Global Journal of Engineering and Technology Advances

eISSN: 2582-5003

Cross Ref DOI: 10.30574/gjeta

Journal homepage: https://gjeta.com/

(Review Article)

Neuro-Schema Adaptation (NSA): AI-Driven Evolution of Database Schemas in Hybrid Environments

Chijioke Cyriacus Ekechi [1], Isatayo Emmanuel Oluwaseye [2], Isiaka O Ibrahim [3], Ayodeji S Saliu [4,*] and Badejoko Eunice Adenrele [5]

[1] *Department of Electrical and Computer Engineering, Tennessee Technological University.*

[2] *Department of Information Technology, School of computing, The Federal University of Technology Akure, Ondo State Nigeria.*

[3] *Department of Engineering Management, Faculty of Science and Engineering Technology, University of Houston Clear Lake, USA.*

[4] *Department of Computer Science, Faculty of Science, University of Adekunle Ajasin Uni, Akungba Akoko, Ondo state, Nigeria.*

[5] *Department of Computer science, Faculty of School of Science, Mathematics and Information Technology, Houdegbe North American University, Republic of Benin.*

Global Journal of Engineering and Technology Advances, 2025, 25(02), 019-028

Publication history: Received on 16 September 2025; revised on 30 October 2025; accepted on 01 November 2025

Article DOI: https://doi.org/10.30574/gjeta.2025.25.2.0314

Abstract

The rapid change in data needs in hybrid computing environments requires smart and flexible database schema management. This paper presents Neuro-Schema Adaptation (NSA), a new framework driven by AI. It uses machine learning and neural networks to automate schema evolution, matching, and optimization across different database systems. NSA tackles key challenges in modern data management, such as schema drift, compatibility problems, and migration difficulties in hybrid cloud-edge environments. Through detailed analysis of recent progress in AI-powered schema management, this research shows how neural methods can greatly improve schema adaptation efficiency, lessen manual work, and keep data safe during changes. The framework includes large language models, graph neural networks, and retrieval-augmented matching techniques to create a self-adjusting schema management system. This system can handle complex data changes in real-time.

Keywords: Schema Evolution; Neural Networks; Database Migration; AI-Driven Systems; Hybrid Environments; Schema Matching; Large Language Models

1. Introduction

Database schema evolution is one of the biggest challenges in modern data management. Organizations are increasingly using hybrid computing setups that include cloud, edge, and on-premises environments [1]. Recent studies on *Collaborative Intelligence Databases (CID)* highlight how privacy-preserving AI frameworks can securely coordinate schema and data management across multiple, heterogeneous environments [27]. Traditional schema management methods, which often depend on manual work and fixed rules, cannot keep up with the dynamic nature of today's data ecosystems [2]. New advancements in artificial intelligence and machine learning technologies have created opportunities for automating and improving schema evolution processes. Recent developments have shown impressive skills in understanding and working with structured data [3]. As a result, research into AI-driven methods for database

* Corresponding author: Ayodeji S Saliu.

schema management has increased, leading to innovative solutions that can adjust schemas based on changing data patterns [1].

Combining large language models with traditional database systems has effectively tackled complex schema management issues [4]. Recent work using machine translation techniques for schema matching has produced encouraging results in automating complicated transformation tasks [5]. Complementary studies, such as ChatGPT and the Future of Generative AI [28], provide a technical foundation for understanding how transformer-based architectures and contextual embeddings power these translation-inspired schema-matching processes. Multi-stage schema matching methods using large language models and retrieval systems have outperformed traditional rule-based techniques [6]. These advancements mark a shift toward more independent and efficient data management practices. Neural networks can now spot schema evolution opportunities and foresee compatibility problems with less human input [3]. Using generative retrieval augmented matching techniques has also improved the level of understanding needed for complex schema transformations [4].

Neuro-Schema Adaptation (NSA) comes from the merging of several technological trends. These trends include the rise of different data sources, the complexity of hybrid computing environments [26], the growth of AI technologies, and the growing need for real-time data processing [7]. NSA frameworks use the pattern recognition skills of neural networks to find schema evolution opportunities, predict compatibility issues, and automate transformation tasks that once needed a lot of manual work [8]. Recent studies show that AI-driven schema evolution systems can achieve significant performance boosts. Some implementations have shown marked increases in accuracy while minimizing migration risks and manual work [9]. The creation of self-supervised learning methods has improved scalability by lowering reliance on labeled training data [8].

Modern hybrid computing setups bring unique challenges for schema evolution. These challenges include concerns about network latency, limits on computational resources at edge locations, and the need to coordinate evolution across distributed systems [10]. Creating specific frameworks that work well in resource-limited environments while keeping in sync with cloud systems has become a key area of research [11]. Recent efforts in AI-enabled embedded systems address these challenges by optimizing schema evolution for resource constraints [12]. Graph neural networks have shown great promise for database schema applications, especially in understanding structural relationships in distributed systems [9]. The addition of schema evolution features to cloud migration services illustrates how AI-driven methods can be applied in real-world hybrid deployment situations [13].

AI-driven schema evolution's quality assurance and reliability aspects have drawn significant attention from researchers. They have developed quality-aware deep learning strategies that enhance the reliability of matching decisions [10]. Improved testing frameworks show how AI can be used not only for schema evolution but also for verifying the outcomes of evolution processes [14]. Literature reviews reveal that, while current research has advanced significantly, comprehensive frameworks for end-to-end schema evolution still need further development [15]. Integrating interactive programming systems has shown potential for better collaboration between humans and AI in schema design and evolution [16]. Visualization tools have effectively improved the understanding of schema evolution effects, building trust in automated systems [17,18].

This research looks at the current state of AI-driven schema evolution technologies, evaluates their effectiveness in hybrid environments, and suggests a thorough framework for implementing neuro-adaptive schema management systems. Through a systematic review and analysis of recent studies, this paper adds to the understanding of how neural techniques can transform database schema management practices. The study covers both the technical capabilities and practical deployment considerations needed for successful implementation in today's data ecosystems. Recent progress in provenance tracking and chronological schema evolution frameworks gives further insights into maintaining schema evolution history and supporting rollback abilities. When multiple AI technologies converge, they offer a transformative chance for organizations that want to manage the complexities of modern data infrastructure while ensuring reliability and performance.

2. Methodology

2.1. Search Strategy

This systematic review employed a comprehensive search strategy to identify relevant literature on AI-driven schema evolution and neural approaches to database management. The search was conducted across multiple academic databases, including IEEE Xplore, ACM Digital Library, arXiv preprint repository, and specialized conference proceedings.

The temporal scope focused on publications from 2022 to 2025 to capture the most recent advances in the field. Search terms included combinations of "schema evolution," "neural networks," "AI-driven database," "schema matching," "large language models," "database migration," and "hybrid environments."

2.2. Selection Criteria

The selection criteria for literature inclusion and exclusion are detailed in the following table

Table 1 Inclusion and Exclusion Criteria for Literature Selection

Criteria Category	Inclusion Criteria	Exclusion Criteria
Publication Type	Peer-reviewed papers, significant preprints, conference proceedings, industry white papers	Opinion pieces, blog posts without technical content, marketing materials
Temporal Scope	Publications from 2022-2025	Publications before 2022, unless seminal works
Technical Focus	AI/ML applications in schema management, neural approaches to database evolution, and hybrid environment solutions	Purely theoretical database concepts without AI integration
Methodology	Novel methodologies, empirical evaluations, and comprehensive frameworks	Studies without experimental validation or concrete implementations
Relevance	Schema evolution, schema matching, and database migration with AI components	Traditional database management without AI/ML elements
Quality	Clear methodology, reproducible results, significant contribution to the field	Incomplete studies, unclear methodologies, and minimal technical contribution

2.3. Selection Process

The selection process involved three stages: initial screening based on title and abstract relevance, followed by full-text review for works that met preliminary criteria, and final evaluation based on technical contribution and relevance to NSA frameworks.

Special attention was paid to research addressing hybrid computing environments, real-time schema adaptation, and the integration of multiple AI technologies for schema management purposes. Priority was given to works demonstrating practical applications and measurable improvements over traditional approaches

3. Result

3.1. Summary of Findings

Table 2 Summary of Key Findings from Recent AI-Driven Schema Management Studies

Source	Key Findings	Inference	AI Technology Used	Performance Metrics	Deployment Environment	Implementation Complexity
Chen et al. [7]	LLM-Matcher demonstrates practical name-based schema matching capabilities	Specialized AI tools can be developed for specific schema management tasks	Large Language Models	85-90% matching accuracy	Cloud-based systems	Medium
Seedat et al. [8]	Self-supervised MATCHMAKER scales without extensive labeled training data	Reduced training requirements enable broader AI deployment in schema management	Self-supervised Learning	Scalable to 10K+ schemas	Hybrid environments	Low
Das et al. [9]	Graph neural networks show strong potential for database schema applications	Structural relationships in schemas can be effectively modeled using graph-based AI	Graph Neural Networks	92% structural accuracy	Distributed systems	High
Roy et al. [10]	Quality-aware deep learning improves matching decision reliability	AI systems can incorporate quality metrics to enhance trustworthiness	Deep Learning + Quality Metrics	95% confidence intervals	Enterprise environments	Medium
Lee et al. [11]	AI-driven evolution shows 20-30% improvement in heterogeneous environments	Significant performance gains justify AI adoption in complex database systems	Multi-modal AI	20-30% efficiency gain	Heterogeneous databases	High
Kumar et al. [12]	AI-based impact analysis reduces migration risks and manual effort	Predictive AI capabilities can anticipate and mitigate schema evolution problems	Predictive Analytics	60% risk reduction	Migration scenarios	Medium
Smith et al. [13]	LLM integration with AWS migration services demonstrates practical deployment	Commercial cloud platforms are successfully adopting AI-driven schema management	LLM + Cloud Services	Production-ready	AWS cloud platform	Low
Edwards [14]	Interactive programming systems benefit from AI-assisted schema evolution	Human-AI collaboration models enhance schema design and evolution processes	Interactive AI	Enhanced user experience	Development environments	Medium

Conf42 [15]	Reliable migration strategies require comprehensive AI-driven testing frameworks	Systematic approaches to AI-enabled schema migration improve success rates	Testing AI frameworks	95% migration success	Production deployments	Medium
QASource [16]	AI enhances data migration testing effectiveness by 40-60%	Automated testing with AI validation significantly improves migration quality	Automated Testing AI	40-60% improvement	Testing environments	Low
Tinybird [17]	Automatic schema migration for ClickHouse enables real-time analytics	Specialized database systems can benefit from tailored AI evolution approaches	Real-time AI	Sub-second response	Analytics platforms	Medium
Li et al. [18]	AI-enabled embedded systems require optimized schema evolution for resource constraints	Edge computing environments present unique challenges requiring specialized AI solutions	Edge AI	Resource-optimized	IoT/Edge devices	High
Curty et al. [19]	PROV-IDEA supports interoperable schema and data provenance tracking	Provenance integration enables better schema evolution history management	Provenance AI	Full traceability	Research environments	High
Pokharel [20]	The chronological schema evolution framework integrates temporal schema changes	Time-aware approaches improve schema evolution decision-making processes	Temporal AI	Time-series accuracy	Longitudinal systems	Medium
Mazilu et al. [21]	Wild schema mapping generation handles real-world complexity effectively	Practical deployment scenarios require robust handling of schema heterogeneity	Robust AI mapping	Real-world validation	Production systems	High
Yakout et al. [22]	Pre-trained language models achieve superior schema mapping performance	Transfer learning approaches reduce training overhead for schema management	Pre-trained LLMs	Superior performance	Various platforms	Low
Brahmia [23]	Literature analysis reveals gaps in automated schema evolution frameworks	Current research lacks comprehensive frameworks for end-to-end schema evolution	Literature Analysis	Gap identification	Academic review	N/A
Wagner et al. [24]	Visualization tools improve understanding of schema evolution impacts	Human-interpretable AI outputs enhance adoption and trust in automated systems	Visualization AI	Enhanced comprehension	User interfaces	Medium

4. Discussion

4.1. Technological Convergence in Schema Evolution

The combination of various AI technologies marks a major shift in current schema evolution research, fundamentally changing how database systems handle schema management issues [3]. The merging of large language models, graph neural networks, and retrieval-augmented systems creates strong hybrid methods that effectively tackle the complexities of real-world schema management situations [9]. This blend of technologies allows systems to utilize the understanding capabilities of language models while also benefiting from the structural analysis strengths of graph-based methods, creating a solution framework that outperforms individual AI approaches [18].

Recent progress in pre-trained language models has shown better schema mapping performance, achieving accuracy rates that far surpass traditional rule-based methods [19]. Using machine translation techniques for schema matching illustrates how AI technologies originally designed for natural language processing can be effectively used in database management tasks [5]. This exchange of methods indicates a strong potential for further innovation through the application of other AI technologies to schema management challenges. The creation of compound schema registry systems has automated schema evolution for streaming data, allowing for real-time processing capabilities that were once impossible [20]. Multi-stage methods that combine retrieval-augmented generation with large language models have been especially successful in managing diverse schema environments [6].

The rise of specialized AI tools for specific schema management tasks highlights the importance of focused algorithm development [1]. Graph neural networks have shown great promise in modeling structural relationships within database schemas, offering insights into complex interdependencies that traditional methods often overlook [9]. Adding quality-aware mechanisms to deep learning systems has improved the reliability and trustworthiness of automated schema matching decisions, addressing important concerns about deploying AI systems in production settings [10]. These technological integrations represent not just small improvements but foundational changes in how intelligent systems understand and work with structured data.

4.2. Scalability and Performance Considerations in Hybrid Environments

The scalability challenges in modern hybrid computing environments demand advanced methods for AI-driven schema evolution that can work efficiently across different computational contexts [10]. Recent studies show that AI-driven schema evolution systems can achieve significant performance gains over traditional methods, with some systems reaching accuracy rates over 90% in complex schema matching tasks while maintaining efficiency in distributed systems [2]. However, scalability is still a key issue, particularly in hybrid environments where schema evolution must take place across distributed systems with varying computational capabilities, network connectivity, and resource availability [11].

The development of self-supervised learning methods tackles important scalability issues by greatly decreasing reliance on labeled training data, which is often limited, costly to obtain, and hard to maintain in schema management situations [8]. These methods allow AI-driven schema evolution systems to operate in environments without comprehensive training datasets, making advanced schema management capabilities accessible to organizations with varying data maturity levels [21]. Schema mapping generation in real-world deployments has shown the practical effectiveness of AI-driven methods in dealing with the complex schema diversity found in modern enterprises [3].

Performance optimization in resource-limited environments poses unique challenges that call for innovative architectural solutions [12]. AI-enabled embedded systems need specialized schema evolution approaches that can function within strict computational and memory limits while staying in sync with cloud systems [18]. The use of chronological schema evolution frameworks has enabled time-aware decision-making processes, taking into account historical schema changes and temporal dependencies, leading to better accuracy and reliability of evolution decisions [20]. Real-time analytics platforms have successfully introduced automatic schema migration features that allow for sub-second response times, proving that high-performance AI-driven schema management is possible in demanding settings [22].

4.3. Quality Assurance and Reliability Frameworks

Incorporating strong quality assurance measures into AI-driven schema evolution systems is vital for effective use in mission-critical environments [10]. Ongoing concerns about the reliability of AI systems in essential infrastructure applications are being systematically addressed through the creation of advanced confidence metrics, uncertainty quantification techniques, and human-in-the-loop verification processes to ensure solid decision-making [14]. Quality-aware deep learning methods have shown notable improvements in matching decision reliability, including multi-dimensional quality assessments that consider not just accuracy but also consistency, completeness, and context appropriateness [9].

Figure 2 Quality assurance framework with AI-driven confidence metrics and human-in-the-loop verification

Enhanced testing approaches for data migration show how AI can be effectively used not only for schema evolution but also for validating the results of evolution processes, creating end-to-end quality assurance systems [14]. These testing frameworks have shown effectiveness improvements of 40-60% compared to traditional validation methods, greatly reducing the risk of schema evolution failures and data integrity problems [23]. Developing reliable migration strategies requires thorough AI-driven testing frameworks that can evaluate schema transformations across various dimensions, ensuring that evolved schemas remain functionally equivalent while improving structural efficiency [15].

Interactive programming systems have emerged as a promising way to balance automation efficiency with human expertise in complex decision-making scenarios [16]. These systems allow developers to work together with AI systems in schema design and evolution processes, providing transparent decision-making processes that keep human oversight while utilizing AI for routine tasks [1]. Visualization tools have played a key role in improving understanding of schema evolution impacts by offering human-readable representations of complex transformation processes, helping foster acceptance and trust in automated systems [17]. The addition of provenance tracking capabilities allows for thorough monitoring of schema evolution history, supporting rollback options when evolution decisions become problematic and providing audit trails for compliance needs [24].

4.4. Hybrid Environment Challenges and Specialized Solutions

The complexity of hybrid computing environments brings multiple challenges for schema evolution, requiring advanced technological solutions to tackle network latency issues, resource limitations at edge locations, compatibility across different platforms, and the necessary coordination of evolution across geographically distributed systems [11]. These challenges are intensified by the varied nature of modern data ecosystems, where schemas must evolve uniformly across cloud platforms, edge devices, and on-premises infrastructures while ensuring data integrity and operational continuity [12].

Recent research has thoughtfully addressed these challenges through the creation of specialized frameworks that can effectively function in resource-constrained environments while maintaining sophisticated synchronization with cloud systems [18]. AI-enabled embedded systems have particularly strict requirements for schema evolution, demanding optimization strategies that can handle intelligent schema management within significant computational and memory constraints [22]. Combining schema evolution capabilities with commercial cloud migration services illustrates the practical viability of AI-driven methods in real-world hybrid deployment situations, providing clear evidence of scalability and reliability in production settings [13].

Figure 3 Hybrid computing infrastructure with coordinated schema evolution across edge-cloud systems

Edge computing environments offer unique opportunities and challenges for AI-driven schema evolution, requiring specialized algorithms that can make smart decisions with limited computational resources while coordinating with centralized management systems [12]. The development of distributed schema evolution protocols has allowed for coordinated transformation processes that can manage network partitioning, variable connectivity, and asynchronous operations while ensuring consistency across the entire system [25]. These specialized solutions demonstrate that AI-driven schema evolution can be effectively applied across a wide range of modern computing environments, from resource-limited IoT devices to high-performance cloud platforms.

4.5. Future Directions and Emerging Research Paradigms

The rapid pace of technological growth in AI-driven schema evolution points to several trends that will shape future research directions and practical deployments. The integration of smart provenance tracking with schema evolution systems is a key area of development. This allows for a clear understanding of evolution history, supports rollback options when decisions go wrong, and provides detailed audit trails for meeting regulations and optimizing systems. Literature analysis shows significant opportunities for creating better frameworks that can manage end-to-end schema evolution processes, addressing current gaps in automated schema evolution that limit practical use. The merging of various AI technologies opens up the potential for unified platforms that can seamlessly integrate language models, graph neural networks, and specialized optimization algorithms to create solid schema management solutions.

Interactive programming environments offer a promising direction for future development. They enable advanced human-AI collaboration that combines the speed of automated processing with the contextual understanding and creative problem-solving skills of human experts. The rise of specialized database systems optimized for AI-driven schema evolution creates opportunities for developing platforms specifically designed to fully utilize modern AI capabilities. Real-time analytics needs are pushing forward innovations in automatic schema migration that can manage fast-moving data while ensuring consistency and performance. These advancements suggest a future where schema evolution becomes a smooth, intelligent process that adjusts to changing requirements while maintaining the reliability and performance vital for current data-driven applications.

5. Conclusion

The rise of Neuro-Schema Adaptation (NSA) signals a major shift in database schema management by using artificial intelligence to tackle complex challenges in today's hybrid computing environments. This review shows that AI-driven methods have made significant progress in schema matching accuracy, evolution automation, and adapting to dynamic data needs, with improvements of 20-30% over traditional methods. The combination of large language models, graph neural networks, and quality-aware mechanisms offers strong solutions for real-world schema evolution issues while addressing scalability and reliability concerns. The merging of AI technologies with database management presents a transformative opportunity that allows for a more agile, responsive data infrastructure capable of managing the complexity of modern data ecosystems.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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