Journal of Global Research in Multidisciplinary Studies (JGRMS)
Volume 2 | Issue 11 | November 2026 | Pages 08–14
DOI: https://doi.org/xxxxxxxxxxxx
e-ISSN: 3049-2963
Review Article OPEN ACCESS Available online: https://saanvipublications.com/journals/index.php/jgrms

An Agentic AI Framework for Autonomous Data Integration and Schema Convergence in Enterprise Systems

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Received: 5 November, 2026 | **Revised:** 8 November, 2026 | **Accepted:** 22 November, 2026

***Abstract*—As corporate systems increasingly rely on heterogeneous databases and applications, the complexities of data integration, schema convergence, and schema matching are intensifying. To enable independent data integration and harmonies diverse organizational schemas, this study examines an AI framework functioning as an agent. Advanced agents that notice variations, contemplate objectives, devise plans, use implements, and operate with little human engagement are integral to the framework's structure. It regards autonomous data pipeline governance, multi-agent synergy, schema integration, data reconciliation, and data synthesis as related abilities to improve the uniformity and effectiveness of corporate data. Access permissions, concurrent schema versions, conflict detection, evolutionary schemas, and transformative schemas are all addressed in the study. The examination of platform independence and organizational transformation is conducted via the framework of established conversion methodologies and design patterns, such as federation, canonical data layers, domain gateways, and comprehensive unification. The model is constructed around applicable investigations into credible AI, data standardization, transparency, and independent agents. The integration of autonomous systems into multifaceted corporate environments that experience constant change introduces essential problems concerning accountability, scalability, validation, governance, and trustworthiness.**

***Keywords*—Agentic Artificial Intelligence, Autonomous Data Integration, Schema Convergence, Schema Matching, Enterprise Data Management.**

I. INTRODUCTION

Intelligent systems are needed in modern business settings so they can handle complicated tasks, adapt to changing conditions, and make decisions on their own with minimal input from humans. Agentic systems incorporate perception, thinking, planning, and execution under one cohesive structure. To allow multistep problem solving across broad contexts, these systems often incorporate Large Language Models (LLMs), reinforcement learning, and multimodal data [1]. Agentic AI systems depend significantly on efficient context management. An agent is required to collect, preserve, and use contextual data from many sources to execute suitable actions [2][3]. Recent innovations in Artificial Intelligence have embedded independent decision-making features inside organizational systems. Agentic AI signifies a novel framework whereby intelligent agents may assess operational circumstances, contemplate goals, devise remedial strategies, and implement judgements with minimal human intervention. In contrast to traditional automation systems that function based on established protocols, Agentic AI systems perpetually adjust to changing conditions and enhance their actions via feedback-oriented learning processes. This feature renders Agentic AI highly effective at overseeing complex data engineering tasks inside cloud-native environments [4]. The framework facilitates the creation of autonomous agents that generate novel management strategies, including perception, reasoning, planning, cooperation, and the execution of processes to attain specified objectives. Unlike current automation systems, Agentic AI may cultivate independent users who collaborate and acquire knowledge while functioning in different environments [5].

Enterprise data management system in Schema Convergence is frequently faced with two primary challenges: enabling fast adaptability to changing business needs while ensuring strong data governance and validation protocols. Schema-driven user interface creation presents an intriguing resolution to this conflict, providing a framework where both the composition of the presentation layer and back-end validation originate from a unified authoritative schema definition. This methodology substantially alters the manner in which organizations conceive, execute, and sustain data-centric systems, especially in areas where field definitions often change but need rigorous validation. The framework of declarative programming, which focuses on expressing the desired outcomes of a program instead of the methods to achieve them, offers a conceptual foundation for schema-driven methodologies. A detailed examination of

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DOI: https://doi.org/xxxxxxxxxxxx

programming paradigms shows that declarative abstractions may significantly decrease inadvertent complexity in software systems. Conventional methods of UI development in corporate settings often need the manual creation of form elements and validation mechanisms, resulting in an ongoing synchronization dilemma between front-end displays and back-end limitations [6].

The integration of data in business systems is a vital operation that facilitates the unification of information from diverse heterogeneous origins into a coherent and valuable structure. Within contemporary corporations, data is created from a diverse set of systems including ERP, CRM, cloud apps, IoT devices, and antiquated databases. In the absence of efficient integration, this data stays confined inside silos, limiting its applicability and worth for decision-making. Data integration confronts this problem by assuring coherence, accessibility, and dependability of information throughout the enterprise. It serves a crucial function in bolstering analytics, optimizing operational efficiency, and fostering digital transformation within data-oriented corporate landscapes [7][8].

This paper is structured as follows: Section II introduces the Agentic Artificial Intelligence architecture designed for independent data integration. Section III examines schema convergence inside enterprise systems, including conventional techniques and convergence designs. Section IV analyses pivotal technologies in Agentic AI frameworks. Section V examines related studies, whereas Section VI summarizes the work and identifies future investigation avenues.

II. Agentic Artificial Intelligence Framework for Autonomous Data Integration

Agentic AI systems consist of one (first-order) or multiple interacting AI agents (second-order) with the capabilities to observe their environment, learn to use and extend their tools, and autonomously reason when and how to act (i.e., through perception, planning, and execution) to achieve goals. Agentic AI systems respond to environmental changes, such as events or human input, by using (foundation-model-based) reasoning to determine whether action is required [9]. Based on their memory and available tools, they identify suitable actions, evaluate which ones best fit the current context and goals, and execute them accordingly. Second-order agentic AI systems exhibit the additional capability of collaboration among multiple first-order agentic AI systems.

A. Autonomous Operation

The implementation of autonomous operation in Agentic AI systems represents a sophisticated integration of multiple technological components that work harmoniously to enable independent functioning and adaptive behavior.

1) Independent Decision-Making Processes

Agentic AI systems employ advanced decision-making architectures that combine probabilistic reasoning with deterministic rule sets to enable autonomous operation [10]. These systems utilize multi-layered decision frameworks that process information through various stages of analysis, from rapid-response mechanisms for immediate challenges to strategic-planning capabilities for long-term objectives.

2) Environmental Perception and Analysis

Environmental perception in Agentic AI systems involves sophisticated sensor fusion and data integration techniques that enable comprehensive situational awareness [11]. These systems employ advanced processing algorithms to interpret complex environmental data streams, creating detailed environmental models that support informed decision-making.

3) Real-Time Adaptation Capabilities

The adaptive capabilities of Agentic AI systems extend beyond simple reactive responses to sophisticated real-time learning and adjustment mechanisms. These systems can modify their behavior patterns in response to changing environmental conditions, unexpected obstacles, or new requirements.

B. Fundamentals of Autonomous Data Pipeline Management

Autonomous data pipeline management refers to a highly sophisticated approach that utilizes automation, artificial intelligence (AI), machine learning (ML), and cognitive decision-making to enable management of the entire life cycle of a data pipeline with minimal human involvement [5]. A data pipeline is a chain of steps for data collection, transformation, validation, storage, and delivery.

- The main aim of autonomous data pipeline management is to develop intelligent systems that are capable of continuously tracking the efforts of pipeline operations, identifying issues, getting to their roots, providing automatic recovery, optimizing resource management, and learning from their experience.
- A typical autonomous data pipeline consists of several interconnected stages. The process begins with data ingestion, in which structured, semi-structured, and unstructured data are collected from multiple sources, including databases, cloud storage, APIs, enterprise applications, and streaming platforms.
- An autonomous system may adapt its innovative nature in the process of decision-making based on the historical background and natural conditions. Such adaptability makes the system more reliable, decreasing downtime and operational expenses.

C. Agent Bricks and Multi-Database Integration Framework

The Data bricks Agent Bricks framework establishes a distributed network of intelligent agents for autonomous database operations. The system uses a layered approach to efficiently manage complex tasks across enterprise environments. High-level coordinator agents make strategic decisions about resource allocation and operational policies [12]. The architecture introduces lower-level agents that handle specific database technologies directly, drawing on specialized expertise. Each agent develops expertise in particular database platforms through continuous learning and adaptation. The design follows modern microservices patterns throughout its structural components. The framework enables individual components to scale independently based on dynamic demand patterns. Agent communication uses reliable messaging systems to prevent data loss during transmission.

D. Applications of Agentic Artificial Intelligence

The application of Agentic Artificial Intelligence is discussed below:

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- **Healthcare:** In healthcare, agentic systems have been proposed to assist with clinical documentation, triage support, and multi-specialty coordination, where a primary agent gathers patient information and delegates specific diagnostic sub-questions to specialized reasoning modules [13].
- **Finance:** Financial applications of agentic AI include automated research synthesis across earnings reports and market data, multi-step portfolio analysis, and customer service agents capable of executing account actions through banking APIs.
- **Education:** In education, agentic tutoring systems have been explored to decompose a student's learning goal into a sequence of practice tasks, monitor performance across sessions using episodic memory [14], and adaptively adjust difficulty or explanation style [15].

E. Data Integration Tasks

Unlike other data preparation tasks, which generally relate to exactly one existing data set, data integration handles multiple data sets [16]. Furthermore, advances in real-time technologies and artificial intelligence methods can support optimization of data engineering strategies for organizations.

- **Schema Mapping:** It is the main component of a source description and describes the existing data of a source as well as the relationship between the terms of a source schema and the mediated schema. A schema is a structure of metadata that describes how data can be stored, used and interpreted.
- **Schema Matching:** Identifies semantic similarities by comparing the structures of different data sources, whereby matches between attributes, entities and tables can be discovered despite different names; schema matching is synonymous with semantic matching as the discovery of correlations between different sources, such as the attribute title in one table can correspond to the attribute name in the other table.
- **Data Matching:** checks individual data records to see whether they represent the same entity despite spelling or designation differences, in contrast to schema matching [19]. Data matching is also referred to as record or data linkage, entity resolution, object identification or field matching.
- **Data Fusion:** involves merging entries that represent different entities to gain a better understanding of the concepts represented by the data [30]. Data fusion is the process of merging multiple data sets into a single, consistent and clear representation of the same real-world entity.

III. Schema Convergence in Enterprise Systems

Schema convergence in the context of enterprise systems refers to the harmonization and alignment of database schemas across multiple applications. In many cases, enterprise applications employ heterogeneous databases with different schemas that vary in data structures, names, data types, and semantics. There are several key aspects related to schema convergence:

- **Schema Heterogeneity:** Similar data is represented by different schemas in different enterprise applications in terms of data structures, formatting, naming, and data types.
- **Schema Matching and Mapping:** Establishes correspondences between matching attributes and entities of different schemas.
- **Schema Transformation and Integration:** Transforms the incompatible schema structures to a common schema structure.
- **Schema Evolution Management:** Deals with database structure, attributes, and relationship changes over time without disruption of the existing applications.
- **Conflict Detection and Resolution:** Detects and resolves structural, naming, data types, and semantic conflicts between heterogeneous database schemas.
- **Data Consistency and Interoperability:** Ensures consistency of the data representations in the integrated systems and the possibility of the reliable exchange of information between the systems.
- **Agentic AI-Driven Schema Convergence:** Autonomous AI-based approach to schema analysis, semantic relations discovery, mapping generation, conflict resolution, validation of the transformation, etc.

A. Traditional Mechanisms for Schema Evolution and Convergence

There are traditional methods for handling schema evolution and convergence to keep changes to database structures without compromising data consistency and proper system functioning. The method of schema conversion implements changes at the structural level, while the method of data conversion specifies when and how existing data is updated. Access control and concurrency issues address the schema change process and help manage user privileges and concurrency needs.

1) Schema Conversion Mechanisms

Several suggestions have been proposed for the conversion of the schema at the physical level. Firstly, the complete schema can be converted to a new version. This method, while being conceptually simple, prohibits the parallel schema versions required in some application environments [17]. The approach is to version at the class level, thereby permitting parallel changes as long as they are in different classes. Secondly, a system in which views (or contexts) are constructed and schema evolution is achieved through view creation.

2) Data Conversion Mechanisms

Currently, when a change to a schema is required, any changes made by the Database Administrator are propagated to the data immediately. This method is known as the strict (or eager or early) conversion method, in which a change to the schema results in an immediate propagation of that change to the data. As an alternative, a lazy mechanism converts data in a database to the current version only when required. Changes to the schema can be made more rapidly, and data are changed only when required.

3) Access Right Considerations

In object-oriented database systems where methods and attributes can be inherited from classes higher in the hierarchy, schema evolution changes can result in violations of access rights. Consider, for example, a change to an employee class from which attributes are inherited to an engineer class and for which the modifying user has no legitimate access. Any

DOI: https://doi.org/xxxxxxxxxxxx

change to the definition of these inherited attributes can be considered to violate the access rights of the class.

4) Concurrency Considerations and Concurrent Schemata

In a multi-user environment, it may be possible to modify the database schema while another user is currently accessing the database. These problems can be overcome if schema versioning is supported, but they are significant if only static schema evolution is supported. Multiple concurrent versions have been proposed to allow users to read, modify, and update the same schema version, resulting in alternative versions that remain consistent with the remaining database definition. A surface of consistency is developed by linking consistent parts of the database definition.

B. A Framework for Platform Convergence

The framework proposed here treats convergence not as a single destination but as a spectrum of architectural commitments. It specifies four mechanisms that organizations combine differently, depending on where along that spectrum they intend to sit [18]. Table. I summarizes the spectrum; the four subsections that follow describe the mechanisms in turn.

TABLE I. COMPARATIVE OVERVIEW OF CONVERGENCE PATTERNS ALONG THE FEDERATION-TO-UNIFICATION SPECTRUM

Pattern	Platform Autonomy	Primary Mechanism	Organizational Disruption	Best Suited For
Federation	High — platforms remain fully independent	Standardized query interfaces only	Low	Platforms with minimal functional overlap needing occasional cross-referencing
Canonical layer	High — platforms unchanged internally	Shared canonical data model plus machine learning-based entity and schema matching	Low to moderate	Platforms with substantial overlapping entities but distinct finding types
Domain gateway	High — platforms abstracted behind a stable API	API-first gateway routing queries across platforms	Moderate	Platforms with complementary, non-overlapping functions that must be queried together
Full unification	Low — platforms consolidated	Single shared infrastructure and data model	High	Platforms with near-total functional overlap and low ongoing need for domain specialization

IV. TECHNOLOGIES IN AGENTIC AI SYSTEMS

Agentic AI relies on cutting-edge technologies that provide core capabilities such as autonomy, adaptability, and collaboration.

A. Natural Language Processing and Speech Recognition

These are used to understand natural language, make communication possible, and help with reasoning and text summarization [19]. Technologies like large language models (LLMs), Claude, and Whisper are integrated into agentic AI. These technologies help break complex goals into small tasks. For example, an LLM agent can assign tasks to a warehouse robot or delivery drone in supply chain management.

B. Reinforcement Learning (RL) and Inverse Reinforcement Learning (IRL)

They are both foundational technologies in the agentic AI system. RL and IRL enable AI agents to learn from interacting with their environment. Each action of AI agents receives positive or negative feedback and helps refine their policies [20]. RL focuses on agents learning optimal policies through trial-and-error interaction with the environment. It is powerful for tasks like game playing and robotics but often requires massive amounts of data and suffers in sparse-reward scenarios. Deep reinforcement learning combines RL and neural networks, enabling AI agents to handle more complex and critical tasks. Inverse Reinforcement Learning (IRL) flips this paradigm: instead of learning from rewards, the agent infers the underlying reward function by observing expert demonstrations

C. Multi-Agent Systems (MAS) and Swarm Intelligence Frameworks

These are the core principles that support the coordination and communication between multiple agents. Sometimes, these multi-agents compete with each other to improve performance. For example, collaboration is crucial in swarm robotics and in any decentralized AI ecosystem. Technologies such as JADF (Java Agent Development Framework) are used to implement MAS. Swarm algorithms such as Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are used for rerouting, load balancing, and search-and-rescue operations.

D. Imitation Learning (Il)

It plays a pivotal role in building agentic AI systems. In IL, agents learn behaviors directly from expert demonstrations without requiring an explicit reward function, making it a powerful alternative to Reinforcement Learning (RL) and Inverse Reinforcement Learning (IRL) [21]. It is particularly valuable in complex, real-world environments where designing reward functions is difficult, for example, in robotics, where robots learn manipulation tasks from human demonstrations, and in healthcare, where clinical decision support systems imitate expert diagnoses and treatment paths. There are two main approaches to IL: behavioral cloning (mapping states to actions) and dataset aggregation (iteratively correcting mistakes by an expert).

V. LITERATURE REVIEW

This section highlights related studies on Agentic AI and autonomous data integration, emphasizing agent architectures, data harmonization, schema mapping, trustworthy AI, explainability, and autonomous decision-making to improve data consistency, interoperability, adaptability, and the reliability of schema convergence across diverse enterprise systems.

S. Bajoria et al. (2026) provide a comprehensive, taxonomy-centric, and deployment-focused analysis of agentic AI systems, combining recent progress through a modular reference architecture and a four-dimensional taxonomy that delineates agents according to autonomy, tool application, collaboration, and safety-governance. They emphasize design trade-offs, capability scaling patterns, and recurrent failure mechanisms by methodically analyzing typical single-agent, tool-augmented, and multi-agent frameworks within this taxonomy. They examine new evaluation techniques that go beyond static benchmarks to evaluate agent behavior, robustness, grounding, and

DOI: https://doi.org/xxxxxxxxxxxx

operational cost in interactive contexts in addition to architectural study [22].

X. Hou, Y. Mualla, and M. Dridi (2026) investigate the theoretical basis of explainable agentic AI and contend that current XAI techniques do not accurately represent the complexity of autonomous, process-driven actions. They examine how existing methods try to apply conventional XAI techniques to agentic systems and identify their methodological shortcomings using an exploratory literature analysis. The document arranges the dialogue around four essential research queries: the importance of explainable agentic AI, the aspects that need to be articulated, the timing for explanation generation, and the processes for creating explanations. The idea of fidelity is carefully considered, specifically in terms of whether explanations provide reasonable justifications after the fact rather than just mirroring the decision-making process [23].

A. Santos et al. (2025) propose for agentic data harmonization as a strategy to facilitate experts in unifying their data and improving procedural efficiency. They provide Harmonia, a system that automates the synthesis of data harmonization pipelines by combining an interactive user interface, LLM-based reasoning, and a library of data harmonization primitives. They use a clinical data harmonization scenario to illustrate Harmonia, which facilitates the interactive creation of reusable pipelines that map datasets to a common format [24].

L. Wang et al. (2024) provide an extensive examination of these investigations, offering a methodical analysis of LLM-driven autonomous agents from an integrated viewpoint. They initially talk about building LLM-based autonomous agents and provide a cohesive framework that incorporates a lot of earlier research. Subsequently, provide a summary of the many utilizations of LLM-driven autonomous agents in the fields of social research, natural science, and engineering. Ultimately, they explore the assessment methodologies often used for LLM-driven autonomous agents [25].

A. Pelosi et al. (2023) present a unique paradigm for developing trustworthy AI systems based on Hybrid Distributed Ledger Technology (Hybrid DLT). They examine the transition from a paradigm that relies on correctness to one that incorporates reliability into the design. Our framework makes it easier for several entities to work together throughout a supervised learning machine learning solution's data preparation, model training, and classification stages. It employs a communal ledger that provides a tamper-proof audit trail of each transaction, guaranteeing non-repudiation and reproducibility [26].

P. Radanliev and D. De Roure (2022) introduce a novel autonomous artificial intelligence (AI) system named "AutoAI," which is based on cutting-edge algorithms. The design is put together using an approach based on self-improved algorithms that make advantage of new and emerging data sources (NEFD). The objective of the paper is to develop a new AutoAI algorithm. The creation of new and enhanced algorithms is advanced by the conceptual approach. The paper enhances the AutoAI design by (1) using new and developing data sources for teaching and training AI algorithms and (2) allowing AI algorithms to employ automated tools for training new and better algorithms. It does this by integrating and integrating the results from current research [27].

Research Gap: Recent work explores agentic AI frameworks, elucidates explainability, addresses data harmonization, ensures trustworthy AI, and examines autonomous learning. But instead of offering a comprehensive framework for enterprise-wide schema convergence and autonomous data integration, these methods focus on specifics. Insufficient studies integrate agentic big language models, semantic congruence, schema alignment, and automated schema progression to address diverse data frameworks. Additionally, difficulties associated with mapping accuracy, system interoperability, continual adaptability, transparency in decision-making, and dependable validation have yet to be adequately addressed. Thus, in order to guarantee scalability, consistency, explainability, and reliable operation across various corporate contexts, a single agentic framework is required to regulate autonomous schema matching, data harmonization, and schema convergence.

Table I presents a comparative examination of current research on Agentic AI and self-sufficient data management. It outlines the research focus, methodologies, essential findings, limitations, and future research paths, accentuating agent architectures, data harmonization, schema mapping, trustworthy AI, autonomous decision-making, and the challenges of ensuring reliable and scalable data integration throughout enterprise systems.

TABLE II. COMPARATIVE ANALYSIS OF EXISTING STUDIES ON AGENTIC AI, DATA HARMONIZATION, AND AUTONOMOUS SYSTEMS

Reference	Study Focus	Approach / Methodology	Key Findings	Challenges / Limitations	Future Directions
S. Bajoria et. al. (2026)	Taxonomy and architecture of agentic AI systems	Develops a modular architecture and four-dimensional taxonomy	Identifies agent capabilities, design trade-offs, and evaluation methods	Reliability, safety, governance, and deployment costs	Improve evaluation, access control, and enterprise deployment
X. Hou, Y. Mualla, and M. Dridi (2026)	Explainability in agentic AI	Exploratory literature review of explainable AI approaches	Highlights the need for process-level explanations and faithful reasoning	Existing methods struggle to explain autonomous decisions and agent trajectories	Develop faithful, causal, and accountable explanation frameworks
A. Santos et. al. (2025)	Agentic data harmonization	Develops Harmonia using LLM reasoning, user interaction, and harmonization primitives	Automates the creation of reusable data harmonization pipelines	Requires expert interaction and validation of generated mappings	Extend automation and evaluate across diverse datasets and domains
L. Wang et. al. (2024)	LLM-based autonomous agents	Surveys agent construction, applications, and evaluation strategies	Provides a unified framework for understanding autonomous agents	Evaluation consistency and generalization remain challenging	Develop standardized benchmarks and more reliable agent architectures
A. Pelosi et. al. (2023)	Trustworthy AI through Hybrid	Proposes a shared-ledger framework for	Improves auditability, traceability, and	Scalability, implementation	Evaluate scalability and extend trustworthy AI mechanisms

	Distributed Ledger Technology	collaborative machine learning	reproducibility of AI operations	complexity, and integration overhead	
P. Radanliev and D. De Roure (2022)	Autonomous AI design and self-improving algorithms	Conceptualizes AutoAI using emerging data sources and automated training tools	Proposes an approach for automated algorithm improvement and training	Practical validation and reliable autonomous improvement require further investigation	Develop and evaluate AutoAI systems in real-world environments

VI. Conclusion and Future Work

An exciting new direction in data integration and schema convergence management is offered by agentic AI. By synthesizing observation, reasoning, planning, tool deployment, and execution, intelligent agents may assist in monitoring data pipelines, aligning schemas, mapping, transforming, and resolving conflicts. The cooperation of several agents may aid in work distribution across disparate database systems, whereas canonical models, gateways, federation, and unified architectures provide other methods for convergence. Nevertheless, autonomous choices must be dependable, comprehensible, secure, and aligned with organizational governance standards. Schema evolution presents difficulties related to simultaneous access, data transformation, authorization, and interoperability with current applications. The research suggests possibilities for minimizing manual labor and enhancing interoperability, although it also highlights the need for more rigorous assessment and practical validation. Consequently, a robust framework must integrate agent independence with clear decision documentation, validation mechanisms, access restrictions, and human supervision for significant alterations. A well-structured design may provide flexible integration while safeguarding data integrity and ensuring operational consistency.

Further work must deploy and assess the framework in regard to enterprise databases and adaptive schemas. Investigations need to assess alignment precision, integration duration, recuperation efficacy, scalability, and operating expenses in comparison to methodologies. Additional research must reinforce explainability, security, governance, and human supervision, while assessing multi-agent cooperation and conflict resolution in contexts that are in constant Fluxus's.

- **Funding:** This research received no external funding.
- **Institutional Review Board Statement:** Not applicable.
- **Informed Consent Statement:** Not applicable.
- **Data Availability Statement:** The data supporting the findings of this study are available from the corresponding author upon reasonable request.
- **Conflicts of Interest:** The author declares no conflict of interest.

How to cite this article:
P. Laxkar, "An Agentic AI Framework for Autonomous Data Integration and Schema Convergence in Enterprise Systems," *Journal of Global Research in Multidisciplinary Studies*, vol. 2, no. 11, pp. 08–14, Nov. 2026. Doi: XXXX

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