The Impact of Text-to-SQL Systems on Student Performance and Satisfaction in SQL Tasks in Higher Education

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***Abstract**. The paper consists of two main sections: theoretical and research-based. The first part presents the fundamental concepts of text-to-SQL systems, their operating principles, and the pedagogical foundations for their implementation in the teaching process. The second part of the paper outlines the results of a study aimed at examining the impact of using text-to-SQL tools (specifically ChatGPT) on students' performance in writing SQL queries. The analysis focused on task accuracy, completion time, and student satisfaction with the tool. The findings indicate a higher level of accuracy and efficiency in the group using these tools, accompanied by a generally positive user experience.*

Keywords. Text-to-sql, Artificial intelligence in education, SQL queries, Intelligent tutoring systems

1 Introduction

It is an undeniable fact that, as a modern society, we are surrounded by data on all sides. Data is generated daily, both in professional and personal contexts, leading to a continuous increase in its volume as well as its significance (Brezočnik, et al., 2022). Consequently, educating students in the field of Databases has become a crucial component of contemporary higher education. Through the course "Databases," students are introduced to the fundamental concepts of data modeling, working with relational databases, and SQL. SQL (Structured Query Language) is the primary standard and tool for managing and manipulating data within a database. Practical work with students in this subject has revealed numerous challenges and difficulties they face.

Most notably, students struggle with formulating accurate and efficient SQL queries, understanding relationships and connections between tables, and applying theoretical knowledge to solve real-world problems and practical tasks.

The idea for this study originated from personal experience and is a direct outcome of pedagogical practice in higher education, based on years of teaching and conducting practical exercises in the subject of Databases. With the aim of providing students with additional support in the learning process, the authors identified potential benefits that could be gained from implementing modern technologies in the instruction of this subject. In particular, this refers to technologies that enable the direct translation of questions posed in natural language into corresponding SQL queries—so-called text-to-SQL systems. These systems emerged as a response to the growing need for processing increasingly large volumes of data, which can no longer be managed effectively using traditional methods (Stupar, Bičo Ćar, Karabegović , & Šahić, 2019).

In recent years, the development of large language models (LLMs) has significantly enhanced the capabilities of text-to-SQL systems. New models such as GPT-4 (AI, 2023) and PaLM 2 (Rohan, et al., 2023) show promising potential for generating SQL queries from natural language, even without additional training for this specific application. Their capacity to understand context, syntax, and semantics of SQL brings new possibilities for educational applications (Hong, Yuan, & Zhang, 2024).

The integration of these systems into the educational process introduces new questions and potential opportunities, such as personalized student support and the automation of learning processes, all aimed at facilitating more efficient and accessible acquisition of applicable knowledge. Given the growing presence of artificial intelligence (AI) technologies in education, it is entirely justified-particularly in the domain of databases-to examine the potential effects of using text-to-SQL tools on students' motivation, comprehension of course material, and overall learning achievement.

The aim of this paper is to explore the application of text-to-SQL systems in teaching database courses and to examine their impact on student performance, as well as to identify the advantages and potential limitations of these technologies within an educational context. The following sections will address the theoretical foundations of AI integration in education, the operational principles of text-to-SQL systems, and the results of the conducted research. Based on the analysis of these results, recommendations will be provided for improving teaching practices through the integration of such technologies.

2 Theoretical Framework

This chapter will explain the key concepts underlying SQL database systems, the challenges (barriers) that students face in the educational process in this field, as well as the potential roles of modern technological systems in overcoming these barriers.

2.1 Databases and the Importance of SQL in Education

Databases represent the foundation of modern information systems, as they enable efficient storage, organization, processing, and access to data that are essential for everyday life and work. In the context of the development of a digital society and the widespread automation of business and social processes, data management has become an indispensable element across almost all fields-from commerce and education to healthcare and public administration. This necessity stems from the fact that modern databases store and process extremely large volumes of data. An illustrative example is Google, which processes more than 20 petabytes of data daily (Delta, 2024). All of this leads to the conclusion that understanding database concepts, as well as mastering query languages used for data retrieval, has become one of the most critical competencies in the education of students in the field of Information Technology.

SQL (Structured Query Language) is a standardized query language that enables users to create and manipulate data within databases. One of SQL's main advantages is that it allows users to interact with data without needing to understand the internal structures or functioning of the database itself. This makes SQL a universal tool, whether it is used for simple data retrieval or for complex analytical operations (Mitsopoulou & Koutrika, 2024). Although SQL was originally designed for relational databases, it is also effectively used in many modern database systems that combine features of both relational and distributed architectures (so-called NewSQL databases). The language is widely applied in the field of analytical data processing, which represents a significant component of contemporary approaches to data management. This is largely due to the expressive power of SQL; however, with high expressiveness comes high complexity (Miedema, 2024).

Regarding the presence of SQL in student education, it is widely integrated into the curricula of faculties and other higher education institutions in the field of technology. It is included in courses related to databases, information systems, and programming. The study of SQL holds dual significance for students: on the one hand, it provides knowledge about the structure and organization of data in real-world systems; on the other, it fosters the development of logical and analytical thinking skills as students solve problems related to query formulation.

However, practice and experience in higher education indicate that students often face difficulties in mastering the SQL. One of the key factors affecting the effectiveness of learning is the student's prior knowledge, which significantly influences their learning approach (Sadiq, Orlowska, Sadiq, & Lin, 2004). In addition to this, students' difficulties in learning SQL are also reflected in the following aspects:

- misunderstanding the relationships between tables in a database and the concept of relations,
- incorrect use of SQL syntax,
- limited ability to translate requirements expressed in natural language into formal SQL queries, and
- lack of confidence when working with real-world databases and solving concrete practical problems.

All of this highlights the need to incorporate modern methods into the teaching process to facilitate the acquisition of relevant skills. One of the key directions in contemporary education is the integration of advanced tools based on artificial intelligence. In the context of databases and SQL, this primarily refers to text-to-SQL systems. These systems allow users to input a query in their natural (native) language (e.g., "Show all employees working in the IT department"), and the system automatically generates the corresponding SQL query that executes the desired functionality on the database. The emergence of models based on neural networks and deep learning concepts has significantly improved the process of translating natural language into SQL (Zhengju, Zhang, Xiaotong, Yang, & Liang, 2024). The usefulness of these tools lies in their potential to support the learning of SQL by enabling students to observe the structure and logic of queries through the automated generation process.

The integration of automated SQL query generation systems into the educational process should not be viewed merely as a technical task, but rather as a crucial component in the development of digital skills, analytical thinking, and problem-solving abilities. The inclusion of intelligent systems in this domain brings numerous benefits to the learning process, as it enables the personalization of instruction according to individual student needs, thereby promoting more active and intuitive learning.

2.2 Challenges in Learning SQL – Cognitive and Technical Barriers

Although learning SQL is essential for understanding and applying database management systems, it often presents a significant challenge for students. Barriers to learning SQL can be divided into *cognitive* and *technical* (Kumar & Kumar, 2018). Both cognitive and technical barriers together influence students' success and motivation during the educational process.

Cognitive barriers refer to the difficulties in understanding and comprehending abstract concepts such as normalization, relational schemas, and relations. These difficulties arise due to the semantic gap between natural language and SQL. Bridging this gap is precisely what makes the coding phase particularly challenging (Shin, 2022). As a result, students often make mistakes when writing SQL expressions, which stem from a misunderstanding of the data itself as well as the relationships between them. The errors that students make when writing SQL expressions can be classified into syntactic, semantic, and logical errors (Fig. 1) (Shin, 2022).

Type of Error	Syntax Error	Semantic Error	Logical Error
Example of Error	`SELECT * FROM students WHERE grade != 'F' AND grade != 'D';`	`SELECT AVG(name) FROM students;`	`SELECT * FROM students WHERE grade != 'F' AND grade != 'D';`
Explanation	**Missing comma between name and age. This will cause a parsing error.**	Trying to apply an aggregate function (AVG) on a non-numeric field (name). Query is syntactically correct, but semantically invalid.	The intention was to select students with grades above 'D', but this logic might exclude other valid grades due to incorrect conditions.

Figure 1. Types of SQL Errors

Semantic errors occur when the rules of SQL writing are violated, meaning that the command is incorrectly formulated from the aspect of syntax - such as misspelled keywords, missing commas, or unclosed parentheses.These errors are the easiest to correct because they are "detectable" - the DBMS system recognizes and reports them.Semantic errors actually represent the incorrect use of correct syntax: the syntax is formally valid, but the query does not produce the expected results. They arise due to a student's misunderstanding of SQL expressions.

Logical errors occur when an SQL expression fails to fulfill the logical objective of the task. The SQL statement executes and produces a result, but the result is incorrect. Semantic and logical errors are the most difficult to detect because the DBMS system does not report them; queries execute successfully, but the obtained results are not as expected. These two types of errors indicate a lower level of knowledge and a deeper misunderstanding of data structure concepts among students.

Technical barriers arise when tools and interfaces used for working with databases and their data further complicate the learning process. The lack of visual feedback during the learning process often hinders students' understanding of how SQL queries operate (Shin, 2022). Moreover, the linear nature of SQL queries, which requires a high level of precision, frequently causes difficulties and frustration among beginners in this field.

In addition to the aforementioned factors, the way SQL is typically presented in educational materials is often more focused on the technical understanding of the language rather than on fostering a deeper comprehension of its purpose and application in real-world systems. As a result, students tend to perceive SQL more as a set of rules to be memorized than as a practical tool for working with real systems and solving concrete problems in practice.

For all these reasons, modern educational approaches to teaching this subject increasingly incorporate the use of interactive and adaptive tools in the process of learning SQL. Tools such as SAVI and DBQA enable the visualization of SQL query execution processes, thereby facilitating students' understanding of how these processes work (Shin, 2022). Contemporary tools help overcome the aforementioned barriers and promote the development of functional knowledge.

2.3 Modern Technologies in Education: AI and NLP

The implementation of modern technologies, Artificial Intelligence (AI), and Natural Language Processing (NLP) in the educational process significantly transforms its concept and methods of realization. These technologies enable the introduction of new approaches, methods, and techniques of learning and teaching. AI systems facilitate the personalization of the learning process, the introduction of automated assessment, and the adaptation of curricula to the needs, prior knowledge, and experience of students (Alqahtani, et al., 2023) (Adhikesaven, 2022). NLP technologies reduce the technical barrier between humans and computers by enabling two-way communication in natural language between them.

2.3.1 AI in education

The integration of AI into the educational process enables the development of intelligent learning support systems such as:

- *Intelligent tutors* - adapt to the pace, style, and progress of students,
- *Recommendation systems* - suggest additional learning materials aligned with previously acquired knowledge and mastered content,
- *Automated assessment and evaluation systems* - conduct assessment and evaluation of student work, thereby providing feedback to instructors about student progress, and

- *Student achievement analysis systems* - analyze student work to identify weaknesses and provide recommendations for further development.

All these AI systems are based on machine learning concepts that are trained with large amounts of data from the educational process. From these data, they derive patterns and regularities and provide feedback at any point in time.

2.3.2 NLP technologies in education

These technologies enable computers to understand, analyze, and generate human language. In education, NLP technologies are most commonly used for:

- *Automatic analysis of textual responses and essays,*
- *Access to knowledge bases through questions posed in natural language,*
- *Translation and summarization of teaching materials,*
- *Interaction with educational chatbots, and*
- *Support for students with learning difficulties (speech-to-text systems)*

From the perspective of database learning, the particular benefit of NLP systems is evident in text-to-SQL systems that enable queries to be posed in ordinary, natural language over databases. This facilitates faster and more efficient query learning, understanding of query logic and purpose, and reduces technical barriers for beginners in this field. Additionally, these technologies allow students to experiment with queries and concepts in a "safe environment" without fear of making errors.

The advantages of using these technologies in education and database instruction are numerous. In addition to the assistance and benefits they provide related to the educational process itself, which we have already mentioned, they also aid in automating administrative tasks, which can be beneficial to both students and instructors (Bolton, 2024).

On the other hand, it is important to consider the challenges associated with implementing these technologies in education. One of the most significant, which requires special attention, is the protection of student data privacy. Additionally, it is necessary to maintain the reliability and accuracy of models, address the need for enhanced digital competencies among instructors, mitigate the reduction of critical thinking skills among students due to excessive reliance on technology, and consider ethics and algorithmic bias... (Alqahtani, et al., 2023).

Recent advancements in LLM technologies introduce revolutionary changes in education. These models demonstrate the ability not only to generate answers but also to explain the reasoning process and provide personalized feedback to students. Research shows that LLMs can enhance the learning experience through interactive dialogues and customized explanations of complex concepts (Tai, Chen, Zhang, Deng, & Sun, 2023). Studies demonstrate that contemporary LLMs can function as effective tutors that assist students in understanding complex programming concepts, including SQL (Pourreza & Rafiei, 2023).

2.4 Text-to-SQL systems: definition, examples, working principles

It is crucial to distinguish between specialized T2SQL systems and general-purpose LLMs when discussing text-to-SQL capabilities. Specialized T2SQL systems such as Seq2SQL (Zhong et al., 2017), Spider (Yu, et al., 2018), and RAT-SQL (Wang, Shin, Liu, Polozov, & Richardson, 2020) are specifically designed and trained for natural language to SQL translation tasks, often incorporating schema-aware architectures and domain-specific optimizations. In contrast, general-purpose LLMs like ChatGPT, while demonstrating competence in T2SQL tasks, are not specifically optimized for SQL generation and rely on their broad language understanding capabilities rather than specialized architectural features for database querying.

Text-to-SQL (T2SQL) systems represent modern intelligent tools that enable the automatic transformation of natural language into SQL commands. T2SQL systems rely on advanced natural language processing (NLP) models, including deep learning and transformer architectures, to accurately interpret user requests expressed in free-form language and generate corresponding queries that align with the user's intent (Xu, Liu, & Song, 2017).

Early T2SQL systems were based on semantic parsing techniques, which served as the foundation for natural language understanding. However, these methods exhibited numerous limitations and shortcomings, particularly in interpreting complex and diverse linguistic constructions. The development of deep learning concepts and neural networks has significantly advanced these processes, allowing for more accurate and efficient translation of natural language into SQL queries (Shi, Tang, & Zhang, 2024).

The primary objective of these systems is to simplify interaction with databases. They enable users who may not possess extensive technical expertise, particularly those with limited knowledge of programming and database management, to easily work with and manipulate data within a database. This is especially beneficial for students, as it provides them with insight into the process and structure of SQL query formulation, while also allowing them to quickly obtain the queries necessary for their work and for solving specific problems. In an educational context, T2SQL systems can be utilized as assistive tools that support students in developing functional knowledge through interactive experimentation (Elgohary, Hosseini, & Awadallah, 2020). The operational principle of T2SQL systems can be divided into several phases. Initially, the system performs natural language analysis, identifying key entities, attributes, and relationships within the user's input (Yu, et al., 2018). Subsequently, it maps the input to the database schema by utilizing a predefined database structure to associate the mentioned terms with the corresponding tables and columns. Following this, the system generates the SQL expression by employing an appropriate learning model to formulate a query that accurately reflects the user's intent. Finally, the generated SQL query undergoes verification and execution, where it is executed against the database and the results are presented to the user (Yu, et al., 2018).

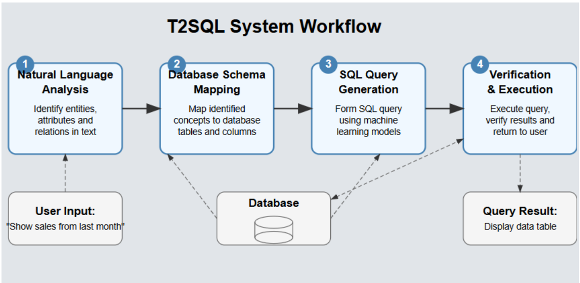

Figure 2. T2SQL System Workflow

The field of T2SQL systems has been significantly advanced by the development of large language models (LLMs) and their integration with pre-trained language models (PLMs). This integration has enabled artificial intelligence to achieve a deeper understanding of natural language semantics, resulting in more accurate SQL query generation (Singh, 2023). Contemporary research in this area places particular emphasis on the contribution of PLMs to the T2SQL parsing process, highlighting their ability to recognize and interpret complex linguistic patterns (Hong, Yuan, & Zhang, 2024). When evaluating the performance of T2SQL systems, it is most commonly based on two parameters: (1) the degree of alignment between the generated SQL queries and the reference queries, and (2) their execution accuracy (Pourreza & Rafiei, 2023).

Advances in LLM development have brought significant changes to the efficiency of T2SQL systems. Unlike earlier specialized systems, contemporary LLMs such as GPT-4 and Claude demonstrate exceptional ability to generate accurate SQL queries from natural language without specific training (Aiwei, Xuming, Lijie, & Philip, 2023). These models can not only generate complex SQL queries but also provide explanations of their logic, which is particularly useful in educational contexts.

Well-known T2SQL systems include:

- *Seq2SQL* – A model that translates natural language into SQL queries using deep neural networks. It takes into account the query structure during processing in order to reduce the search space for generation (Zhong, Xiong, & Socher, 2017).
- *Spider* – A large dataset designed for complex and cross-domain semantic parsing and natural language-to-SQL translation tasks. It contains 10,181 questions and 5,693 unique, complex queries executed over 200 databases (Yu, et al., 2018).
- *Codex* – A large language model (LLM) developed by OpenAI, capable of generating SQL queries from natural language without additional fine-tuning. It demonstrates high performance on standard T2SQL benchmark tasks such as Spider (Chen, et al., 2021).

An important feature of these systems is that many commercial tools integrate T2SQL system functionalities into the user interfaces of business analytics platforms (e.g., Microsoft Power BI, Tableau, etc.). This further promotes the application of such systems in fields that are not directly related to technology or education.

2.5 Pedagogical Foundations of the Application of Intelligent Tutoring Systems

The primary goal of developing Intelligent Tutoring Systems (ITS) is to simulate the work of a human tutor (teacher). Their task is to provide students with real-time feedback, assistance, and suggestions while simultaneously accounting for individual differences in knowledge, learning pace, and problem-solving approaches. These systems are most commonly based on the principles of personalized learning, experiential learning, and adaptive instruction (VanLehn, 2006).

One of the most important pedagogical principles underlying ITS-if not the most important- is the adaptation of instruction. This principle implies that the system continuously monitors and analyzes user activities in real time. Based on the results of this analysis, it adjusts the types and difficulty levels of tasks, as well as the forms of active support, to the specific needs of each user. This type of learning personalization leads to greater student engagement and a deeper, more thorough processing of information (Ma, Adesope, Nesbit, & Liu, 2014).

ITS frequently employ the principles of formative assessment, meaning that they provide immediate feedback following task completion. This helps students promptly correct misconceptions and develop metacognitive awareness. Additionally, ITS systems are particularly valuable because they support learning through mistakes, allowing students to experiment without limits and learn from unsuccessful attempts without fear of negative consequences (Roll, Aleven, McLaren, & Koedinger, 2011).

From a pedagogical perspective, the significance of ITS is also reflected in their continuous monitoring of student progress. This enables instructors to have real-time insight into the effectiveness of the learning process and to identify potential "bottlenecks." As a result, they can intervene promptly and provide targeted learning recommendations. All of this indicates that the role of ITS is not to replace traditional teachers, but rather to support and empower them in making pedagogical decisions during the learning process (Woolf, 2010).

3 Review of Previous Work and Contributions in the Field

3.1 Evolution of T2SQL Systems and Their Application

If we observe the development process of T2SQL systems, it can be stated that it has progressed through several stages. The earliest systems were rule-based, followed by systems founded on semantic parsing, leading up to contemporary models based on large language models (LLMs) and deep learning techniques.

Among the first works that made a significant contribution to this field is the study by Yin & Neubig, which introduced a sequential neural network-based approach in the form of the Seq2SQL model, aiming at structured SQL query generation (Yin & Neubig, 2017). The introduction of this approach enabled improved translation from natural language into SQL syntax, while also taking into account the structure of the query itself.

A subsequent important milestone in this domain is the development of benchmark datasets such as WikiSQL (Zhong, Xiong, & Socher, 2017) and Spider (Yu, et al., 2018), which allowed for standardized evaluation of T2SQL system performance. The Spider dataset, in particular, emphasizes the ability to generalize across multiple databases, thus promoting model robustness.

With the emergence of LLMs such as Codex (Chen, et al., 2021), various evaluations have demonstrated that such models are capable of generating complex SQL queries without additional fine-tuning. These automatically generated SQL queries have exhibited high success rates on benchmark tests such as Spider. This development opened a new chapter in the application of pretrained models for T2SQL parsing tasks.

Additionally, numerous authors have explored hybrid systems that combine rule-based and neural approaches. These systems leverage the precision of rule-based methods and the flexibility of neural networks, focusing particularly on reducing errors in complex queries.

Beyond technical and technological advances, there are also works that explore the pedagogical potential of T2SQL systems within educational contexts. A common theme among these studies is the suggestion to integrate T2SQL models into database learning tools, as they provide students with a more natural interface for query formulation, thus facilitating the process of learning SQL queries.

3.2 Critical Review of T2SQL and LLM Systems Application in Education

The existing literature on T2SQL systems primarily focuses on technical aspects, while their application in education remains insufficiently explored. Stupar et al. (2019) and Shin (2022) analyze concepts without empirical validation of learning outcomes, whereas Alqahtani (2023), Adhikesaven (2022), and Bolton (2024) examine general aspects of AI in education without specific attention to SQL. Hong (2024) provides an overview of T2SQL systems but lacks analysis of their educational potential, and existing evaluations of ChatGPT are predominantly qualitative.

3.3 Research Contribution

Our research distinguishes itself through its specific focus on T2SQL in SQL learning, empirical measurement of student performance, combination of quantitative and qualitative data, evaluation of ChatGPT as a contemporary language model, and concrete pedagogical implications, while acknowledging the methodological limitations described in section 5.1.

4 Research

The following section will present the objectives, methodology, implementation process, and data analysis of the conducted research. The aim of the study was to examine the effectiveness of applying T2SQL systems in learning SQL.

4.1 Description of the Research

The research presented in the following sections was designed to examine the effects of using T2SQL systems as a support tool in database education. The study was conducted on a sample of 25 students enrolled in the Information Technology program, all of whom were attending the Database Systems course. For the purposes of the study, students were divided into six groups (with 3–5 members per group). The objective of the research was to investigate whether the application of artificial intelligence-based systems-specifically T2SQL systems- could contribute to improving students' ability to learn and write SQL queries.

The groups were assigned tasks consisting of 10 SQL queries, methodically arranged from the simplest to the most complex.

All groups received the same tasks and had the same amount of time- 45 minutes- to complete them. The key difference lay in the method of task completion: three groups solved the tasks using traditional methods, relying on their knowledge and available materials (in written or digital form), while the other three groups completed the tasks using ChatGPT as a general-purpose LLM capable of T2SQL functionality*[1].

Students received tasks in the form of textual instructions, which they then entered into ChatGPT to generate the corresponding SQL queries.

At the end of the session, students who used the T2SQL system were asked to complete a survey to express their opinions and satisfaction with this approach. Throughout the process, the teacher monitored the students' work and recorded the parameters necessary for further analysis.

4.2 Formulated Hypotheses

The hypotheses formulated in accordance with the stated research objective are as follows:

- ***H1*** – Students who utilize the T2SQL system (ChatGPT) in their work achieve a higher number of correct SQL queries compared to students who solve tasks using traditional methods.
- ***H2*** – The time required to complete the tasks is shorter for students who use the T2SQL system than for those who solve the tasks in a traditional manner.

4.3 Analysis of Research Results

As previously mentioned, the study involved 25 Information Technology students enrolled in the "Database Systems" course. The students were divided into six groups (G1–G6), with three groups (G1, G2, and G3) solving the tasks (writing SQL code) using the traditional method, while the other three groups (G4, G5, and G6) used ChatGPT, functioning as a T2SQL system, to support query writing.

All groups were assigned the same number of tasks (10 SQL queries) and had the same amount of time available to complete them (45 minutes). The analysis focused on the number of correctly solved tasks and the total time taken to complete the tasks for each group.

Table 1. Results of Correct Answers and Completion Time by Group

Group	Method	Members (N_o)	Correct Answ.	Time (min)
G1	Traditional	4	6	42
G2	Traditional	5	5	44
G3	Traditional	4	7	41
G4	T2SQL	4	9	34
G5	T2SQL	4	10	32
G6	T2SQL	4	9	33

Table 2. Average Results by Method

Method	Average Number of Correct Answers	Average Completion Time (min)
Traditional	6	42.3
T2SQL	9.3	33

4.3.1 Accuracy analysis

Observing the results, we can see that the number of correct answers for the groups that solved the tasks in the traditional way was: G1–6, G2–5, and G3–7 correct answers. On the other hand, the groups that had the support of the T2SQL system achieved: G4–9, G5–10, and G6–9 correct answers (Fig. 3).

The average number of correct answers for the groups working in the traditional way was 6, while for the groups with T2SQL system support it was 9.3 (Fig. 4). This indicates a significant advantage in the accuracy of answers among the T2SQL groups. Expressed in percentages, these groups had a 55% higher average accuracy of answers.

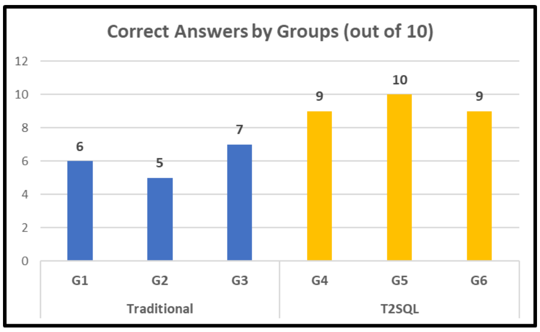

Figure 3. Number of correct answers by groups

[1] ChatGPT is a general-purpose generative model that has shown promising results in T2SQL tasks. Research indicates that LLM models can achieve competitive results compared to specialized T2SQL systems (Pourreza & Rafiei, 2023; Chen et al., 2021), though additional research is needed for definitive comparison across different domains and task complexity levels.

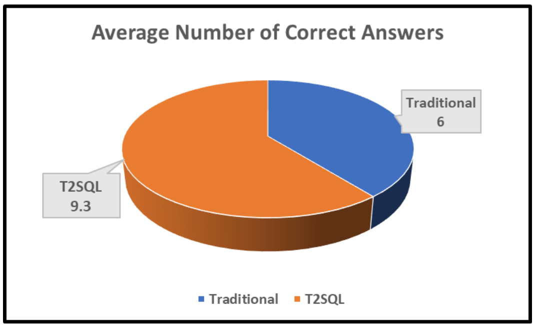

Figure 4. Number of correct answers by groups

4.3.2 Analysis of completion time

Regarding the time needed to complete the tasks, the groups working in the traditional way completed the assignments in G1–42, G2–44, and G3–41 minutes. The T2SQL groups completed the assignments in G4–34, G5–32, and G6–33 minutes (Fig. 5). The average completion time for the traditional groups was 42.3 minutes, while for the T2SQL groups it was 33 minutes (Fig. 6). From this, we can see that the average task completion time for the T2SQL groups was almost 10 minutes shorter, which supports the efficiency of artificial intelligence-based tools (T2SQL) in solving SQL tasks.

The presented analysis confirms the initial research hypotheses (H1 and H2) that T2SQL systems (in this case, ChatGPT) can contribute to increased accuracy and reduced time required for solving SQL tasks by students.

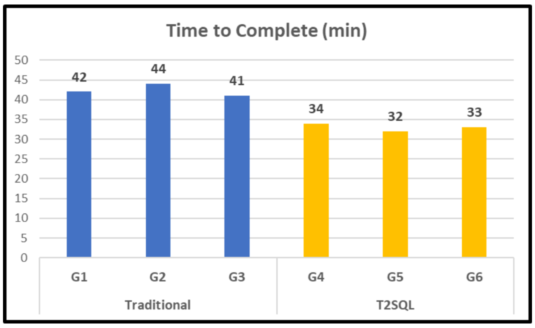

Figure 5. Time Taken by Groups to Complete Tasks

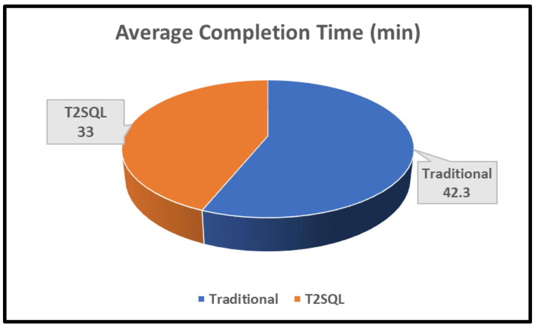

Figure 6. Average Completion Time

The use of these tools enabled students to focus on understanding the tasks during their work, while the T2SQL system assisted them in the precise formulation of SQL queries.

4.3.3 Analysis of user satisfaction survey results

After completing the tasks, all students from the groups that used the T2SQL system—ChatGPT (G4, G5, and G6)—completed an anonymous questionnaire in which they expressed their satisfaction with this method of work. The questionnaire contained five statements rated on a five-point Likert scale, where 1 indicated complete disagreement and 5 indicated complete agreement with the statement.

The statements in the questionnaire were as follows:

1. Using T2SQL tools made it easier for me to solve the tasks (*average score 4.7*).
2. I felt more confident writing SQL queries with the help of the tool (*average score 4.5*).
3. Using the tool helped me better understand the structure of queries (*average score 4.3*).
4. I believe that this kind of tool should be used more often in teaching (*average score 4.8*).
5. I am satisfied with the overall experience of using the tool (*average score 4.6*).

The analysis of the questionnaire indicates a high level of student satisfaction with the use of the T2SQL system in the teaching process. The highest average rating-4.8 (Fig. 7)- was given to the statement suggesting that such tools should be regularly integrated into instruction. This reflects a positive student attitude toward the inclusion of new technological advancements as support in the learning process. Additionally, most students emphasized that the T2SQL tool made completing tasks easier and that using the tool increased their sense of security and self-confidence during the work process. Although slightly lower than the others, the average rating of 4.3 still indicates a very high level of agreement, suggesting that, besides providing support in query writing, these tools also have the potential to enhance students' knowledge.

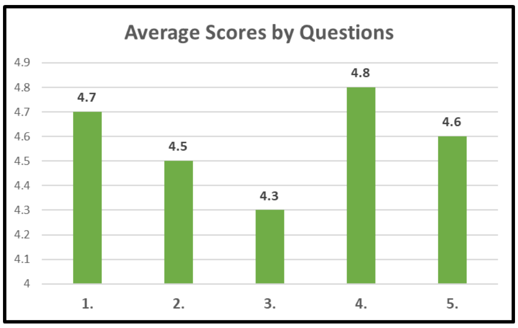

Figure 7. Average Scores by Statements

5 Discussion

The results of the conducted research unequivocally indicate the advantages brought by the use of T2SQL tools in solving SQL queries within the *Database Systems* course. Students who utilized this approach (ChatGPT as a representative of the T2SQL model) achieved higher accuracy and significantly shorter task completion times compared to students from groups that solved tasks using traditional learning methods.

The average number of correct answers for the groups that used ChatGPT as a T2SQL tool was 9.3 out of a possible 10, whereas the groups that employed the traditional approach averaged 6 correct answers. In practice, this means that the groups supported by T2SQL tools achieved approximately 55% greater accuracy, suggesting that these systems can play a crucial role in the learning process, particularly in helping students overcome challenges associated with mastering SQL queries. This benefit is especially pronounced during the initial stages of learning.

Furthermore, a positive impact was observed concerning the time required to complete the tasks. Groups using T2SQL systems completed the assignments in an average of 33 minutes, while the traditional groups needed approximately 42.3 minutes. This time difference represents a savings of nearly 22%. Importantly, the increased speed did not compromise the accuracy of the work, implying more efficient organization and use of time for learning activities.

The analysis of the survey results revealed a high level of student satisfaction regarding the use of T2SQL systems in the educational process. Students emphasized that the tools helped them better understand the tasks, reduced their uncertainty when writing SQL queries, and increased their confidence. These factors contribute to deeper and higher-quality learning, understanding, and application of the acquired knowledge.

However, it is important to recognize a potential risk in educational practice: these systems may lead to an excessive reliance on automated tools. Therefore, it is recommended that the use of such tools be carefully pedagogically planned and closely monitored and controlled. The greatest value of these tools lies in their role as assistants in the learning process, rather than as complete substitutes for exercises and the development of skills in writing SQL queries.

5.1 Study Limitations and Guidelines for Future Research

In this specific research, it is important to highlight the methodological limitations it carries. Firstly, the study was conducted on a relatively small sample of 25 students from a single higher education institution, which limits the possibilities for statistical analysis and generalization of results. This sample size restricts the statistical power of the research, although tests have shown statistical significance in the differences between groups. For more definitive results, it would be necessary to conduct research on a more diverse sample across multiple higher education institutions. Nevertheless, despite this limitation, the obtained results provide valuable insight into the potential benefits of these technologies and establish a solid foundation for future research.

The second, more fundamental limitation relates to the depth of assessed learning. While the study did establish improved accuracy and efficiency in solving SQL tasks using T2SQL systems, it did not effectively evaluate the long-term benefits of implementing these tools. To overcome this limitation, a longer time period would be necessary to monitor these effects. Additionally, it is recommended that future research employ a longitudinal approach with pre- and post-tests, tasks requiring explanation of query logic, and analysis of independent problem-solving without AI support. This approach would enable differentiation between superficial assistance in task completion and genuine understanding of SQL concepts.

Also, a notable limitation of this study concerns the selection of ChatGPT as a representative T2SQL system. Although there are indications that generic LLM models can achieve good results in T2SQL tasks, direct comparison with specialized systems such as Spider or the latest academic models was not conducted within the scope of this study. Future research should include systematic comparison of different T2SQL approaches in educational contexts.

6 Conclusion

Based on the findings presented, it can be concluded that the research objective has been achieved. The initial hypotheses were confirmed with empirical data collected through the study, validating the assumptions made prior to the research process.

Recommendations for future research include expanding the sample of participants (students) across multiple educational institutions and investigating the long-term effects of using such tools. Additionally, it would be valuable to examine the impact of these systems on the development of students' algorithmic and logical thinking skills. Moreover, efforts should be directed toward developing instructional materials integrated with these systems to support their deeper inclusion in the educational process.

The study has methodological limitations including a small and homogeneous sample, as well as a focus solely on short-term efficiency without assessing the depth of SQL concept understanding. Future research should employ a longitudinal design that would evaluate fundamental comprehension and long-term knowledge retention among students using T2SQL systems. Despite these limitations, the results provide valuable insight into the potential of AI technologies in education and serve as a foundation for more comprehensive research in this field.

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