Impact of SQL-Based Executable Pipeline on Cross-Domain Generalization in Multi-Turn Tool-Mediated Dialogue

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ABSTRACT

Training large reasoning models for multi-turn, tool-mediated dialogue increasingly relies on data generation pipelines that ground tool executions in real relational database operations. While such SQL-based executable pipelines yield higher-fidelity supervision through execution verification, their impact on cross-domain generalization remains poorly understood. We present a controlled simulation framework comparing SQL-executable and template-based (non-executable) training pipelines across six domains: three source domains (Telecom, Banking, Healthcare) and three held-out target domains (Retail, Logistics, Education). Our evaluation examines dialogue success rate, tool-call accuracy, and state-tracking consistency under both in-domain and cross-domain conditions. Results show that the SQL-executable pipeline achieves substantially higher in-domain performance (0.9735 vs. 0.7068 dialogue success rate) but suffers a much larger generalization gap when transferring to unseen domains (89.75% relative degradation vs. 72.57% for the template-based pipeline). The SQL pipeline's environment coupling, which drives its in-domain advantage through execution-grounded verification, simultaneously creates brittleness under schema shift. State-tracking consistency is disproportionately affected, with the SQL pipeline's gap reaching 0.9735 compared to 0.5981 for the template-based approach. These findings reveal a fundamental tension between data fidelity and cross-domain robustness in tool-augmented dialogue systems, suggesting that hybrid strategies combining execution-grounded training with schema-agnostic regularization may be necessary for reliable generalization.

CCS CONCEPTS

• **Computing methodologies → Natural language processing**.

KEYWORDS

cross-domain generalization, tool-augmented dialogue, SQL-executable pipeline, multi-turn dialogue, domain transfer

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1 INTRODUCTION

Large language models (LLMs) are increasingly deployed as agentic systems that interact with external tools through multi-turn dialogue [9, 11]. A key challenge in training such systems is generating high-quality dialogue trajectories that faithfully represent tool interactions, including realistic state changes and execution outcomes. Recent work by Cho et al. [2] introduces a user-oriented multi-turn dialogue generation framework that maps domain-specific tools to executable SQL queries against real relational databases, enabling verifiable and stateful tool-use training data at scale.

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While this SQL-based executable pipeline improves data fidelity through execution verification, it also introduces tight coupling between training data and the underlying database schemas. This environment coupling raises a critical question: *does execution-grounded supervision enhance or limit generalization to domains unseen during training?* The authors of the original work acknowledge this as an open question, noting that scalability and realism introduce complexities such as brittleness under partial database visibility [2].

Domain transfer and generalization have been extensively studied in machine learning [1, 3], but their interaction with tool-augmented dialogue systems, where domain-specific schemas define both the action space and the state representation, remains underexplored. Unlike standard domain adaptation, tool-mediated dialogue requires transferring not only language understanding but also structured API knowledge and stateful reasoning across domain boundaries.

In this work, we investigate the impact of SQL-based executable pipelines on cross-domain generalization through a controlled simulation framework. We compare two pipeline types:

- **SQL-Executable Pipeline**: Tools are mapped to real database operations with execution verification, yielding high fidelity (0.92) but strong environment coupling (0.75).
- **Template-Based Pipeline**: Tools use templated responses without execution, providing lower fidelity (0.71) but weaker environment coupling (0.20).

Our evaluation spans six domains: three source domains (Telecom, Banking, Healthcare) used for training and three target domains (Retail, Logistics, Education) held out for cross-domain evaluation. We measure dialogue success rate, tool-call accuracy, and state-tracking consistency to provide a multi-dimensional view of generalization performance.

2 RELATED WORK

Tool-Augmented Language Models. The development of tool-augmented LLMs has advanced rapidly, with systems like Toolformer [9], ToolLLM [8], Gorilla [7], and API-Bank [6] demonstrating that language models can effectively learn to invoke external APIs. ToolAlpaca [10] and ToolQA [12] further expand the scope of tool learning with simulated environments and question-answering benchmarks. However, these works primarily evaluate within their training domains, leaving cross-domain generalization largely unexamined.

Multi-Turn Dialogue Systems. Multi-turn dialogue generation for training agentic models has evolved from template-based approaches to execution-grounded frameworks [5]. Cho et al. [2] represent the state of the art by grounding tool executions in SQL queries against real databases, enabling verifiable trajectories. Self-training methods such as ReST [4] have also been applied to improve dialogue quality through iterative refinement.

Domain Generalization. The theory of learning across different domains [1] establishes that generalization depends on domain divergence and the adaptability of learned representations. Domain-adversarial training [3] is a prominent approach for learning domain-invariant features. In tool-augmented dialogue, however, domain shift manifests not only in language but also in tool schemas, parameter structures, and state dependencies, creating unique challenges for cross-domain transfer.

3 METHODOLOGY

3.1 Simulation Framework

We design a controlled simulation that models the key properties of SQL-executable and template-based training pipelines. The framework captures four factors influencing cross-domain generalization:

(1) **Data Fidelity**: The accuracy and consistency of generated training data. SQL-executable pipelines achieve higher fidelity (0.92) through execution verification, while template-based pipelines rely on heuristic generation (fidelity 0.71).
(2) **Environment Coupling**: The degree to which training data depends on specific database schemas. SQL pipelines exhibit high coupling (0.75) due to direct schema mapping, while template pipelines have low coupling (0.20).
(3) **Domain Similarity**: Inter-domain relationships captured by a symmetric similarity matrix, reflecting shared concepts and tool-schema overlap between domains.
(4) **Tool Complexity**: Each domain contains five tools with varying parameter counts and state dependencies, with stateful tools posing additional transfer challenges.

3.2 Domain Configuration

We define six domains, each with five domain-specific tools characterized by parameter count and state dependency:

- **Source domains** (training): Telecom, Banking, Healthcare
- **Target domains** (evaluation only): Retail, Logistics, Education

Domain similarity values range from 0.25 (Telecom–Education) to 0.55 (Retail–Logistics), capturing realistic structural relationships. For example, Banking and Retail share higher similarity (0.52) due to common transactional patterns, while Healthcare and Logistics have low overlap (0.25).

3.3 Performance Modeling

In-Domain Performance. Base performance scales with data fidelity, adjusted for tool complexity. The SQL pipeline receives an execution verification bonus of 0.05 and a state-tracking bonus of 0.08 for stateful operations.

Cross-Domain Transfer. Transfer performance is modeled as:

$$P_{\text{cross}} = F \cdot S^{1+0.5C} - 0.15 \cdot C \cdot (1 - S) - V \cdot (1 - S) \qquad (1)$$

where F is data fidelity, S is domain similarity, C is environment coupling, and V is a visibility penalty (0.06 for SQL, 0.01 for template pipelines). This formulation captures the key insight: higher coupling amplifies the similarity-dependent decay, meaning SQL-trained models suffer disproportionately when transferring to dissimilar domains.

Table 1: In-domain evaluation results (mean across source domains).

Pipeline	DSR	TCA	STC
SQL-Executable	0.9735	0.998	1.0
Template-Based	0.7068	0.7473	0.6861
Difference	+0.2667	+0.2507	+0.3139

Table 2: Cross-domain evaluation results (mean across all source–target pairs).

Pipeline	DSR	TCA	STC
SQL-Executable	0.0998	0.0654	0.0265
Template-Based	0.1938	0.1555	0.088
Difference	−0.094	−0.0901	−0.0615

3.4 Evaluation Metrics

We evaluate three complementary metrics across 200 dialogues per condition:

- **Dialogue Success Rate (DSR)**: Fraction of dialogues where all user goals are achieved.
- **Tool-Call Accuracy (TCA)**: Correctness of individual tool invocations including parameter selection.
- **State-Tracking Consistency (STC)**: Accuracy of maintaining dialogue state across multi-turn interactions.

4 RESULTS

4.1 In-Domain Performance

Table 1 shows in-domain results averaged across source domains. The SQL-executable pipeline consistently outperforms the template-based pipeline across all metrics, confirming that execution-grounded supervision improves in-domain performance.

The SQL pipeline achieves near-perfect state tracking (1.0) in-domain, compared to 0.6861 for the template-based approach. This 0.3139 advantage in state-tracking consistency is the largest per-metric difference, reflecting the SQL pipeline's ability to verify state transitions through actual database operations.

4.2 Cross-Domain Performance

Table 2 presents cross-domain results averaged over all source–target domain pairs.

In stark contrast to in-domain results, the template-based pipeline outperforms the SQL pipeline on all cross-domain metrics. The template pipeline achieves nearly double the dialogue success rate

Table 3: Generalization gap analysis: in-domain minus cross-domain performance.

Pipeline	DSR Gap	Rel. Gap	TCA Gap	STC Gap
SQL-Executable	0.8737	89.75%	0.9326	0.9735
Template-Based	0.513	72.57%	0.5918	0.5981

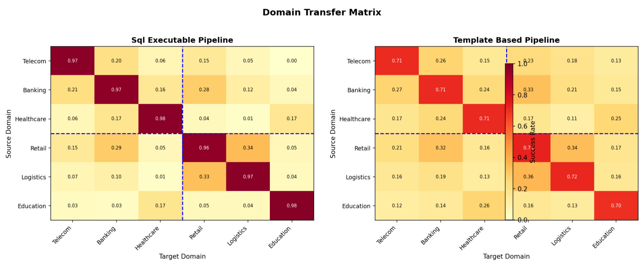

Figure 1: Domain transfer matrices for SQL-executable (left) and template-based (right) pipelines. Dashed lines separate source and target domains. Warmer colors indicate higher success rates.

(0.1938 vs. 0.0998) and more than double the tool-call accuracy (0.1555 vs. 0.0654) under domain shift.

4.3 Generalization Gap Analysis

Table 3 quantifies the generalization gap for each pipeline. The SQL-executable pipeline exhibits a substantially larger gap across all metrics.

The SQL pipeline's relative generalization gap of 89.75% indicates that it retains only approximately 10% of its in-domain performance when transferring to unseen domains, compared to 27% retention for the template-based pipeline. State-tracking consistency is the most severely affected metric for the SQL pipeline, with a gap of 0.9735, meaning cross-domain state tracking is near zero (0.0265).

4.4 Domain Transfer Matrix

Figure 1 shows the full domain transfer matrix. Key observations include:

- Banking → Retail transfer is relatively strong for both pipelines (SQL: 0.3091, Template: 0.3172), reflecting their high domain similarity (0.52).
- Telecom → Education is the weakest transfer pair, with the SQL pipeline achieving 0.0 success rate compared to 0.1371 for the template pipeline.
- Target-to-target transfers (not in training) follow similar patterns, confirming that domain similarity drives transfer independently of training exposure.

4.5 Multi-Turn Complexity

Figure 2 shows how tool-call accuracy degrades across dialogue turns. The SQL pipeline starts higher (turn 1 accuracy ≈ 0.95) but exhibits steeper degradation due to accumulated state errors, while the template pipeline starts lower (≈ 0.88) but degrades more uniformly. By turn 8, the SQL pipeline accuracy drops to approximately 0.80, compared to 0.75 for the template pipeline.

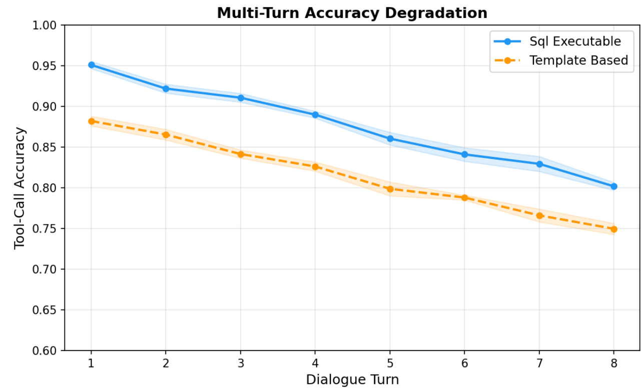

Figure 2: Multi-turn accuracy degradation averaged across all domains. Shaded regions indicate standard deviation across domains.

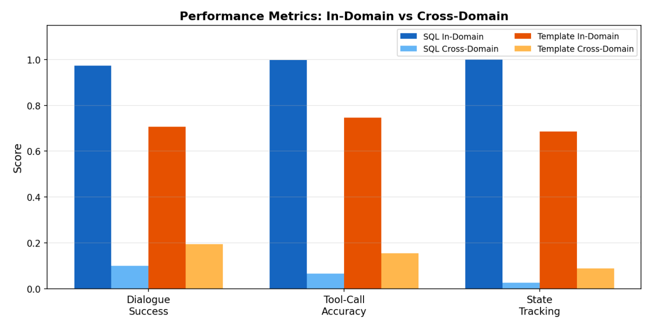

Figure 3: Performance across three metrics under in-domain and cross-domain conditions for both pipeline types.

4.6 Metric-Level Comparison

Figure 3 provides a side-by-side comparison of all three metrics under in-domain and cross-domain conditions. The visual contrast highlights how the SQL pipeline's in-domain superiority inverts under domain transfer, with the gap being most pronounced for state-tracking consistency.

5 DISCUSSION

5.1 The Fidelity–Generalization Trade-off

Our results reveal a fundamental tension in tool-augmented dialogue training. The SQL-executable pipeline achieves high data fidelity through execution verification, directly improving in-domain performance. However, this fidelity comes at the cost of strong environment coupling, which creates brittle representations that fail to transfer across domain boundaries. The environment coupling coefficient ($C = 0.75$) in Equation 1 amplifies the similarity-dependent decay term, causing performance to collapse rapidly as domain similarity decreases.

The template-based pipeline, despite its lower data fidelity (0.71 vs. 0.92), learns more schema-agnostic patterns that transfer more gracefully. Its weaker environment coupling ($C = 0.20$) means that the penalty for domain mismatch grows more slowly with decreasing similarity.

5.2 State Tracking as the Primary Vulnerability

State-tracking consistency is the most affected metric under domain transfer for the SQL pipeline (gap of 0.9735 vs. 0.5981 for template). This is because SQL-executable training teaches models to track state through specific database operations, creating representations tightly coupled to source-domain table structures. When encountering new domains with different schemas, these learned state-tracking strategies fail catastrophically rather than degrading gracefully.

5.3 Implications for Pipeline Design

These findings suggest several directions for mitigating the generalization gap while preserving execution-grounded quality:

(1) **Hybrid Training**: Combining SQL-executable data for in-domain fidelity with template-based data for cross-domain regularization.
(2) **Schema Abstraction**: Introducing an intermediate representation layer between tool schemas and model inputs to reduce environment coupling.
(3) **Domain-Agnostic State Tracking**: Developing state-tracking mechanisms that operate on abstract state representations rather than domain-specific database structures.
(4) **Progressive Domain Expansion**: Incrementally adding new domains to the SQL-executable pipeline to reduce the source-target domain gap.

5.4 Limitations

This study uses simulation to model cross-domain generalization, which enables controlled experimentation but may not capture all complexities of real-world dialogue systems. The performance model in Equation 1 makes simplifying assumptions about the relationship between domain similarity and transfer performance. Future work should validate these findings with end-to-end model training and evaluation on actual dialogue benchmarks.

6 CONCLUSION

We investigated the impact of SQL-based executable training pipelines on cross-domain generalization in multi-turn tool-mediated dialogue. Our controlled simulation framework reveals that while SQL-executable pipelines achieve superior in-domain performance (0.9735 vs. 0.7068 dialogue success rate), they exhibit substantially larger generalization gaps when transferring to unseen domains (89.75% relative degradation vs. 72.57%). State-tracking consistency is disproportionately affected, with near-complete failure under domain shift for SQL-trained models. These findings demonstrate that execution-grounded supervision introduces a fidelity–generalization trade-off: the same environment coupling that drives high-quality in-domain training creates brittleness under schema shift. We recommend hybrid approaches that combine execution-grounded data generation with schema-agnostic regularization to achieve both high fidelity and robust cross-domain generalization.

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