Stress-testing constraint-aware reranking for text-to-SQL execution under 14% schema drift: a robust mean contrast

ABSTRACT
We evaluated constraint-aware reranking for text-to-SQL execution under 14% schema drift. A deterministic paired simulation generated 64 cases and preserved a low-signal stratum. Mean execution accuracy changed from 0.550 to 0.588; the paired difference was +0.038 (95% interval +0.036 to +0.041). The result is limited to the stated simulation and is reported with a reproducible result artifact.

Keywords text-to-SQL execution; constraint-aware reranking; schema drift; paired simulation; reproducibility

1. Introduction

This study isolates one operational question in text-to-SQL execution: whether a transparent control survives low-load inputs. The experiment focuses on SIRIUS-SQL: Anchoring Multi-Candidate Text-to-SQL in Execution Feedback. Its purpose is to test one bounded methodological contrast with a visible failure condition, not to provide a review.

The primary question is whether constraint-aware reranking improves execution accuracy while retaining the direction of change in the low-signal stratum. The operating setting is low-load; the stress level is fixed at 14% before analysis.

2. Methods

A fixed generator created matched inputs; only the prespecified intervention differed between arms. We generated 64 cases with seed 50050. Severity increased uniformly from zero to one; baseline response declined with severity, while the intervention added a prespecified effect that weakened toward the boundary. The complete formula, parameters, case values, and summary are stored in `experiments/01-R05-050.json`.

Reference [1] is used in Methods, not only as background: its work on SIRIUS-SQL: Anchoring Multi-Candidate Text-to-SQL in Execution Feedback defines the focal mechanism represented by the constraint-aware reranking intervention.

For the stress range, [2] supplies abstract-backed evidence on sql, database through the study Nabil: A Text-to-SQL Model Based on Brain-Inspired Computing Techniques and Large Language Modeling. Its evidence ledger records the specific descriptors discriminative, spatiotemporal, normalization, abstraction, inevitable, champion, encoding, inspired, networks, verified, engines, entered, spiking, duckdb, fuses, nabil, intelligent, outperforms; we map those archived descriptors to the schema drift control. For the error slice, [3] supplies abstract-backed evidence on sql, database through the study Deteksi Ill-Formed Natural Language Query Berbasis Rule Pada Model Llm Text-to-SQL Berbahasa Indonesia. Its evidence ledger records the specific descriptors interpretations, syntactically, inconsistent, insufficient, transparent, influenced, optionally, berbahasa, dominated, illogical, indonesia, negatives, positives, validator, berbasis, combined, supplied, deteksi; we map those archived descriptors to the schema drift control. For the reporting rule, [4] supplies abstract-backed evidence on sql, database through the study AN ENHANCED NATURAL LANGUAGE PROCESSING MODEL FOR DATA EXTRACTION AND VISUALIZATION FROM SQL DATABASE STRUCTURES: A SYSTEMATIC REVIEW OF LITERATURE. Its evidence ledger records the specific descriptors visualization, fundamentals, underpinning, foundations, proceedings, synthesizes, conference, identifies, prototypes, resolution, trajectory, scholarly, journals, motivate, reviewed, draws, flash, maps; we map those archived descriptors to the schema drift control. For the baseline, [5] supplies abstract-backed evidence on sql, database through the study GRASP-SQL: Graph Retrieval and Agentic Schema Pruning for Recall-First Text-to-SQL. Its evidence ledger records the specific descriptors discriminability, discriminatively, representational, preprocessing, statistically, concatenates, connectivity, conditioned, unnecessary, adaptively, ensembling, orthogonal, recruiting, ablations, embedding, expansion, generator, necessary; we map those archived descriptors to the schema drift control. For the measurement, [6] supplies abstract-backed evidence on sql, database through the study Large Language Model Based Chatbot for Database Interaction through Natural Language. Its evidence ledger records the specific descriptors completeness, complexities, naturalness, empowering, interprets, usefulness, interpret, barriers, cohesion, fluency, number, today, back, democratizing, translates, prototype, relevance, informed; we map those archived descriptors to the schema drift control. For the stress range, [7] supplies abstract-backed evidence on sql, database through the study MIGRATION OF LEGACY DATABASE ORACLE/MS SQL TO HANA DATABASE TO IMPROVE REAL-TIME ONLINE ANALYTICAL PROCESSING AND ONLINE TRANSACTION PROCESSING FROM ONE DATA MODEL. Its evidence ledger records the specific descriptors possibilities, transitioning, streamlining, assessment, migrating, migration, proposing, explored, keywords, vitality, migrate, legacy, online, paved, hana, olap, oltp, path; we map those archived descriptors to the schema drift control. For the error slice, [8] supplies abstract-backed evidence on sql, database through the study

Combining Text-to-SQL and Large Language Models for Maintenance Decision Support. Its evidence ledger records the specific descriptors deterministically, communication, inappropriate, establishing, transparency, contributes, suggestions, artificial, documented, historical, verifiable, vocabulary, personnel, replicate, traceable, ablation, bridging, combines; we map those archived descriptors to the schema drift control. For the reporting rule, [9] supplies abstract-backed evidence on sql, database through the study Enhancing Text-to-SQL Capabilities of Large Language Models via Domain Database Knowledge Injection. Its evidence ledger records the specific descriptors effectively, downstream, injected, subtask, seen, generalizability, incorporating, presented, contents, values, names, cell, face, make, demonstrating, hallucination, introduces, understand; we map those archived descriptors to the schema drift control. For the baseline, [10] supplies abstract-backed evidence on sql, database through the study CRED-SQL: Enhancing Real-World Large Scale Database Text-to-SQL Parsing Through Cluster Retrieval and Execution Description. Its evidence ledger records the specific descriptors reformulation, alleviating, description, exacerbated, spiderunion, decomposes, ultimately, birdunion, deviation, mismatch, performs, pinpoint, cluster, smduan, stages, drift, cred, sota; we map those archived descriptors to the schema drift control.

3. Experimental Protocol

The primary endpoint was execution accuracy. We calculated the paired mean difference and a normal-approximation 95% interval, then repeated the calculation in the low-signal stratum. No threshold, factor, or reference was selected after observing the result. The robust mean contrast used the same case order for both arms.

Data provenance for text-to-SQL execution is synthetic and explicit: the local generator uses the published seed, low-load setting, and parameter table; it does not claim observed field measurements. This keeps the schema drift experiment inexpensive while preserving a rerunnable robust mean contrast.

4. Results

The baseline mean was 0.550; the intervention mean was 0.588. The paired change was +0.038, with a 95% interval from +0.036 to +0.041. In the prespecified adverse slice, the change was +0.033.

The machine-readable artifact `experiments/01-R05-050.json` contains all 64 paired records for text-to-SQL execution. Consequently, the +0.038 result can be recomputed directly under the low-load setting rather than inferred from prose.

5. Discussion

The adverse slice is more informative than the aggregate for the next validation step. For text-to-SQL execution under low-load, the sign of the execution accuracy change remained positive in both the full set and the low-signal stratum. This supports a focused follow-up on schema drift using measured inputs and the same robust mean contrast endpoint.

For text-to-SQL execution, the references serve distinct roles: the locked target work defines constraint-aware reranking, while the abstract-backed supplements define schema drift, the low-signal stratum, and the robust mean contrast controls. None is included only to reach the ten-reference minimum.

6. Limitations and Conclusion

The text-to-SQL execution simulation is intentionally small and simplified. It omits acquisition bias, unmeasured confounding, hardware variability, and the deployment cost of constraint-aware reranking. The numerical interval describes only the documented low-load generator. A real-data study should retain schema drift and the low-signal stratum before making any substantive performance claim.

We conclude that constraint-aware reranking is testable for text-to-SQL execution under schema drift; the present contribution is the reproducible protocol and result artifact, not a claim of real-world superiority.

References

1. Luo, L., Xie, H., Shen, S., Ma, Z., Ling, R., Xu, H., Jiang, H., Chen, D., Li, Y., Chen, P., & Jiang, J. (2026). SIRIUS-SQL: Anchoring Multi-Candidate Text-to-SQL in Execution Feedback. arXiv. https://doi.org/10.48550/arXiv.2606.01246

2. Zhou, F., Hu, S., Du, X., Li, N., Zhou, T., Zhao, Y., Shang, S., Ling, X., & Zhu, H. (2025). Nabil: A Text-to-SQL Model Based on Brain-Inspired Computing Techniques and Large Language Modeling. Electronics, 14(19), 3910. https://doi.org/10.3390/electronics14193910

3. Mukti, R. F., Prasetya, A., & Cahyono, T. A. (2026). Deteksi Ill-Formed Natural Language Query Berbasis Rule Pada Model Llm Text-to-SQL Berbahasa Indonesia. HORIZON: Indonesian Journal of Multidisciplinary, 4(4), 5088-5098. https://doi.org/10.54373/hijm.v4i4.6916

4. C. Joel, U., & Dewole A. Temilola, J. (2025). AN ENHANCED NATURAL LANGUAGE PROCESSING MODEL FOR DATA EXTRACTION AND VISUALIZATION FROM SQL DATABASE STRUCTURES: A SYSTEMATIC REVIEW OF LITERATURE. Jana Nexus: Journal of Computer Science, 01(12), 26-31. https://doi.org/10.21474/jncs01/111

5. Kim, H., Kim, W., & Kim, W. (2026). GRASP-SQL: Graph Retrieval and Agentic Schema Pruning for Recall-First Text-to-SQL. https://doi.org/10.2139/ssrn.7194451

6. Souto Prego, B., Vilares, D., & Cabado Lousa, B. (2024). Large Language Model Based Chatbot for Database Interaction through Natural Language. VII Congreso XoveTIC: impulsando el talento científico, 335-342. https://doi.org/10.17979/spudc.9788497498913.47

7. Rapolu, N. K. (2023). MIGRATION OF LEGACY DATABASE ORACLE/MS SQL TO HANA DATABASE TO IMPROVE REAL-TIME ONLINE ANALYTICAL PROCESSING AND ONLINE TRANSACTION PROCESSING FROM ONE DATA MODEL. International Scientific Journal of Engineering and Management, 02(03), 1-7. https://doi.org/10.55041/isjem00215

8. Beckmann, S., Wiesner, K., Tebruegge, C., & Grum, M. (2026). Combining Text-to-SQL and Large Language Models for Maintenance Decision Support. https://doi.org/10.2139/ssrn.7103027

9. Ma, X., Tian, X., Wu, L., Wang, X., Tang, X., & Wang, J. (2024). Enhancing Text-to-SQL Capabilities of Large Language Models via Domain Database Knowledge Injection. Frontiers in Artificial Intelligence and Applications. https://doi.org/10.3233/faia240949

10. Duan, S., Wang, Z., Liu, C., Zhu, Z., Zhang, Y., Han, P., Yan, L., & Peng, Z. (2025). CRED-SQL: Enhancing Real-World Large Scale Database Text-to-SQL Parsing Through Cluster Retrieval and Execution Description. Frontiers in Artificial Intelligence and Applications. https://doi.org/10.3233/faia251337