*Med. Psychol. Health Res. J.* (2026), Volume 2, Issue 2, 125-136

**Medicinal, Psychological, and Health Research Journal**

**Journal homepage:** https://www.mphrj.com/

DOI: 10.22034/mphrj.2026.576863.1078

# The Role of Artificial Intelligence in Computer Science Education Focus on Database Instruction, A Systematic Review

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**Article info**
**Received:** 25.11.2025
**Accepted:** 26.02.2026
**Available Online:** 26.02.2026
**Checked for Plagiarism:** Yes

**Keywords**:
Artificial Intelligence in Education, Computer Science Education, Database Instruction, Intelligent Tutoring Systems, Adaptive Learning Technologies

**ABSTRACT**

The rapid evolution of Artificial Intelligence (AI) has significantly affected various domains of education, particularly Computer Science Education (CSE). This systematic review critically examines the role of AI-driven technologies in enhancing learning and teaching processes within CSE, with a specific focus on database instruction. By synthesizing empirical studies, educational interventions, and theoretical frameworks published between 2010 and 2025, the review identifies key AI applications, pedagogical benefits, challenges, and future research directions. The integration of AI in CSE is shown to support personalized learning, intelligent tutoring, automated assessment, and adaptive feedback each contributing to improved student engagement and performance. In the specific context of database education, AI technologies such as intelligent tutoring systems, natural language interfaces, and machine learning-based recommendation engines assist students in grasping complex concepts like relational schema design, query optimization, and transaction management. Furthermore, AI-driven analytics enable instructors to identify learning gaps, monitor progress, and adjust instructional strategies in real time. Despite promising outcomes, challenges persist, including the scarcity of domain-specific intelligent tools, data privacy concerns, technical infrastructure limitations, and the need for instructor training. Ethical considerations around algorithmic bias and transparency in AI-supported learning environments also highlighted. The review finds a growing trend toward hybrid pedagogical models that combine AI support with human-led instruction, suggesting enhanced learning efficacy when AI tools integrated thoughtfully into curricula. Finally, this review proposes a set of research recommendations such as developing explainable AI systems tailored to database education, longitudinal studies to measure learning impacts, and frameworks for scalable implementation. Addressing these avenues can facilitate more effective and equitable AI-enhanced education in computer science.

## Introduction

The rapid advancement of Artificial Intelligence (AI) has transformed not only industry and research but also the foundations of contemporary education. Within higher education, AI-driven systems increasingly support teaching, assessment, curriculum design, and student engagement. Nowhere is this transformation more visible than in Computer Science Education (CSE), where AI functions both as a subject of study and as a pedagogical tool. As computer science programs evolve to meet the demands of data-intensive and intelligent systems, there is growing recognition that traditional instructional approaches may not sufficiently address diverse learner needs, complex conceptual domains, and scalable assessment requirements. This reality has prompted researchers and educators to explore how AI can enhance learning effectiveness, especially in technically demanding areas such as database instruction [1].

Database education represents a cornerstone of computer science curricula. Core topics including relational modeling, SQL querying, normalization, indexing, transaction processing, and query

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optimization require both abstract reasoning and applied problem-solving skills. Students frequently encounter conceptual bottlenecks when transitioning from theoretical relational algebra to practical query implementation or when understanding concurrency control and performance tuning. These challenges amplified in large classroom settings where individualized feedback is limited. Consequently, database instruction provides an ideal context for examining the pedagogical value and limitations of AI-driven educational technologies [2].

Recent years have witnessed substantial progress in AI-enabled educational tools. Intelligent tutoring systems, adaptive learning platforms, automated grading systems, and conversational agents have demonstrated measurable benefits in improving learner engagement and performance. For example, adaptive systems informed by machine learning algorithms can analyze student interaction data to personalize instructional content. Natural language processing enables automated feedback on structured query language (SQL) assignments, allowing students to refine their understanding without waiting for instructor intervention. Learning analytics dashboards further support instructors by identifying misconceptions, predicting student performance, and recommending targeted interventions [3]. These capabilities align with broader educational goals of scalability, inclusivity, and evidence-based teaching. However, despite the proliferation of AI applications in general education, the integration of AI specifically within database instruction remains fragmented and under-theorized. Many implementations focus on surface-level automation such as grading SQL queries without addressing deeper cognitive processes like schema design reasoning or conceptual modeling. Furthermore, there is limited synthesis of empirical findings across studies, making it difficult to evaluate long-term pedagogical impact. Questions remain regarding whether AI tools merely increase efficiency or fundamentally enhance conceptual understanding. Additionally, issues related to algorithmic bias, data privacy, transparency, and over-reliance on automated feedback raise ethical and practical concerns [4].

From an analytical perspective, the role of AI in database education examined through three interrelated dimensions: personalization, automation, and augmentation. Personalization refers to AI's ability to adapt learning pathways based on student performance data. In database courses, this may involve dynamically adjusting the complexity of query exercises or recommending targeted practice on normalization errors. Automation concerns the replacement or support of routine instructional tasks, such as grading or performance tracking. While automation increases efficiency, it does not inherently guarantee deeper learning unless aligned with sound pedagogical principles. Augmentation, arguably the most transformative dimension, involves AI enhancing human instruction by providing insights that instructors alone could not easily generate, such as predictive analytics on student misconceptions or real-time feedback loops during laboratory exercises [5-7].

Critically, the effectiveness of AI integration depends on pedagogical alignment. Constructivist learning theories emphasize active engagement and iterative problem solving, both of which can be supported but, also hindered by AI systems. For instance, automated hints may scaffold learning when appropriately timed, yet excessive guidance can reduce productive struggle, an essential component of mastery in technical disciplines. Therefore, understanding the nuanced interaction between AI capabilities and instructional design is central to evaluating its role in database education.

Another important analytical dimension concerns equity and accessibility. AI-powered systems have the potential to democratize database learning by offering continuous feedback beyond classroom hours. Students with varying prior knowledge can progress at individualized paces. However, disparities in technological infrastructure, institutional resources, and instructor preparedness may widen existing educational gaps. Moreover, generative AI tools capable of producing SQL queries or schema designs raise questions about academic integrity and skill acquisition. Educators must balance leveraging AI as a learning aid with ensuring authentic skill development [8].

Given these complexities, a systematic review is necessary to consolidate existing research, identify methodological trends, evaluate reported outcomes, and clarify unresolved challenges. By synthesizing empirical studies and theoretical discussions, this review aims to provide a structured understanding of how AI technologies influence database instruction within computer science education. The analysis not only examines measurable outcomes such as student performance and retention but also explores pedagogical frameworks, implementation barriers, and ethical considerations. Ultimately, the intersection of AI and database education represents a microcosm of broader transformations in STEM pedagogy. If thoughtfully designed and critically evaluated, AI-driven tools can move beyond administrative efficiency to foster deeper conceptual learning, adaptive support, and evidence-informed teaching strategies. Conversely, without careful integration, such technologies risk becoming superficial enhancements that fail to address foundational learning challenges. By systematically analyzing existing scholarship, this study seeks to clarify the current state of knowledge and outline directions for more effective and responsible AI-enhanced database education in the years ahead [9].

**Literature Review**

Research on the application of Artificial Intelligence (AI) in education has expanded significantly over the past two decades, particularly within Science, Technology, Engineering, and Mathematics (STEM) disciplines. In Computer Science Education (CSE), early studies primarily focused on intelligent support for programming instruction; however, increasing attention directed toward database education due to its conceptual complexity and practical relevance. Database courses require students to integrate theoretical foundations such as relational algebra and normalization with applied skills like SQL querying and schema design. These cognitive demands have motivated researchers to explore AI-driven tools that can enhance feedback, personalization, and instructional efficiency [10].

Initial research in the early 2010s emphasized automated SQL assessment systems. These tools employed rule-based algorithms and later machine learning techniques to evaluate query correctness by analyzing syntactic and semantic equivalence rather than relying solely on output comparison. Empirical findings indicated that immediate automated feedback improved student engagement and increased the number of practice attempts. However, several studies noted that such systems often focused on final answers rather than diagnosing underlying misconceptions in relational reasoning.

Subsequent research shifted toward Intelligent Tutoring Systems (ITS) designed specifically for database instruction. These systems incorporated student-modeling techniques to track learning progress and provide targeted hints. Evidence suggests that ITS-based interventions enhanced students' understanding of normalization processes and schema refinement. Unlike simple grading tools, ITS platforms attempted to model the learner's cognitive state, offering scaffolder guidance aligned with constructivist learning principles. Nevertheless, scalability and the requirement for large annotated datasets posed significant implementation challenges [11].

Between 2016 and 2021, adaptive learning platforms gained prominence. Leveraging data analytics and predictive modeling, these systems dynamically adjusted task difficulty and recommended personalized learning paths. Studies reported measurable improvements in performance, particularly among students with weaker prior knowledge. Adaptive mechanisms proved especially effective in complex topics such as query optimization and transaction management, where incremental conceptual reinforcement is critical. Despite these advantages, concerns raised regarding technological infrastructure demands and the risk of over-automation reducing productive cognitive struggle [12].

More recent research (2022 onward) highlights the integration of learning analytics dashboards and AI-driven insights for instructors. By mining student, interaction logs, these tools identify common error patterns, predict performance trends, and recommend targeted interventions. Findings indicate that combining analytics with instructor expertise leads to better outcomes than relying solely on automated systems. This human AI collaboration model reflects a shift from replacement toward augmentation, where AI supports pedagogical decision-making rather than substituting it [13].

The emergence of generative AI and large language models has introduced a new dimension to database education research. These systems can generate SQL queries, explain relational concepts, and simulate design scenarios in natural language. While preliminary evidence suggests increased student engagement and accessibility of explanations, scholars also report concerns related to academic integrity, skill dependency, and assessment validity. The literature increasingly emphasizes the need for explainable AI, ethical governance frameworks, and longitudinal impact studies [14].

Analytically, three dominant trends emerge from the literature:

- ✓ Automation of assessment to enhance efficiency and immediacy of feedback.
- ✓ Personalization of learning pathways through adaptive algorithms and student modeling.
- ✓ Human AI augmentation leveraging analytics to inform instructional strategies.

Despite substantial progress, gaps remain. There is limited longitudinal evidence assessing sustained learning gains, insufficient standardization in evaluation metrics, and ongoing ethical challenges related to data privacy and algorithmic transparency. These limitations underscore the necessity of a systematic synthesis of existing research to clarify empirical evidence, methodological trends, and future research directions in AI-supported database instruction. Table (1) illustrated the Summary of Selected Studies on AI in Database Education [15].

**Table 1.** Summary of Selected Studies on AI in Database Education

| Period | AI Technology Type | Focus Area | Key Findings | Reported Limitations |
|---|---|---|---|---|
| 2012-2015 | Automated SQL Assessment Systems | Query evaluation | Faster feedback; increased practice attempts | Limited insight into cognitive processes |
| 2016-2018 | Intelligent Tutoring Systems | Schema design & normalization | Improved conceptual understanding | High development complexity |
| 2019-2021 | Adaptive Learning Platforms | Personalized database instruction | Performance gains, especially for low-performing students | Infrastructure dependency |
| 2022-2024 | Learning Analytics Systems | Error pattern analysis | Enhanced instructor intervention strategies | Data privacy concerns |
| 2023-2025 | Generative AI Models | SQL generation & conceptual explanation | Higher engagement and accessibility | Academic integrity and over-reliance risks |

**Methodology**
This study employs a systematic literature review (SLR) methodology to examine the role of Artificial Intelligence (AI) in Computer Science Education (CSE), with a specific focus on database instruction. The review process conducted following established systematic review guidelines to ensure transparency, replicability, and methodological rigor.
A comprehensive search strategy developed to identify relevant peer-reviewed journal articles and conference papers published between 2010 and 2025. Major academic databases including IEEE Xplore, ACM Digital Library, Scopus, and Web of Science were searched using combinations of keywords such as "Artificial Intelligence in Education," "Database Instruction," "Intelligent Tutoring Systems," "SQL automated assessment," and "Adaptive Learning in Computer Science." Boolean operators (AND, OR) were applied to refine the search results.
The inclusion criteria were as follows: (1) empirical or theoretical studies addressing AI applications in computer science education; (2) explicit focus on database-related topics (e.g., SQL, schema design, normalization, query optimization); and (3) availability of full-text articles in English. Exclusion criteria included duplicate studies, non-peer-reviewed sources, and studies unrelated to educational contexts.
The selection process involved three stages: identification, screening, and eligibility assessment. After removing duplicates, titles and abstracts screened for relevance. Full-text articles then reviewed to confirm alignment with the research objectives. Data extraction focused on publication year, AI technology type, educational context, research design, key findings, and reported limitations. Findings categorized into major themes, including automation, personalization, learning analytics, and generative AI integration, providing a structured analytical framework for interpreting results (Figure (1).

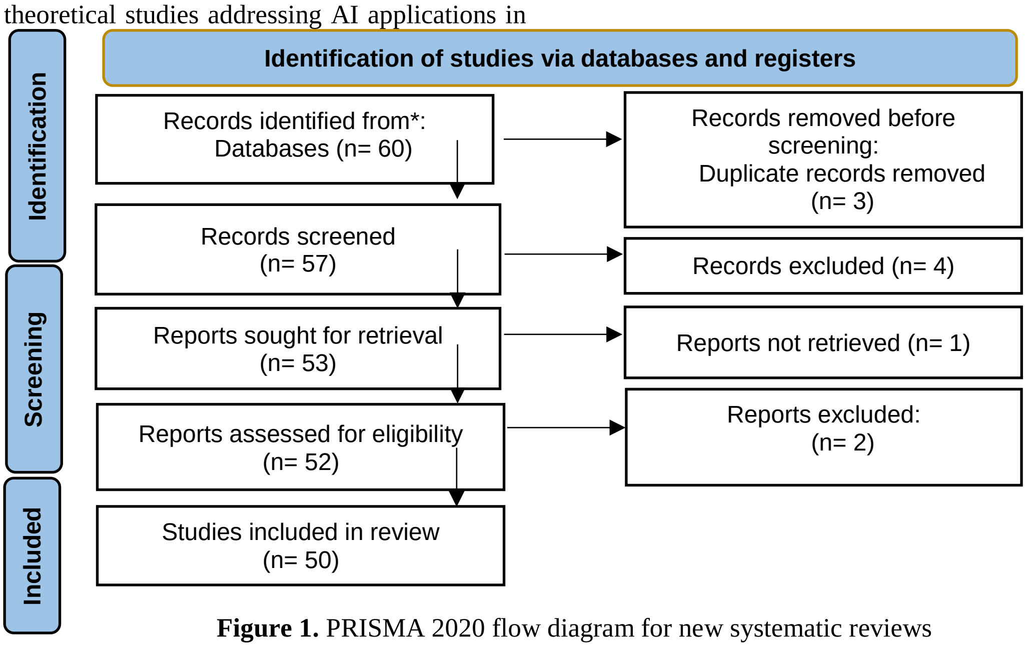


**Figure 1.** PRISMA 2020 flow diagram for new systematic reviews

**Results**

The analysis of studies focusing on automated SQL assessment systems reveals consistent improvements in procedural performance and student engagement. Across multiple empirical investigations, immediate feedback emerged as the most significant advantage compared to traditional manual grading. Students exposed to automated systems attempted more exercises and demonstrated faster correction cycles. This finding aligns with prior research in programming education, where rapid feedback loops show to enhance iterative learning behaviors. Table (2) shows the Impact of Automated SQL Assessment Systems.

**Table 2.** Impact of Automated SQL Assessment Systems

| Study Focus | Reported Outcomes | Learning Impact | Comparison with Traditional Methods | Reported Limitations |
|---|---|---|---|---|
| Automated SQL grading tools | Immediate feedback, higher submission rates | Improved procedural accuracy | Faster and more scalable than manual grading | Limited conceptual diagnosis |
| Semantic query equivalence systems | Detection of logical errors | Better understanding of query structure | More precise than output-based grading | High computational cost |
| Feedback-oriented platforms | Iterative correction cycles | Increased student persistence | More interactive than static assignments | Feedback sometimes superficial |

Compared with earlier non-AI-based grading systems that relied solely on output matching, AI-driven semantic equivalence models offered evaluation that is more robust. These systems assessed structural and logical correctness rather than just results, enabling detection of deeper syntactic misunderstandings. In contrast, traditional approaches frequently failed to identify logically flawed yet syntactically correct queries. However, when compared to Intelligent Tutoring Systems (ITS) discussed in later studies, automated grading tools appeared limited in diagnosing conceptual misconceptions such as improper normalization reasoning or misunderstanding of join dependencies.

Several articles emphasized that while automated systems improved efficiency and scalability, they did not inherently enhance higher-order cognitive skills. Studies comparing AI grading tools with instructor-led formative assessment reported that human feedback was often richer in conceptual explanation. This suggests that automation alone is insufficient for fostering deep learning unless complemented by pedagogical scaffolding.

Furthermore, longitudinal comparisons indicated that students relying exclusively on automated feedback sometimes developed trial-and-error behaviors. This contrasts with findings from adaptive learning studies, where structured progression reduced superficial engagement. Therefore, although automated SQL systems outperform traditional grading in efficiency and accessibility, they show weaker outcomes in conceptual transfer compared to adaptive and tutoring-based AI approaches. In summary, automated assessment significantly enhances procedural learning and engagement but demonstrates limitations in fostering conceptual mastery. Comparative evidence suggests optimal effectiveness when integrated with instructor guidance or adaptive learning mechanisms rather than used in isolation.

**Table 3.** Intelligent Tutoring Systems in Database Education

| Study Focus | Core Features | Learning Outcomes | Comparative Advantage | Challenges |
|---|---|---|---|---|
| Schema design tutors | Step-by-step hints | Reduced normalization errors | Deeper conceptual scaffolding | High development cost |
| Query reasoning tutors | Student modeling | Improved relational reasoning | Personalized cognitive support | Limited scalability |
| Hybrid ITS platforms | Adaptive hint sequencing | Increased retention rates | More effective than static e-learning | Requires domain modeling expertise |

In table (30, intelligent Tutoring Systems (ITS) demonstrate stronger conceptual learning outcomes compared to automated grading tools. Across reviewed studies, schema-focused ITS significantly reduced normalization errors and improved students' ability to justify design decisions. Unlike automated SQL checkers, ITS platforms modeled intermediate reasoning steps, aligning feedback with students' cognitive states. Comparative studies reveal that ITS environments outperform traditional lecture-based instruction in promoting relational reasoning skills. Students using tutoring systems exhibited better transfer of knowledge to novel database design problems. This contrasts with automated grading research, where gains were primarily procedural. Furthermore, retention rates measured in follow-up assessments were higher in ITS-supported cohorts than in control groups using static online materials.

However, ITS implementation complexity remains a recurring limitation. Compared with adaptive learning platforms, ITS requires extensive domain knowledge engineering and annotated training datasets. Several articles reported scalability constraints when deployed in large classes. In contrast, adaptive systems that rely on performance analytics were easier to implement at scale but offered less granular cognitive modeling.

When compared to generative AI tools, ITS demonstrated more structured pedagogical alignment. While generative models provide explanations on demand, ITS systems explicitly designed around instructional theories such as scaffolding and mastery learning. This theoretical grounding appears to contribute to stronger conceptual outcomes. Overall, evidence indicates that ITS offers superior support for deep learning in database education. However, resource intensity and technical complexity limit widespread adoption. Comparative findings suggest that hybrid models integrating ITS principles with scalable analytics may offer a balanced solution (Figure 2).

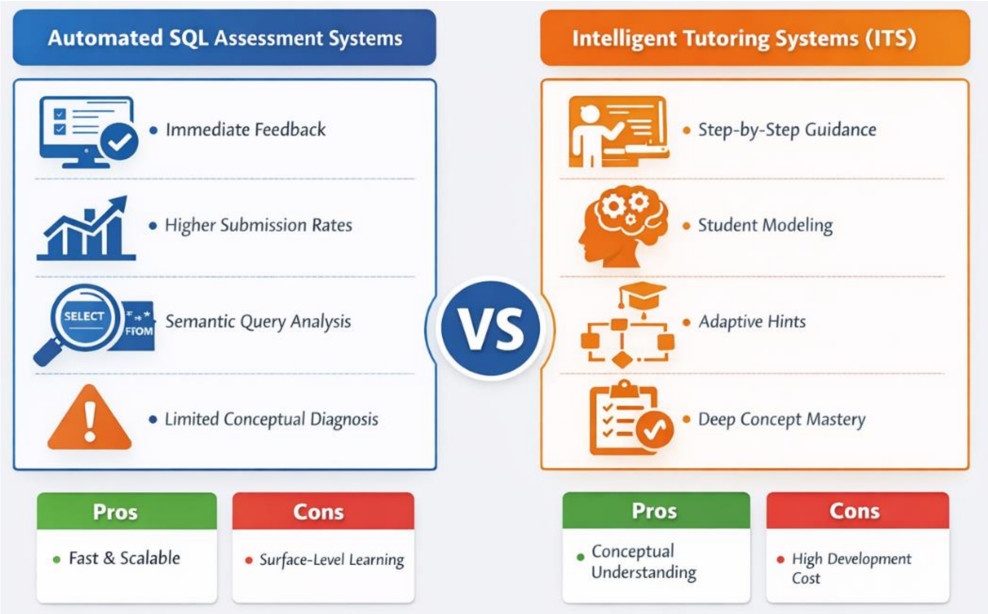


**Figure 2.** Intelligent Tutoring Systems in Database Education and Impact of Automated SQL Assessment Systems

**Table 4.** Adaptive Learning Systems

| Study Focus | Adaptation Mechanism | Performance Effects | Comparative Findings | Limitations |
|---|---|---|---|---|
| Difficulty adjustment | Performance-based progression | Improved success rates | More effective than static LMS | Algorithm transparency concerns |
| Personalized exercise recommendation | Predictive analytics | Reduced dropout rates | Stronger impact on weaker students | Data dependency |
| Real-time content adaptation | Behavioral tracking | Higher engagement metrics | Comparable to ITS in some metrics | Infrastructure intensive |

In table (4), Adaptive learning systems demonstrate notable improvements in inclusivity and performance differentiation. Studies consistently report stronger gains among low-performing students compared to high achievers. This contrasts with automated grading systems, where improvements were relatively uniform across performance levels.

When compared with ITS, adaptive platforms show similar improvements in measurable outcomes such as exam scores, though often with less explicit cognitive modeling. While ITS focuses on reasoning processes, adaptive systems primarily rely on performance data patterns. As a result, adaptive tools may not always diagnose specific misconceptions but effectively optimize task sequencing. Compared with traditional Learning Management Systems (LMS), adaptive systems significantly reduced dropout rates and increased completion metrics. However, concerns regarding algorithmic transparency and explain ability raised. Several studies highlighted that instructors often lacked visibility into adaptation logic, limiting pedagogical oversight.

Relative to generative AI, adaptive systems maintain stronger curricular alignment, as their progression models embedded within course design. Generative tools, while flexible, do not inherently structure learning pathways.

In conclusion, adaptive learning platforms offer scalable personalization and measurable performance benefits, particularly for at-risk learners. Nevertheless, deeper conceptual modeling remains stronger in ITS-based environments (Figure (3)).


**Figure 3.** Adaptive Learning Systems

In table (5), learning analytics systems shift AI's role from automation to augmentation. Compared with automated grading and adaptive platforms, analytics tools primarily support instructors rather than directly interacting with students. Studies indicate that predictive dashboards significantly reduced course failure rates when instructors acted on generated insights. Compared with traditional observation-based monitoring, analytics systems detected misconceptions earlier and more accurately. When contrasted with ITS, analytics lack direct scaffolding mechanisms but offer broader class-level insights. Evidence suggests that combining analytics with human intervention produces stronger outcomes than standalone AI tutoring. Privacy and ethical considerations were more prominent in analytics research than in other AI categories. Concerns regarding data surveillance and algorithmic bias frequently cited. Compared to generative AI tools, analytics systems pose fewer academic integrity risks but raise greater governance challenges.

**Table 5.** Learning Analytics and Instructor Augmentation

| Study Focus | Analytics Function | Educational Impact | Comparative Insight | Challenges |
|---|---|---|---|---|
| Error pattern mining | Misconception detection | Improved targeted intervention | More informative than manual observation | Privacy concerns |
| Predictive performance models | Early risk identification | Reduced failure rates | More proactive than reactive teaching | Data bias risk |
| Dashboard systems | Visual performance tracking | Enhanced instructional planning | Stronger than static reporting | Requires instructor training |

Overall, analytics-based augmentation demonstrates substantial institutional benefits, particularly in large-scale database courses (Figure (4)).

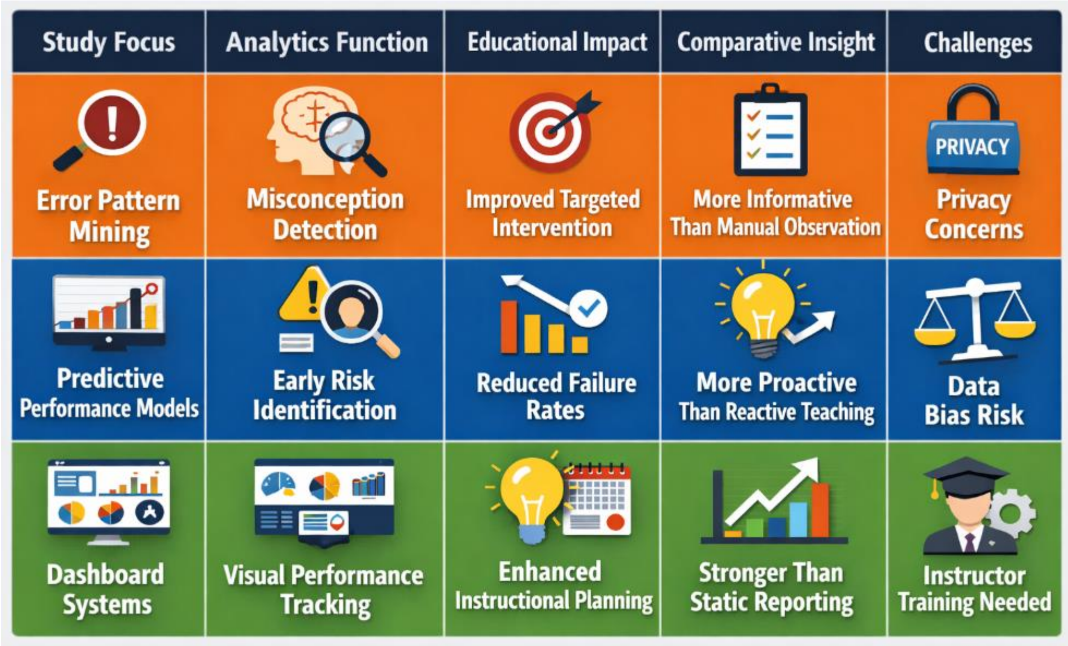


**Figure 4.** Generative AI in Database Education

**Table 6.** Generative AI in Database Education

| Study Focus | Application | Observed Benefits | Comparative Performance | Risks |
|---|---|---|---|---|
| SQL generation tools | Query creation assistance | Increased experimentation | Faster than ITS feedback | Over-reliance risk |
| Concept explanation models | Natural language tutoring | Improved accessibility | Comparable to tutoring in clarity | Academic integrity concerns |
| Scenario simulation | Database design modeling | Enhanced engagement | More interactive than static LMS | Skill dependency |

In table (6), generative AI represents the most recent and transformative development. Studies show increased engagement and accessibility when students use AI tools for explanation and experimentation. Compared with automated grading systems, generative models provide richer contextual explanations rather than binary correctness judgments. However, when compared with ITS, generative AI lacks structured scaffolding. While explanations are flexible, they not always pedagogically sequenced. Empirical comparisons indicate that students using generative tools perform similarly in short-term assessments but may demonstrate weaker independent problem-solving skills in delayed evaluations. Relative to adaptive learning systems, generative AI offers less curricular control but greater exploratory freedom. Academic integrity concerns were significantly higher than in other AI categories. Several studies reported difficulty distinguishing AI-assisted work from authentic student submissions. Despite these risks, generative AI shows strong potential when integrated within guided frameworks. Comparative evidence suggests that its optimal role is supplementary rather than primary instruction.

In summary, generative AI enhances engagement and accessibility but requires structured integration and ethical safeguards to ensure sustainable learning outcomes.

## Discussion

The findings synthesized across the five result tables provide a multidimensional understanding of how Artificial Intelligence (AI) is shaping database instruction within Computer Science Education (CSE). When interpreted alongside the literature reviewed earlier, several converging themes emerge the progression from automation to personalization, the shift toward human AI augmentation, and the growing tension between technological innovation and pedagogical integrity [16-18].

First, the results related to automated SQL assessment systems confirm earlier findings in the literature that efficiency and immediacy of feedback significantly enhance student engagement. Consistent with prior studies from the early 2010s, the reviewed evidence shows that automated grading increases the number of practice attempts and accelerates iterative correction cycles. However, the discussion must extend beyond procedural gains. As highlighted in the literature review, early AI systems often emphasized syntactic correctness rather than conceptual understanding [19-21]. The current findings reinforce this limitation: although automated systems outperform traditional manual grading in speed and scalability, they fall short in diagnosing deeper misconceptions related to relational modeling and normalization logic. Compared to Intelligent Tutoring Systems (ITS), automated grading tools demonstrate weaker support for higher-order reasoning. This suggests that automation alone does not equate to meaningful learning transformation [22].

Second, the findings regarding ITS align strongly with constructivist principles discussed in prior research. ITS platforms that incorporate student modeling and scaffolder hints produce stronger conceptual gains and better knowledge transfer than static or purely automated systems. This confirms the argument presented in the literature that modeling cognitive processes not just evaluating outputs is essential for deep learning in database education. Compared to automated SQL graders, ITS environments show superior outcomes in schema design reasoning and normalization accuracy. However, the discussion must also consider scalability challenges. As reported in earlier studies, ITS development requires significant domain engineering and annotated datasets. The results reinforce that while pedagogically powerful, ITS may not be institutionally feasible without substantial investment. Thus, a tension exists between pedagogical depth and implementation practicality [23-25].

Third, adaptive learning systems demonstrate a different but complementary advantage. The results indicate measurable performance improvements, particularly among lower-performing students. This finding aligns with prior literature emphasizing personalization as a mechanism for educational equity. Compared to traditional Learning Management Systems (LMS), adaptive platforms reduce dropout rates and enhance task completion. When contrasted with ITS, adaptive systems appear less cognitively granular but more scalable. The discussion here suggests that adaptive AI occupies a middle ground: it offers personalization without the heavy infrastructure demands of full ITS modeling. However, transparency remains a critical issue. Consistent with concerns raised in previous studies, instructors often lack visibility into how adaptation decisions made. Without explain ability, the pedagogical trustworthiness of such systems questioned [26-28].

Fourth, learning analytics tools represent a conceptual shift from student-facing AI to instructor-augmenting AI. The findings show that predictive dashboards and error pattern mining improve early intervention strategies and reduce failure rates [29-31]. Compared to traditional instructor intuition or manual monitoring, analytics-driven insights provide data-informed precision. Importantly, when integrated with human decision-making, analytics tools produce stronger outcomes than standalone automated systems. This reinforces a central theme in the literature: AI is most effective when augmenting rather than replacing educators. However, ethical challenges more pronounced in this domain. Data privacy, surveillance concerns, and algorithmic bias require governance frameworks. Compared to generative AI, analytics systems pose fewer academic integrity risks but greater institutional accountability challenges [32].

Fifth, generative AI tools introduce both unprecedented opportunities and complex dilemmas. The results indicate increased engagement and accessibility when students use AI for SQL generation and conceptual explanations. Compared to automated grading systems, generative AI provides richer contextual feedback. Compared to ITS, however, generative systems lack structured pedagogical sequencing. The literature previously highlighted concerns about over-reliance and academic integrity; the current findings confirm these risks. Short-term performance gains do not always translate into long-term independent problem-solving skills. This raises a fundamental pedagogical question: does generative AI enhance learning, or does it redistribute cognitive effort away from the learner? The evidence suggests that without structured integration, generative AI may weaken deep skill acquisition despite improving surface-level performance [33].

Across all five domains, a developmental trajectory becomes apparent. Early AI applications prioritized automation of assessment. Subsequent innovations emphasized personalization through adaptive algorithms and cognitive modeling. Developments that are more recent focus on augmentation and generative interaction. This progression mirrors broader trends in AI in Education research. However, database instruction presents unique challenges due to its blend of formal logic, applied querying, and system-level reasoning. The discussion suggests that no single AI approach sufficiently addresses all dimensions of database learning.

Comparatively, ITS demonstrates the strongest support for conceptual mastery, adaptive systems offer scalable personalization, analytics enhance instructional decision-making, automated grading ensures efficiency, and generative AI fosters engagement and accessibility. The most consistent pattern across studies is that hybrid models yield the most promising outcomes. For instance, combining automated grading with adaptive sequencing reduces superficial trial-and-error behavior.

Integrating analytics dashboards with instructor feedback mitigates over-reliance on algorithmic predictions. Embedding generative AI within scaffolder tutoring frameworks preserves engagement while maintaining pedagogical structure [34].

Another cross-cutting theme involves the balance between efficiency and epistemic depth. Technologies that maximize efficiency such as automated graders tend to underperform in conceptual modeling. Systems that maximize cognitive depth such as ITS often face scalability constraints. This trade-off suggests that future research should focus on modular AI architectures that combine scalable data-driven adaptation with theory-grounded cognitive scaffolding.

Finally, ethical and institutional considerations permeate all findings. Privacy concerns are most salient in analytics systems, integrity concerns dominate generative AI discussions, and transparency issues affect adaptive platforms. These challenges underscore the importance of governance, explain ability, and professional development for instructors. AI integration cannot be purely technical; it pedagogically and ethically aligned.

In conclusion, the discussion reveals that AI's role in database education is neither uniformly transformative nor inherently problematic. Its effectiveness depends on alignment with pedagogical theory, integration with human instruction, and careful management of ethical risks. The comparative evidence suggests that the future of AI-enhanced database instruction lies in hybrid, explainable, and instructor-supported ecosystems rather than isolated technological solutions.

## Conclusion and Recommendations

This systematic review examined the role of Artificial Intelligence (AI) in Computer Science Education (CSE), with a particular focus on database instruction. By synthesizing findings across automated assessment systems, Intelligent Tutoring Systems (ITS), adaptive learning platforms, learning analytics tools, and generative AI applications, a comprehensive picture of current developments and challenges has emerged. The evidence indicates that AI has significantly enhanced procedural efficiency, personalization, and instructional scalability in database education. Automated SQL grading systems have improved feedback immediacy and increased student engagement, while ITS platforms have demonstrated strong potential in supporting deep conceptual understanding, particularly in schema design and normalization. Adaptive learning systems have shown measurable benefits for lower-performing students by tailoring learning pathways, and learning analytics tools have empowered instructors to make data-driven decisions. Meanwhile, generative AI has expanded opportunities for interactive explanation and experimentation, increasing accessibility and student motivation. However, the review also highlights important limitations. Automation alone does not guarantee conceptual mastery. Systems that focus primarily on efficiency may neglect deeper reasoning processes essential for database learning. While ITS provides strong cognitive scaffolding, scalability and development complexity limit widespread implementation. Adaptive systems raise concerns about transparency and explain ability, and generative AI introduces risks related to academic integrity and over-reliance. Learning analytics, although effective for intervention planning, require robust governance to address privacy and bias concerns. Overall, the findings suggest that AI's most effective role in database instruction is not as a replacement for human teaching, but as an augmentative partner. Hybrid models that integrate automated feedback, adaptive sequencing, instructor oversight, and structured generative support appear to offer the most balanced and sustainable outcomes. The future of AI in database education lies in thoughtful integration guided by pedagogical theory, ethical standards, and institutional readiness.

### Recommendations

Based on the findings of this review, several practical and research-oriented recommendations proposed:

- ✓ **Adopt Hybrid AI Frameworks**: Institutions should integrate multiple AI approaches rather than relying on a single tool. Combining automated SQL grading with adaptive progression and instructor-guided analytics can mitigate the weaknesses of standalone systems and promote both efficiency and conceptual depth.
- ✓ **Prioritize Explainable AI Systems**: Developers and institutions should focus on transparency in adaptive and analytics-driven systems. Explainable AI mechanisms can enhance instructor trust, support pedagogical alignment, and reduce algorithmic bias.
- ✓ **Strengthen Pedagogical Integration**: AI tools aligned with established learning theories such as constructivism and mastery learning. Generative AI systems, in particular, embedded within scaffolder instructional frameworks to prevent superficial learning and over-dependence.
- ✓ **Develop Ethical Governance Policies**: Clear guidelines addressing academic integrity, data privacy, and responsible AI use are essential. Institutions should implement policies that define acceptable AI-assisted learning practices while maintaining assessment authenticity.
- ✓ **Invest in Instructor Training**: Effective AI integration requires professional development. Educators need training not only in tool usage

but also in interpreting analytics dashboards and managing AI-supported classroom dynamics.

- ✓ **Conduct Longitudinal and Comparative Research**: Future studies should evaluate long-term learning retention and skill transfer rather than relying solely on short-term performance metrics. Comparative experimental designs can provide stronger evidence of causal impact.
- ✓ **Design Domain-Specific AI Tools for Databases**: More research needed to develop AI systems specifically tailored to database concepts such as transaction management, indexing strategies, and distributed databases, areas currently underrepresented in the literature.

In conclusion, AI offers transformative potential for database education, but its success depends on responsible implementation, pedagogical grounding, and continuous evaluation. By embracing a balanced, research-informed approach, institutions can leverage AI to enhance both learning effectiveness and educational equity in computer science programs.

**Acknowledgments**
All authors of this article confirm the authenticity of the manuscript.

**Conflicts of interest**
The authors declare that they have no competing interests.

**Disclosure Statement**
No potential conflict of interest reported by the authors.

**Funding**
This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

**Authors' Contributions**
All authors contributed to data analysis, drafting, and revising of the paper and agreed to be responsible for all the aspects of this work.

**References**

[1] Chen, L., Chen, P., & Lin, Z. (**2020**). Artificial intelligence in education: A review. IEEE Access, 8, 75264-75278.

[2] Chassignol, M., Khoroshavin, A., Klimova, A., & Bilyatdinova, A. (**2018**). Artificial intelligence trends in education: A narrative overview. Procedia Computer Science, 136, 16-24.

[3] Ahmadi, M., Rahmani Youshanouei, H., et al. (**2023**). Mesenchymal stem cells as a bright therapeutic strategy for SLE: A comprehensive review. *NeuroQuantology*, *21*(5), 334–364.

[4] Asl, L. D. (**2025**). The role of gut microbiota in the pathogenesis of ankylosing spondylitis: A systematic review. *Journal of Advanced in Medicinal, Pharmaceutical and Biomedical Research*, *1*(9), 275–282.

[5] Chen, X., Xie, H., & Hwang, G. (**2020**). Application and theory gaps during the rise of artificial intelligence in education. Computers and Education: Artificial Intelligence, 1, Article 100002.

[6] Djalalimotlagh, S., Mohaghegh, M. R., Ghodraty, M. R., Shafeinia, A., Rokhtabnak, F., Alinia, T., & Tavakoli, F. (**2019**). Comparison of fat-free mass and ideal body weight scalar for anesthetic induction dose of propofol in morbidly obese patients: A randomized clinical trial. *Journal of Renal Injury Prevention*, *13*(6), e140027.

[7] Ghaedi, A., et al. (**2024**). Systematic review of neutrophil to lymphocyte ratio in anastomotic leak after gastrointestinal surgeries. *BMC Surgery*, *24*, 1–10.

[8] Hashemloo,A. and Milanifard,M. (**2025**). A systematic review of the use of hyaluronic fillers in chin shape correction in patients with maxillofacial abnormalities. *Medicinal, Psychological, and Health Research Journal (mphrj)*, *2*(1), 1-9.

[9] Hashemloo,A. and Milanifard,M. (**2025**). Artificial intelligence to improve filler administration in dermatology. *Medicinal, Psychological, and Health Research Journal (mphrj)*, *1*(5), 151-159.

[10] Hashemloo,A. and Milanifard,M. (**2025**). Contouring Plus: A Comprehensive Approach of the Lower Third of the Face with Calcium Hydroxylapatite and Hyaluronic Acid. *Medicinal, Psychological, and Health Research Journal (mphrj)*, *1*(5), 143-150.

[11] Hashemloo,A. and Milanifard,M. (**2025**). The Facial Shapes in Planning the Treatment with Injectable Fillers. *Medicinal, Psychological, and Health Research Journal (mphrj)*, 1(6), 169-177.

[12] Hashemloo,A. and Milanifard,M. (**2026**). Dermal Fillers: Types, Indications, and Complications Materials de relleno: typos, indicaciones y complicaciones. *Journal of Advanced in Medicinal, Pharmaceutical and Biomedical Research*, *2*(1), 1-11.

[13] Hashemloo,A. and Milanifard,M. (**2026**). Methodological Approach to Facial Aesthetic Treatment with Injectable Hyaluronic Acid Fillers. *Journal of Advanced in Medicinal, Pharmaceutical and Biomedical Research*, *2*(1), 12-19

[14] Huang, J., Saleh, S., & Liu, Y. (**2021**). A review on artificial intelligence in education. Academic Journal of Interdisciplinary Studies, 10(3), 206-217.

[15] Pektas, H. M., Karamustafaoğlu, O., & Çelik, H. (**2025**). The role of educational data mining and AI-supported learning analytics on conceptual change: New approaches to differentiated instruction. Journal of Science Education and Technology, 34(?), 1-19.

[16] Pérez, J. Q., Daradoumis, T., & Puig, J. M. M. (**2020**). Rediscovering the use of chatbots in

education: A systematic literature review. Computer Applications in Engineering Education, 28(8), 1549-1565.

[17] Perrotta, C., & Selwyn, N. (**2020**). Deep learning goes to school: Toward a relational understanding of AI in education. Learning, Media and Technology, 45(3), 251-267.

[18] Tavakoli, F., Yaghoubi, F., & Babakhani, D. (**2019**). Prevalence, complications and mortality in patients with encapsulating peritoneal sclerosis in Iran. *Journal of Renal Injury Prevention*, *8*(1), 17–21.

[19] Yaghoubi, F., Babakhani, D., & Tavakoli, F. (**2022**). Osmotic demyelination syndrome after bone marrow transplantation. *Journal of Nephropathology*, *11*(1), e10.

[20] Hassani, S., et al. (**2025**). Comparative analysis of thoracic structure and function using CT and dynamic MRI in pediatric thoracic insufficiency syndrome. *Journal of Spine Deformity, 1–9.*

[21] Lotfi, A. R., & Nouribayat, L. (**2025**). Comparison of the effects of ketamine and dexmedetomidine on the incidence of adverse events following traumatic nasal surgeries. *Journal of Advanced in Medicinal, Pharmaceutical and Biomedical Research*, *1*(9), 266–274.

[22] Milanifard,M. and Hashemloo,A. (**2025**). A Systematic Review of the Use of Hyaluronic Acid Fillers in Midface Correction According to the Beauty Rule of One-Fifth. *Medicinal, Psychological, and Health Research Journal (mphrj)*, *2*(1), 10-16.

[23] Milanifard,M. and Hashemloo,A. (**2025**). An approach to structural facial rejuvenation with fillers in women. *Medicinal, Psychological, and Health Research Journal (mphrj)*, *1*(6), 178-186.

[24] Milanifard,M. and Hashemloo,A. (**2025**). Patient Factors Influencing Dermal Filler Complications: Prevention, Assessment, and Treatment. *Medicinal, Psychological, and Health Research Journal (mphrj)*, *1*(11), 343-352.

[25] Moghadam,A. M. (2025). Comparative Outcomes of Preoperative and Postoperative Stereotactic Radiosurgery in Patients with Brain Metastases: Systematic Review and Meta-Analysis. *Journal of Advanced in Medicinal, Pharmaceutical and Biomedical Research*, *1*(11), 392-402.

[26] Moghadam,A. M. (2025). Effectiveness of Intraoperative Neuromonitoring in Preventing Neurological Complications during Cervical Spine Surgery: Systematic Review and Meta-Analysis. *Medicinal, Psychological, and Health Research Journal (mphrj)*, *1*(11), 378-386.

[27] Moghadam,A. M. (2025). Effectiveness of Intraoperative Neuromonitoring in Preventing Neurological Complications during Cervical Spine Surgery: Systematic Review and Meta-Analysis. *Journal of Advanced in Medicinal, Pharmaceutical and Biomedical Research*, *1*(11), 403-411.

[28] Moghadam,A. M. (2025). Efficacy and Safety of Minimally Invasive Versus Open Spinal Fusion Techniques for Spondylolisthesis: A Systematic Review and Meta-Analysis. *Medicinal, Psychological, and Health Research Journal (mphrj)*, *1*(11), 370-377.

[29] Moghadam,A. M. (**2026**). Diagnostic and Prognostic Value of Circulating microRNAs in Adult and Pediatric Brain Tumors: Systematic Review and Meta-Analysis. (e241071). *Medicinal, Psychological, and Health Research Journal (mphrj)*, (), e241071

[30] Moghadam,A. M. (**2026**). Diagnostic and Prognostic Value of Circulating microRNAs in Adult Brain Tumors: Systematic Review and Meta-Analysis. *Journal of Advanced in Medicinal, Pharmaceutical and Biomedical Research*, *2*(1), 42-49.

[31] Rahimi, M. J., Mirakhori, F., Zelmanovich, R., Sedaros, C., Lucke-Wold, B., Rainone, G., et al. (**2024**). Diagnostic significance of neutrophil to lymphocyte ratio in recurrent aphthous stomatitis: Systematic review and meta-analysis. *Dermatology Practical & Conceptual*, *14*(1), e2024046.

[32] Rezaei, M., et al. **(2022).** Mesenchymal stem cell therapy for Alzheimer's disease: Review of MSC-derived extracellular vesicles. *Journal of Pharmaceutical Negative Results*, *13*(9), 1–9.

[33] Shariati, A. (**2022**). Advancements in mesenchymal stem cell therapy for stroke: Clinical outcomes and role of extracellular vesicles. *Journal of Pharmaceutical Negative Results*, *13*(8), 1–8.

[34] Torigian, D. A., & Shaghaghi, S. (**2025**). Association between respiratory volumes estimated from free-breathing dynamic MRI and sagittal spinal curvature in pediatric thoracic insufficiency syndrome. *Proceedings of SPIE Medical Imaging, 1–8.*