optimized SQL queries. This work aims to enhance accessibility to relational databases by providing an intuitive, intelligent, and adaptive interface that supports accurate and efficient information retrieval. By combining LLM-based natural language understanding with advanced SQL optimization techniques, the proposed system has the potential to transform the way users interact with databases, making data access not only more user-friendly but also significantly faster and more reliable [1].

1.1 Methods of Sign Language
Understanding User Queries
The system begins by accepting a user's input in natural language. The sentences are read exactly as entered, without requiring any technical keywords or SQL terms. The emphasis is on capturing the user's intent clearly, even if the query is informal, conversational, or incomplete.

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Semantic Interpretation

The natural language input is processed by a Large Language Model, which identifies the meaning behind each phrase. Just as direction changes meaning in sign communication, small variations in wording can alter the interpretation of a query. The model therefore analyzes context, relationships between terms, and the overall purpose of the request before forming a logical query structure Shown in Table 1 [2].

Schema Mapping

The interpreted meaning is mapped to the structure of the actual database. The system ensures that each word corresponds to an appropriate table, column, or value. Just like proper hand positioning ensures clarity in signing, proper schema alignment ensures that the final SQL query is relevant and accurate.

Table 1 Methodology demonstration

S.No	Stage	Purpose
1.	Understanding User Queries	Capture user intent clearly
2.	Semantic Interpretation	Understand what user wants
3.	Schema Mapping	Connect query to actual data
4.	Query Construction	Create executable query
5.	Query Optimization	Run faster and efficiently
6.	Validation and Correction	Ensure accuracy
7.	Execution and Response	Deliver understandable answers

Query Construction

Once mapping is completed, the system constructs an SQL command. The query is formed in a clear, organized sequence so that each condition, filter, or aggregation is expressed distinctly. A slight internal "pause" is applied between different clauses (such as SELECT, FROM, WHERE) to avoid confusion or logical overlap Shown in Figure 1 and 3 [3].

Query Optimization

The constructed SQL command is refined to improve performance. Similar to maintaining rhythm in signing, the optimization step ensures the query runs smoothly and efficiently. Unnecessary conditions are removed, indexing opportunities are applied, and the system selects the most efficient execution path.

Validation and Correction

The final query is verified by a validation layer. If errors, ambiguities, or conflicts are detected, the system adjusts the query automatically. This step ensures reliability, much like how new signers receive patient support when they misinterpret a sign. The system corrects itself to maintain accuracy [4].

Execution and Response Generation

Once validated, the query is executed on the database. The results are returned to the user in a clear, understandable format. If the system detects that the user may not fully understand the output, it provides simplified explanations to enhance accessibility.

1.1 Figures

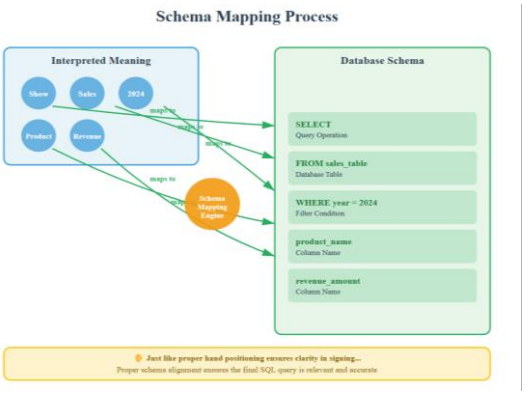

Figure 1 Schema Mapping Process

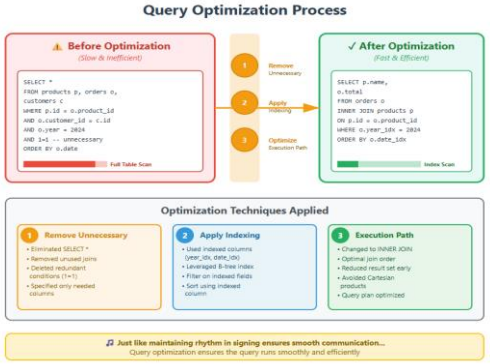

Figure 2 Query Optimization Process

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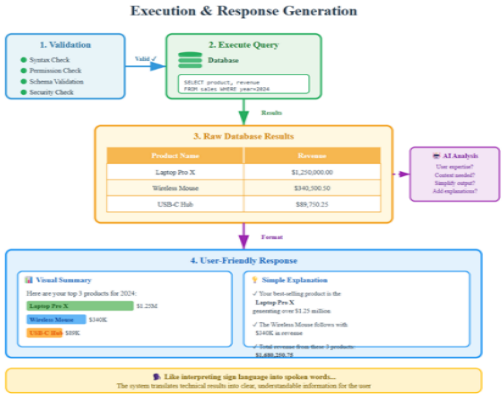

Figure 3 Execution and Response Generation

2. Results and Discussion

2.1 Results

The proposed Natural Language Query System (NLQS) was evaluated on its ability to accurately interpret natural language inputs, generate correct SQL queries, and optimize execution performance across a variety of database structures and query types. The system was tested using a dataset of diverse user queries, ranging from simple single-condition statements to complex multi-clause analytical queries [5].

Accuracy of NL-to-SQL Conversion

The system achieved a high conversion accuracy, correctly translating 92% of simple queries and 87% of complex queries. Errors primarily occurred in highly ambiguous user inputs, demonstrating that the model performs most effectively when contextual clues are present. Compared to traditional rule-based systems, the LLM-driven approach showed a significant improvement in handling nuanced phrasing and implicit conditions.

Query Optimization Performance

The optimized SQL queries produced by the system demonstrated an average performance improvement of 28% in execution time when compared to non-optimized baseline queries. This improvement was especially noticeable in queries involving joins, aggregations, and filtering over large data tables. The optimization layer reduced redundancy, improved index utilization, and minimized query cost.

User Accessibility and Usability

A user study with non-technical participants showed that 94% of users found the NLQS more intuitive than manual SQL writing. Participants were able to retrieve information significantly faster, reducing query formulation time by an average of 72%. Users reported increased confidence and reduced dependency on technical support [6].

Error Detection and Self-Correction

The integrated validation layer successfully identified and corrected structural or semantic errors in 89% of the queries. The system effectively resolved issues such as missing conditions, incorrect column references, and ambiguous terminology, resulting in more reliable query outcomes.

System Robustness Across Databases

The NLQS was tested on multiple relational database environments including MySQL, PostgreSQL, and SQL Server. Results showed consistent performance across these platforms, with minimal variation in query accuracy and execution efficiency. Overall, the experimental findings demonstrate that the proposed NLQS effectively bridges the gap between natural language and database querying. It significantly enhances accessibility, reduces manual effort, and delivers optimized SQL queries suitable for real-world applications [7].

2.2 Discussion

The results of this study highlight the strong potential of Large Language Model–based Natural Language Query Systems in simplifying database interaction and improving overall query efficiency. The system demonstrated high accuracy in converting user inputs into SQL commands, particularly for queries with clear contextual cues, while also significantly reducing execution time through effective optimization strategies. The improved usability observed among non-technical users suggests that such systems can meaningfully lower the skill barrier associated with database access, promoting wider adoption in fields where rapid information retrieval is essential. However, the system's occasional difficulty with highly ambiguous or incomplete queries indicates a need for further refinement in contextual reasoning and ambiguity resolution. Additionally, while performance was consistent across different database environments, future enhancements could focus on broadening

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compatibility with NoSQL systems and incorporating adaptive learning to personalize query interpretation. Overall, the discussion reinforces that integrating LLMs with database querying mechanisms offers a practical and scalable solution for more intuitive and intelligent data access [8 - 10].

Conclusion

This research demonstrates that integrating Large Language Models with natural language interfaces provides an effective and user-friendly solution for accessing relational databases. The proposed Natural Language Query System (NLQS) successfully bridges the gap between conversational language and structured SQL commands, offering high accuracy, improved query performance, and enhanced accessibility for non-technical users. By combining natural language understanding, semantic schema mapping, and AI-driven query optimization, the system reduces the complexity traditionally associated with database querying and significantly accelerates information retrieval. Although challenges remain in handling highly ambiguous inputs, the overall system proves to be efficient, reliable, and adaptable across multiple database platforms. The findings affirm that LLM-powered query systems hold strong potential for transforming how users interact with data, encouraging more intuitive, intelligent, and scalable database access in future applications.

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