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Construction and Efficacy Evaluation of an Intelligent Response System for Chemical Production Customer Audits Based on Knowledge Graphs

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Abstract

Chemical production customer audits face intractable challenges, including heterogeneous audit standards, inefficient manual responses, and inadequate handling of complex cross-standard issues. Traditional manual response models have struggled to meet the evolving demands of high-stakes supply chain audits. This study integrates 236 heterogeneous audit standards from 127 core customers—including industry leaders such as Contemporary Amperex Technology Co. Limited (CATL) and Tesla—to construct a ternary knowledge graph (TKG) centered on "process parameters-quality indicators-compliance clauses." An NLP-driven intelligent response system was developed to enable rapid semantic understanding, precise knowledge retrieval, and standardized response generation for audit queries. Comprehensive validation, including laboratory testing and 12 months of industrial application, demonstrates that the system achieves a question matching accuracy of 91.3%, reduces response time from 48 hours (traditional manual) to 15 minutes, and supports 27 customer audits with a 100% pass rate. The complex issue resolution rate reaches 89.6%, significantly reducing enterprise audit costs and compliance risks. The proposed technical framework effectively addresses the core pain points of multi-customer heterogeneous standard integration and intelligent audit response, providing a replicable technical pathway for audit management in the chemical industry and offering practical insights for the application of knowledge graphs and NLP in industrial compliance scenarios.

Keywords: chemical customer audit, knowledge graph, intelligent response, Natural Language Processing (NLP), compliance management, heterogeneous standard integration, ternary association modeling, complex issue resolution

1. Introduction

1.1 Research Background and Industry Pain Points

Core chemical products (e.g., lithium-ion battery electrolytes, specialty surfactants) are critical to the reliability of end products in new energy, electronics, and automotive sectors. Customer audits have become a decisive gateway for supply chain access, with leading enterprises such as CATL and Tesla establishing rigorous audit frameworks covering process control, quality assurance, environmental compliance, and safety management (Ferenčíková & Briš, 2019). Audit outcomes directly determine cooperation eligibility and order scales, making audit management a strategic priority for chemical enterprises. (Chen, M., Li, J., & Zhao, Y., 2022)

Traditional audit response models face four interrelated pain points:

1) **Heterogeneous standard integration difficulties**: Audit criteria vary widely in expression, indicator thresholds, and compliance bases (e.g., US EPA vs. EU REACH vs. domestic GB standards), leading to ambiguous adaptation and logical conflicts.

2) **Low response efficiency**: Manual collation of materials and clause matching typically requires 48 hours, failing to meet the timeline requirements of urgent audits.
3) **Weak complex issue handling**: Cross-validation of multiple standards and ambiguous queries often result in logical loopholes or inconsistent responses in manual workflows.
4) **High compliance risks and costs**: Sustained investment in specialized personnel (with 5+ years of experience) is costly, and human errors may lead to audit failures or termination of cooperation.

These challenges highlight the urgent need for an intelligent system to streamline audit response processes and enhance compliance reliability.

1.2 Domestic and International Research Status

Knowledge graphs (KGs) have been preliminarily applied in the chemical industry for process optimization and quality tracing (Wang et al., 2021), but existing research suffers from critical limitations:

- Most studies focus on single-standard systems, lacking the ability to integrate multi-customer heterogeneous standards and establish a “process parameters-quality indicators-compliance clauses” association mechanism.
- Industrial audit response systems rely primarily on keyword matching, with insufficient semantic understanding to handle complex cross-standard queries (Liu et al., 2023).
- Few specialized systems are tailored to the chemical industry, failing to account for process particularities (e.g., high-sensitivity process parameters) and audit standard attributes (e.g., regional compliance differences).

Overall, current research has not formed a closed technical loop of “multi-customer standard integration-ternary association modeling-complex issue response,” leaving a gap in addressing the core pain points of chemical customer audits.

1.3 Research Objectives and Core Content

The primary objective of this study is to develop an intelligent response system that enables efficient integration of heterogeneous audit standards and precise, rapid response to audit queries. The core research content includes:

- Systematic disassembly, normalization, and conflict resolution of 236 heterogeneous audit standards from 127 core customers, covering new energy, electronics, and automotive sectors.
- Design and construction of a ternary knowledge graph (TKG) with the schema “process parameters-quality indicators-compliance clauses,” including ontology definition, knowledge extraction, and fusion.
- Development of NLP-driven core modules (question understanding, knowledge retrieval, response generation, and machine learning iteration) to realize end-to-end intelligent response.
- Comprehensive efficacy evaluation across five dimensions: accuracy (question matching accuracy), efficiency (average response time), practicality (audit pass rate), complex issue handling capability (complex issue resolution rate), and cost-effectiveness (audit cost reduction rate).

2. Related Theories and Technical Foundations

2.1 Core Theories of Knowledge Graphs

Knowledge graph construction relies on standardized ontology design and efficient knowledge processing:

- **Ontology design**: Using OWL (Web Ontology Language), we define core entities (process parameters, quality indicators, compliance clauses), their attributes, and hierarchical/association rules, providing a unified semantic framework for the TKG.
- **Knowledge extraction and fusion**: A hybrid framework combining rule engines (for structured clauses) and BERT pre-trained models (for unstructured text) ensures complete and accurate knowledge capture. Entity alignment unifies synonymous concepts (e.g., “VOC emissions” vs. “volatile organic compound emissions”), while conflict resolution coordinates contradictory indicators (e.g., varying VOC thresholds across customers) (Chen et al., 2022).

2.2 Key Natural Language Processing (NLP) Technologies

NLP provides core support for intelligent query processing:

- **Intent recognition**: The BiLSTM-CRF model parses the semantic structure of audit questions, identifying eight core intents (e.g., process parameter queries, compliance verification) with high accuracy.
- **Entity linking and semantic retrieval**: Key concepts in queries are mapped to TKG nodes, and graph neural networks (GNNs) enable multi-hop reasoning to discover cross-entity associations, upgrading from

"keyword matching" to "semantic understanding" (Chen et al., 2022; Ferenčíková, D., & Briš, P., 2019).

2.3 Core Logic of Chemical Production Customer Audits

To guide system design, audit standards are classified into five categories (process, quality control, environmental compliance, safety management, supply chain) with clear core indicators and internal associations. Audit questions are graded into three levels (simple, moderately complex, complex) based on cross-standard validation needs, ambiguity, and data verification requirements, enabling differentiated response strategies.

3. Integration of Multi-Customer Audit Standards and TKG Construction

3.1 Audit Standard Data Sources and Preprocessing

Data sources: 236 complete audit documents from 127 core customers (covering new energy, electronics, automotive sectors), including CATL's "Lithium-ion Battery Electrolyte Supplier Audit Standards" and Tesla's "Chemical Raw Material Production Compliance Audit Standards." Compliance bases include US EPA, EU REACH, and domestic GB standards, ensuring comprehensiveness and representativeness.

Preprocessing workflow:

1) **Text cleaning**: Remove redundant explanations and format markers, standardize terminology (e.g., unifying "$LiPF_6$ purity" and "hexafluorophosphate lithium purity").
2) **Clause disassembly**: Transform each standard into structured data of "core requirements-indicator thresholds-compliance basis-verification methods."
3) **Conflict resolution**: Establish a "customer priority-application scenario" dual-dimension rule to resolve indicator threshold differences (e.g., VOC limits of 0.03–0.05 kg/h across customers), prioritizing core customer key indicators and flexibly matching general customer requirements.

3.2 Ternary Ontology Design

The TKG ontology centers on three core entities and six key relationships:

Table 1.

Entity Type	Core Attributes	Example Entities
Process Parameters	Name, value range, control method	Reaction temperature (80–120°C, PID control), vacuum degree (-0.1~-0.08 MPa, vacuum pump regulation)
Quality Indicators	Name, qualified threshold, detection method	Impurity content (≤100 ppm, ICP-OES), moisture content (≤15 ppm, Karl Fischer)
Compliance Clauses	Clause number, core requirement, applicable region	EPA 40 CFR Part 60 (VOC ≤0.05 kg/h, US), REACH Annex XVII (heavy metal ≤0.1 ppm, EU)

Core relationships:

- "Influences": Process parameters affect quality indicators (e.g., reaction temperature → impurity content).
- "Bases": Quality indicators are grounded in compliance clauses (e.g., VOC emissions → EPA 40 CFR Part 60).
- "Adapts to": Process parameters must comply with clauses (e.g., vacuum degree → REACH Annex XVII).

3.3 TKG Construction and Optimization

Knowledge extraction: A three-tier mechanism ("rule engine + BERT + manual verification") ensures accuracy:

- Rule engines extract structured information (e.g., "reaction temperature 5–25°C") using regular expressions.
- Fine-tuned BERT models extract implicit knowledge from unstructured text (extraction accuracy: 89.7%).
- 10% of results are manually verified to correct errors and supplement missing relationships.

Knowledge fusion: Entity alignment eliminates redundancy, and attribute fusion integrates multiple detection methods for the same indicator. The TKG is stored in Neo4j, supporting efficient associated queries and reasoning, with 532 entity nodes and 1286 relationship edges.

Dynamic update: A "standard update-incremental extraction-graph iteration" process enables integration of new customer standards within 72 hours, ensuring timeliness.

4. Development of NLP-Driven Intelligent Response Module

4.1 Overall System Architecture

The system adopts a four-layer microservice architecture, with clear separation of concerns and efficient collaboration between layers:

- **Data layer**: Serves as the foundation for system operation, storing raw audit documents, structured clause data, historical audit records (5000+ entries), and TKG data. Data security is ensured through role-based access control (RBAC) and data encryption.
- **Graph layer**: Encapsulates core TKG operations, including node/relationship query, addition, deletion, and modification. It provides a unified application programming interface (API) for the algorithm layer, enabling efficient knowledge invocation and dynamic updates.
- **Algorithm layer**: The intelligent core of the system, integrating four core modules: question understanding, knowledge retrieval, response generation, and machine learning iteration. This layer realizes end-to-end intelligent processing from query input to response output.
- **Application layer**: A user-friendly visual interface developed with Vue.js, providing functions such as audit query input, intelligent response viewing, historical record retrieval, and data statistical analysis. It supports multiple input formats (text, document upload) and output formats (Word, PDF, Excel), adapting to diverse audit scenarios.

4.2 Core Module Development

4.2.1 Question Understanding Module

This module transforms unstructured audit queries into structured semantic representations, laying the foundation for precise retrieval:

- **Text preprocessing**: Perform Chinese word segmentation (Jieba), part-of-speech tagging (HanLP), and stop-word removal to clean up invalid information (e.g., “please,” “confirm”) and extract key semantic components.
- **Intent classification**: A BiLSTM-CRF model is trained on a labeled dataset of 8,000 audit queries to identify eight core intents: process parameter query, quality indicator confirmation, compliance clause verification, cross-standard validation, test method query, risk warning consultation, historical record inquiry, and others. The model achieves an intent classification accuracy of 92.5%.
- **Entity linking**: Key entities in queries (e.g., “reaction temperature,” “EPA standards”) are mapped to TKG nodes using a combination of string matching and semantic similarity calculation. This step resolves semantic ambiguity (e.g., “emissions” → VOC emissions) and achieves an entity linking accuracy of 93.1%.

4.2.2 Knowledge Retrieval Module

A differentiated retrieval strategy is designed to handle queries of varying complexity, ensuring both efficiency and precision:

- **Simple queries**: For queries involving single entities or relationships (e.g., “What is the qualified threshold for moisture content?”), SPARQL query language is used to perform direct matching in the TKG. The average retrieval time is only 0.3 seconds, enabling rapid response.
- **Complex queries**: For queries involving cross-standard validation or multi-entity associations (e.g., “Does the reaction temperature of 95°C meet both Tesla’s quality requirements and EPA environmental standards?”), a GNN-based multi-step reasoning algorithm is adopted. The algorithm constructs semantic association paths (e.g., reaction temperature → VOC emissions → EPA 40 CFR Part 60; reaction temperature → impurity content → Tesla’s quality standard) to discover implicit relationships and retrieve relevant knowledge. (Liu, J., Zhang, L., & Wang, H., 2023)
- **Similarity ranking**: Retrieval results are sorted by a combination of entity matching degree, relationship relevance, and customer priority, increasing the TOP1 hit rate to 88.6% and improving response accuracy.

4.2.3 Response Generation Module

The module generates standardized, professional responses tailored to audit scenarios:

- **Explicit query response**: For simple and moderately complex queries, responses follow a structured format of “core conclusion-basis clause-process/quality association explanation.” For example, the response to “What is the VOC emission threshold for US customers?” is: “Core conclusion: The VOC emission threshold for US customers is ≤0.05 kg/h. Basis clause: EPA 40 CFR Part 60. Association explanation: This threshold is influenced by the distillation vacuum degree (-0.1~-0.08 MPa) and reaction temperature (80–95°C), which are controlled through vacuum pump regulation and PID temperature control."

- **Complex query response**: For cross-standard or ambiguous queries, additional components are added: "standard difference explanation-verification method suggestion-compliance risk warning." For example, the response to "Does Process X meet both Tesla and EPA requirements?" includes an explanation of differences between Tesla's and EPA's thresholds, a suggested verification method (GC-MS + ICP-OES), and a warning of potential risks if parameters deviate.
- **Format support**: Responses can be exported in Word, PDF, or Excel formats with one click, directly usable for audit submission, reducing the workload of secondary editing by 90%.

4.2.4 Machine Learning Iteration Module

The module enables continuous optimization of the system based on real-world application feedback:

- **Feedback collection**: Record customer feedback (e.g., response corrections, supplementary requirements) and audit outcomes (e.g., pass/fail, key issues) in real time. Over 12 months of industrial application, 3200+ valid feedback entries are accumulated.
- **Model fine-tuning**: Use feedback data to fine-tune the BERT extraction model and GNN retrieval model, increasing entity recognition accuracy by 3.2% and complex reasoning ability by 5.8%.
- **TKG optimization**: Analyze high-frequency queries and common errors to automatically update TKG relationship weights and response strategies. For example, if "cross-standard validation" queries increase by 40%, the weight of cross-entity relationships is adjusted to improve retrieval priority.

4.3 System Technical Implementation

- **Development languages and frameworks**: The system adopts a multi-language collaborative development scheme: Python 3.9 for model training (TensorFlow 2.10) and algorithm implementation; Java 11 for backend service construction (Spring Boot 2.7) and business logic processing; Vue.js 3.0 for frontend visualization.
- **Core technologies**: TensorFlow 2.10 is used for training and deploying BERT, BiLSTM-CRF, and GNN models; Neo4j 5.10 serves as the TKG storage and query engine; Spring Boot 2.7 builds a stable, scalable backend service; Redis 6.2 is used for caching frequent queries to improve response speed; Nginx 1.21 provides load balancing and reverse proxy (Wang, Y., Li, Z., & Zhang, H., 2021).

5. System Efficacy Evaluation

5.1 Evaluation Indicator System

To comprehensively assess the system's performance, a five-dimensional evaluation indicator system is constructed, covering the core needs of audit management:

Table 2.

Dimension	Indicator	Definition and Calculation Method
Accuracy	Question matching accuracy	The proportion of queries for which the system retrieves the correct and relevant knowledge. Calculation: (Number of correctly matched queries / Total queries) × 100%.
Efficiency	Average response time	The average time from query input to response generation. Calculation: Total response time for all queries / Number of queries.
Practicality	Audit pass rate	The proportion of audits that pass successfully with the support of the system. Calculation: (Number of passed audits / Total audits) × 100%.
Complex Issue Handling	Complex issue resolution rate	The proportion of complex queries (cross-standard, ambiguous) that are correctly resolved. Calculation: (Number of resolved complex queries / Total complex queries) × 100%.
Cost-Effectiveness	Audit cost reduction rate	The percentage reduction in audit preparation costs (personnel, time, materials) after system application. Calculation: (1-Post-system audit cost / Pre-system audit cost) × 100%.

5.2 Evaluation Plan

- **Test set construction**: A test set of 500 audit queries is constructed, covering all five standard categories and three query levels: 200 simple queries, 200 moderately complex queries, and 100 complex queries.

Queries are derived from historical audit records and designed by senior audit specialists to ensure realism and representativeness.

- **Comparison groups**: Two comparison groups are established to benchmark the system's performance: (1) Traditional manual team: 3 senior audit specialists with 5+ years of experience; (2) Industry keyword matching system: A widely used commercial audit response system based on keyword retrieval.
- **Evaluation environment**: Laboratory testing is conducted on a cloud server with 32-core CPU, 64GB memory, and 1TB SSD. Industrial application verification is carried out in a large chemical enterprise (Tinci Materials) over 12 months, tracking real-world audit data.

5.3 Evaluation Results and Analysis

The system's performance across all dimensions is superior to the comparison groups, demonstrating its practical value and technical advancement:

Table 3.

Indicator	Proposed System	Manual Team	Keyword Matching System	Improvement (vs. Manual)	Improvement (vs. Keyword System)
Question Matching Accuracy	91.3%	93.0%	72.5%	-1.7pp (nearly equivalent)	+18.8pp
Average Response Time	15 minutes	48 hours	360 minutes	99.5% reduction	97.9% reduction
Audit Pass Rate	100%	92.3%	89.1%	+7.7pp	+10.9pp
Complex Issue Resolution Rate	89.6%	90.2%	45.2%	-0.6pp (nearly equivalent)	+44.4pp
Audit Cost Reduction Rate	68.3%	-	-	-	-
Annual Cost Savings	≈1.2 million yuan	-	-	-	-

Key insights from the results:

- The system's accuracy is comparable to manual work, thanks to semantic understanding and TKG-based retrieval.
- Response efficiency is drastically improved, meeting urgent audit requirements.
- 100% audit pass rate reduces compliance risks, while complex issue handling is nearly equivalent to experienced specialists.
- Significant cost savings are achieved by reducing personnel reliance.

6. Conclusions and Future Prospects

6.1 Research Conclusions

This study addresses the core pain points of chemical customer audits by integrating 236 heterogeneous standards from 127 customers to construct a ternary knowledge graph and develop an NLP-driven intelligent response system. Key achievements include:

- A unified TKG framework that resolves multi-customer standard conflicts and establishes clear "process-quality-compliance" associations.
- An end-to-end intelligent response module with high accuracy (91.3%) and efficiency (15-minute response time).
- 100% audit pass rate and 89.6% complex issue resolution rate in 12 months of industrial application, reducing costs by 68.3%.

The proposed technical framework provides a replicable solution for chemical industry audit management, bridging the gap between heterogeneous standard integration and intelligent response.

6.2 Future Prospects

Future optimization will focus on four directions:

- **Standard coverage expansion**: Incorporate audit standards for pharmaceutical and food chemicals to enhance industry adaptability.
- **Production data integration**: Link the system to manufacturing execution systems (MES) for dynamic "standard-data-response" linkage.
- **Technological upgrades**: Integrate large language models (LLMs) to improve response fluency and logical explanation, and computer vision to handle image-based audit queries (e.g., on-site photos).
- **Application scenario extension**: Extend the "KG + NLP" architecture to supply chain audits and regulatory compliance, building a full-scene industrial compliance platform.

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