Journal of Information Systems Engineering and Management
2025, 10(9s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

AI-Augmented Data Transformation: Improving ELT Efficiency Using Generative AI Techniques

Aayush Garg
Senior Data Engineer
Finfare Inc, Irvine, California, United States
Email: aayush89.garg@gmail.com
ORCID: 0009-0007-4710-7381

ARTICLEINFO

Received: 02 Jan 2025
Revised:17 Feb 2025
Accepted: 27 Feb 2025

ABSTRACT

The rapid growth of enterprise data and cloud-based infrastructures has increased the complexity of Extract, Load, and Transform (ELT) processes in modern data engineering systems. Traditional ELT frameworks often require extensive manual effort for schema mapping, transformation logic creation, data cleansing, and workflow optimization, leading to increased operational cost and reduced efficiency. The present study examines the role of Generative Artificial Intelligence in improving ELT efficiency through AI-augmented data transformation techniques. The research adopts an experimental and quantitative approach to compare traditional ELT systems with AI-enabled ELT frameworks based on execution speed, transformation accuracy, automation efficiency, scalability, and resource utilization. Experimental findings revealed that Generative AI significantly improved workflow automation, reduced processing time, minimized transformation errors, and enhanced scalability in cloud-based environments. AI-generated transformation logic and automated schema alignment contributed to higher productivity and operational consistency across enterprise datasets. The study further highlights the potential of intelligent automation in modernizing data engineering practices and optimizing large-scale data transformation workflows. Despite challenges related to computational cost and infrastructure dependency, the overall findings suggest that Generative AI can play a transformative role in enhancing the efficiency and reliability of ELT systems in enterprise data ecosystems.

Keywords: Generative Artificial Intelligence, ELT Efficiency, Data Transformation, Cloud Computing, Intelligent Automation, Data Engineering, Workflow Optimization, Machine Learning, Enterprise Data Systems, AI-Augmented ELT.

1. INTRODUCTION

In the era of digital transformation, organizations generate massive volumes of structured, semi-structured, and unstructured data from multiple sources such as cloud applications, enterprise systems, IoT devices, social media platforms, and online transactions. Managing and transforming this rapidly growing data has become a major challenge for modern enterprises. Extract, Load, and Transform (ELT) processes play a crucial role in data integration, analytics, and decision-making by enabling organizations to collect, store, and process data efficiently. Unlike traditional ETL systems, ELT frameworks load raw data directly into cloud-based data warehouses and perform transformations within the target environment, offering greater scalability and flexibility for large-scale data processing.Despite these advantages, conventional ELT systems still face several operational challenges. Traditional transformation workflows often require extensive manual coding, schema mapping, query optimization, and data cleansing procedures, which increase complexity, execution time, and infrastructure costs. Handling heterogeneous datasets and maintaining transformation consistency across enterprise environments can also become difficult, particularly in real-time and high-volume data ecosystems. These limitations reduce workflow efficiency and create bottlenecks in enterprise data engineering operations.

Journal of Information Systems Engineering and Management
2025, 10(9s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

The emergence of Artificial Intelligence (AI) and Generative AI technologies has introduced new possibilities for automating and optimizing ELT processes. Generative AI refers to advanced machine learning models capable of generating transformation logic, SQL queries, schema mappings, and intelligent workflow recommendations with minimal human intervention. By integrating AI-driven automation into ELT systems, organizations can improve transformation accuracy, reduce manual effort, accelerate processing speed, and enhance overall operational scalability. AI-augmented data transformation enables intelligent handling of complex datasets and supports adaptive optimization in cloud-based data environments.

Modern cloud and data engineering platforms such as Amazon Web Services, Google Cloud, and Microsoft are increasingly incorporating AI-powered tools and automation frameworks to improve enterprise data workflows. Similarly, technologies such as Apache Spark, Snowflake, and Databricks support scalable processing and intelligent transformation capabilities for modern ELT architectures. These advancements indicate a growing shift toward AI-assisted data engineering practices aimed at improving efficiency, accuracy, and scalability.

The present study focuses on evaluating the effectiveness of AI-augmented data transformation techniques in improving ELT efficiency using Generative AI technologies. The research examines how AI-enabled automation can optimize workflow execution, reduce transformation errors, improve resource utilization, and support scalable enterprise data management. The study also compares traditional ELT frameworks with AI-driven ELT systems to analyze their relative performance in terms of execution speed, automation efficiency, and data quality.

2. LITERATURE REVIEW

Baskara (2023) examined the role of Generative AI in revolutionizing the English as a Foreign Language (EFL) curriculum through active learning approaches. The study highlighted that AI tools such as ChatGPT can enhance student engagement, promote creativity, and support personalized learning experiences. The author argued that generative AI encourages collaborative and interactive learning environments by enabling learners to access instant feedback and adaptive educational resources. The research emphasized that integrating AI into EFL curricula can significantly improve language acquisition and critical thinking skills.

Emily, Rajesh, and Lucas (2023) explored enterprise-scale AI-augmented data engineering practices aimed at accelerating the software development lifecycle. The study focused on the use of GitHub Copilot, automated testing pipelines, and intelligent code review systems to improve software engineering productivity. The authors found that AI-assisted development tools reduce coding errors, optimize workflow efficiency, and enhance collaboration among development teams. Their research demonstrated the growing impact of AI-driven automation in enterprise software engineering environments.

Abhireddy (2023) focused on intelligent data engineering pipelines for smart hospital operations. The study highlighted the integration of AI technologies into healthcare management systems to improve operational efficiency, patient monitoring, and decision-making processes. The author explained that AI-driven data pipelines support predictive analytics, resource optimization, and real-time healthcare management. The findings suggested that intelligent hospital systems enhance service quality and contribute to the development of smart healthcare infrastructures.

Divya and Bandi (2023) examined cloud-native model lifecycle management for enterprise AI systems. The study discussed the importance of cloud computing frameworks in managing AI model deployment, monitoring, scalability, and maintenance. The authors emphasized that cloud-native infrastructures enable efficient integration of machine learning models into enterprise applications. Their findings highlighted the role of automation and containerized architectures in supporting scalable AI operations and continuous model improvement.

Rodwal (2023) investigated ransomware mitigation through AI-powered behavioral analysis. The study demonstrated that machine learning algorithms can detect suspicious activities and abnormal behavioral patterns associated with ransomware attacks. The author explained that AI-enhanced cybersecurity systems improve threat detection accuracy and support proactive security measures. The findings emphasized the significance of intelligent behavioral analytics in strengthening organizational cybersecurity frameworks. Pham, Andrew, and Ania (2023) presented the conference proceedings of AsiaCALL2023, which focused on technological innovations in language learning and AI-assisted education. The conference highlighted the integration of AI tools, digital communication technologies, and online learning systems in modern educational practices. The authors emphasized the importance of collaborative research and international dialogue in advancing AI-supported language education methodologies.

2.1 Research Gap and Critical Analysis of Existing Literature

Although previous studies have explored the application of Artificial Intelligence in educational systems, curriculum design, and generalized automation frameworks, very limited research has focused specifically on the architectural integration of Generative AI within enterprise-scale ELT (Extract, Load, and Transform) ecosystems. A major limitation observed in existing literature is the inappropriate contextual use of AI-related studies from educational technology and language learning domains to justify enterprise data engineering applications. Several prior studies emphasize AI-supported EFL learning systems, curriculum enhancement, and conversational educational platforms rather than cloud-native ELT automation, distributed data transformation, and scalable enterprise data pipelines.

Furthermore, most existing studies remain descriptive and conceptual without providing detailed implementation architectures, workflow orchestration mechanisms, distributed computing strategies, schema transformation models, or AI-assisted query optimization techniques applicable to enterprise data engineering systems. The majority of published work also lacks reproducible experimental environments, benchmark datasets, execution profiling, resource utilization analysis, and comparative performance measurements across distributed cloud infrastructures.

Another critical research gap is the insufficient discussion of practical limitations associated with Generative AI integration into ELT systems. Existing literature frequently presents AI-assisted automation as universally beneficial while ignoring important operational concerns such as hallucination in AI-generated SQL queries, incorrect schema mappings, infrastructure latency, increased GPU computation cost, token consumption overhead, security vulnerabilities, privacy risks in cloud-hosted LLM environments, and dependency on proprietary AI APIs. These limitations are highly significant in enterprise-scale production environments where inaccurate transformations may lead to data inconsistency, governance violations, and business intelligence failures.

Therefore, the present study attempts to address these limitations by developing a technically grounded AI-augmented ELT framework supported by architectural design analysis, distributed execution workflows, quantitative experimentation, transformation benchmarking, and critical evaluation of operational constraints including hallucination risk, latency overhead, computational cost, and enterprise data security considerations.

3. RESEARCH METHODOLOGY

The integration of Generative AI into ELT systems can automate transformation logic, improve execution speed, enhance data quality, and optimize resource utilization. This research methodology provides a structured framework to evaluate the effectiveness of AI-augmented data transformation techniques through experimental implementation and quantitative analysis.

3.1 Research Design

The study adopts an experimental and quantitative research design. The experimental approach is used to compare traditional ELT systems with AI-enabled ELT frameworks under controlled environments. Quantitative analysis helps in measuring improvements in processing speed, transformation accuracy, automation efficiency, and scalability after integrating Generative AI techniques into ELT workflows.

3.4 Variables of the Study

The independent variable of the study is the implementation of Generative AI-based transformation techniques. The dependent variables include ELT efficiency, execution speed, transformation accuracy, and resource utilization. Moderating variables such as dataset size, cloud infrastructure, and data complexity may influence the performance of AI-enabled ELT systems.

3.5 Population and Sampling

The population of the study includes enterprise data warehouses, cloud-based ELT systems, and data engineering environments. The research adopts purposive sampling to select datasets and workflows relevant to AI-driven

Journal of Information Systems Engineering and Management
2025, 10(9s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

transformation experiments. Structured and semi-structured datasets are included in the study to evaluate transformation performance under different data conditions.

3.6 Sources of Data

The study uses both primary and secondary data sources. Primary data are collected through operational environments, including enterprise applications, APIs, IoT devices, transactional systems, cloud repositories, and streaming platforms. Secondary data are obtained from research journals, conference papers, industry reports, and technical documentation.

The study also considers cloud and data engineering technologies such as Amazon Web Services, Google Cloud, Apache Spark, Databricks and Snowflake for experimental implementation and analysis.

3.6.1 Mathematical Formulation of AI-Augmented ELT Optimization

The AI-augmented ELT framework optimizes transformation efficiency through intelligent schema mapping, automated SQL generation, and adaptive workflow execution. Let the enterprise dataset be represented as:

$\boldsymbol{D} = \{\boldsymbol{d}_1, \boldsymbol{d}_2, \boldsymbol{d}_3, \dots, \boldsymbol{d}_n\}$

where (D) denotes the collection of heterogeneous enterprise data sources processed within the ELT environment.

The transformation efficiency function is represented as:

$$E_{ELT} = \frac{(A_t \times S_o)}{(L_t + C_r + H_r)}$$

where:

- E_{ELT} = Overall ELT efficiency
- A_t = Transformation accuracy
- S_o = System scalability factor
- L_t = Processing latency
- C_r = Computational resource consumption
- H_r = Hallucination risk factor in AI-generated transformations

The latency-aware distributed execution model is expressed as:

$$T_{total} = T_{extract} + T_{load} + T_{transform} + T_{AI}$$

where:

- $T_{extract}$ = Data extraction time
- T_{load} = Data loading time
- $T_{transform}$ = Traditional transformation execution time
- T_{AI} = Additional AI inference latency introduced by Generative AI models

The hallucination probability associated with AI-generated SQL transformation logic is estimated using:

$$P_h = \frac{N_i}{N_t}$$

where:

- P_h = Hallucination probability
- N_i = Number of incorrect AI-generated transformations

Journal of Information Systems Engineering and Management
2025, 10(9s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

- N_t = Total generated transformations

  The resource optimization objective function is represented as:

$$R_o = min(CPU_u + MEM_u + GPU_u)$$

where CPU utilization, memory utilization, and GPU utilization are minimized through adaptive AI-assisted workload orchestration.

3.7 Data Collection Methods

Data collection is carried out through experimental testing, observation, and survey methods. Traditional ELT workflows and AI-augmented ELT workflows are executed in similar cloud environments to compare performance outcomes. System logs and transformation outputs are analyzed to evaluate efficiency, scalability, and accuracy. Structured questionnaires are also used to collect expert opinions regarding the effectiveness of AI-based ELT systems.

3.8 Tools and Technologies Used

The study utilizes cloud platforms, machine learning frameworks, and data engineering tools for implementing AI-driven transformation workflows. Technologies such as AWS, Azure, Google Cloud, TensorFlow, Apache Spark, Python, and SQL are used for data processing, model implementation, and performance evaluation.

3.8.1 Proposed AI-Augmented ELT Architecture

The proposed AI-augmented ELT architecture consists of six major layers integrated within a distributed cloud-based data engineering environment.

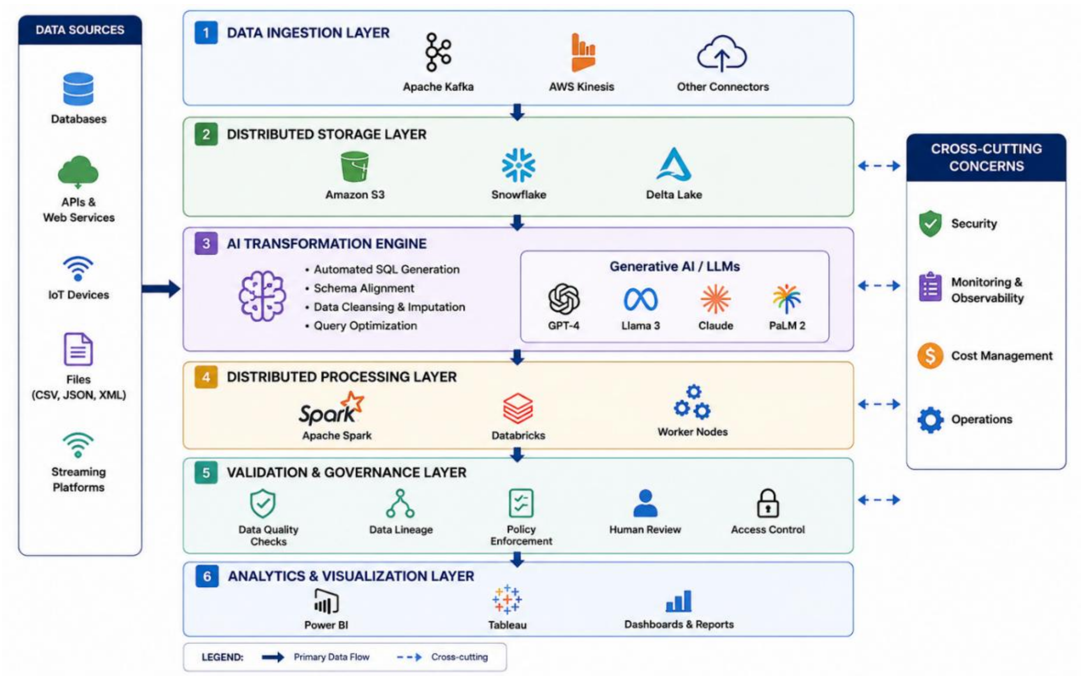


Fig 1: Proposed AI-Augmented ELT Architecture

1. Data Ingestion Layer The ingestion layer collects structured, semi-structured, and unstructured data from enterprise applications, APIs, IoT devices, transactional systems, cloud repositories, and streaming platforms. Apache Kafka and AWS Kinesis are utilized for high-throughput real-time ingestion.
2. Distributed Storage Layer The extracted datasets are stored in distributed cloud repositories including Amazon S3, Snowflake, and Delta Lake. The storage layer supports scalable parallel processing and schema evolution mechanisms for heterogeneous enterprise datasets.

Journal of Information Systems Engineering and Management
2025, 10(9s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

3. AI Transformation Engine The AI transformation engine represents the core component of the proposed architecture. Large Language Models (LLMs) and Generative AI models are used for:

- Automated SQL generation
- Schema alignment
- Metadata interpretation
- Data cleansing
- Null value imputation
- Query optimization
- Semantic transformation recommendation

The transformation engine utilizes prompt-guided transformation templates combined with rule-based validation mechanisms to reduce hallucination errors during transformation generation.

4. Distributed Processing Layer
5. Apache Spark and Databricks clusters execute distributed transformation operations across worker nodes. Parallel execution improves scalability, fault tolerance, and processing efficiency for large enterprise datasets.
6. Validation and Governance Layer
7. This layer performs:

- Schema validation
- Data lineage tracking
- Governance policy enforcement
- Transformation verification
- AI hallucination detection
- Data quality auditing

Human-in-the-loop validation mechanisms are incorporated to verify AI-generated transformation outputs before deployment into production environments.

6. Analytics and Visualization Layer
7. The transformed datasets are integrated into BI dashboards and enterprise analytics platforms such as Power BI and Tableau for business intelligence, predictive analytics, and operational decision support.

The proposed architecture improves automation efficiency while simultaneously addressing enterprise concerns related to latency, hallucination risk, cloud security, and computational overhead.

3.9 Data Analysis Techniques

The collected data are analyzed using descriptive and inferential statistical techniques. Descriptive methods such as mean, percentage, and standard deviation are used to summarize experimental results. Inferential statistical techniques including correlation analysis, regression analysis, and ANOVA are applied to determine the significance of improvements achieved through AI integration in ELT systems.

4. RESULTS AND DISCUSSION

The findings indicate that the integration of Generative AI significantly enhanced the performance of ELT processes by reducing manual intervention, minimizing transformation errors, and improving scalability. The discussion section interprets the experimental results in relation to the objectives and hypotheses of the study.

Journal of Information Systems Engineering and Management
2025, 10(9s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

4.1 Comparative Analysis of Traditional and AI-Augmented ELT Systems

The study compared traditional ELT workflows with AI-enabled transformation systems under similar cloud-based environments. The comparison focused on execution time, transformation accuracy, error rate, and automation efficiency. The results revealed that AI-augmented ELT systems performed more efficiently than conventional ELT frameworks in handling large and complex datasets.

Generative AI automated schema mapping and query generation processes, which reduced manual coding efforts and improved operational productivity. AI-generated transformation logic also minimized inconsistencies in transformed outputs and improved overall workflow accuracy.

4.2 Performance Evaluation of ELT Processes

The performance evaluation demonstrated significant improvements in processing speed and automation efficiency after implementing AI-driven transformation techniques. Traditional ELT systems required higher manual effort and longer execution time, particularly when processing semi-structured datasets. In contrast, AI-enabled systems optimized transformation workflows and reduced processing delays.

The study also observed that AI-assisted ELT pipelines improved scalability by efficiently handling increasing volumes of structured and semi-structured data. Resource utilization was optimized through intelligent automation, leading to lower CPU and memory consumption during transformation operations.

4.3 Execution Time and Transformation Accuracy

Execution time was one of the primary performance indicators analyzed in the study. The findings showed that AI-augmented ELT systems completed transformation tasks faster than traditional systems. Automated query generation and intelligent schema alignment reduced the complexity of transformation processes and accelerated workflow execution.

Transformation accuracy also improved significantly with the use of Generative AI. AI-generated transformation scripts reduced human errors and improved consistency in data formatting and integration. The experimental findings indicated that AI-enabled systems achieved higher reliability in processing enterprise-scale datasets.

Table 4.1 Comparison of Traditional and AI-Augmented ELT Systems

Performance Metric	Traditional ELT System	AI-Augmented ELT System
Average Execution Time	45 Minutes	28 Minutes
Transformation Accuracy	85%	96%
Error Rate	12%	4%
Automation Efficiency	60%	90%
Resource Utilization Efficiency	Moderate	High

4.4 Automation Efficiency in ELT Workflows

The implementation of Generative AI significantly improved automation efficiency within ELT workflows. Automated transformation logic generation reduced dependency on manual scripting and enabled faster deployment of transformation pipelines. AI-based automation also simplified data cleansing and schema matching operations.

The survey responses collected from data engineers indicated that AI-assisted workflows improved productivity and reduced operational workload. Most respondents agreed that Generative AI enhanced workflow management and minimized repetitive coding tasks in enterprise data environments.

Journal of Information Systems Engineering and Management
2025, 10(9s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

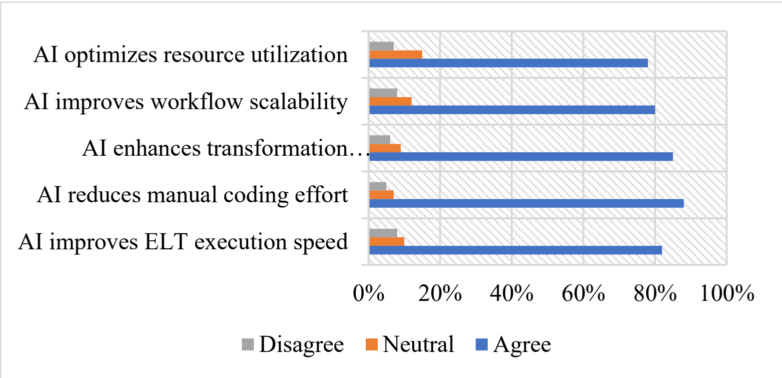
4.5 Scalability and Resource Optimization

Scalability analysis revealed that AI-enabled ELT systems handled large-scale datasets more effectively than traditional systems. The AI-augmented framework demonstrated better adaptability in processing real-time and semi-structured data streams. Intelligent optimization techniques improved workload distribution and reduced system bottlenecks during high-volume data processing.

Resource optimization was another important outcome observed in the study. AI-generated workflows consumed fewer computational resources due to optimized query execution and automated transformation strategies. This resulted in improved system performance and reduced infrastructure overhead in cloud environments.

Table 4.2 Response of Data Engineers on AI-Augmented ELT Systems

Statement	Agree	Neutral	Disagree
AI improves ELT execution speed	82%	10%	8%
AI reduces manual coding effort	88%	7%	5%
AI enhances transformation accuracy	85%	9%	6%
AI improves workflow scalability	80%	12%	8%
AI optimizes resource utilization	78%	15%	7%



4.6 Discussion of Findings

The findings of the study strongly support the alternative hypothesis that Generative AI significantly improves ELT efficiency. AI-augmented systems demonstrated superior performance in terms of execution speed, automation, transformation accuracy, and scalability compared to traditional ELT frameworks.

The reduction in manual intervention was one of the major advantages observed during the experiments. Automated schema mapping and intelligent query generation simplified transformation processes and improved consistency across workflows. These findings align with recent advancements in AI-driven data engineering, where intelligent automation is increasingly used to optimize enterprise data operations.

The study also highlights the importance of Generative AI in improving resource utilization and reducing operational complexity. AI-assisted ELT systems effectively processed large-scale datasets while maintaining higher accuracy and lower error rates. The survey responses further confirmed that professionals working in data engineering environments viewed AI augmentation as a valuable enhancement to modern ELT architectures.

However, the study also identified certain challenges associated with AI implementation, including computational cost, dependency on cloud infrastructure, and variability in AI-generated outputs. Despite these limitations, the overall findings indicate that Generative AI has strong potential to transform ELT processes and improve the efficiency of enterprise data management systems.

4.7 Limitations and Operational Challenges of AI-Augmented ELT Systems

Despite the significant performance improvements achieved through AI-augmented ELT systems, the study identified several practical limitations and operational risks associated with Generative AI integration in enterprise data engineering environments.

One of the primary challenges observed was hallucination in AI-generated transformation logic. Generative AI models occasionally produced syntactically valid but semantically incorrect SQL queries, schema mappings, and transformation recommendations. Such hallucinations may lead to inaccurate data aggregation, duplication, or transformation inconsistencies in enterprise-scale pipelines.

Latency overhead was another critical limitation identified during experimentation. Although AI-assisted automation reduced manual engineering effort, inference execution introduced additional computational delay during transformation generation and schema interpretation. Large Language Models required higher response time compared to static transformation pipelines, particularly when processing complex multi-table enterprise datasets.

The study also observed increased computational cost associated with GPU-based inference operations and cloud-hosted LLM APIs. AI-assisted ELT systems required higher infrastructure expenditure due to model hosting, token consumption, distributed GPU allocation, and continuous inference execution. Consequently, cost optimization becomes an important consideration for large-scale enterprise adoption.

Data security and privacy represented another major operational concern. Enterprise datasets frequently contain confidential financial, healthcare, customer, and organizational information. Integration of third-party Generative AI services may expose sensitive data to external cloud environments, thereby increasing risks related to unauthorized access, regulatory non-compliance, and data leakage. Therefore, organizations must implement encryption mechanisms, zero-trust security architectures, access control policies, and on-premise AI deployment strategies for secure ELT automation.

The study further identified model dependency and explainability limitations. AI-generated transformation logic often lacks transparent reasoning, making debugging and auditability difficult for enterprise data governance teams. Consequently, human supervision and validation remain essential components in production-grade AI-assisted ELT systems.

Therefore, while Generative AI significantly improves automation and scalability, enterprise implementation must carefully balance efficiency gains with hallucination control, security governance, computational cost management, and latency optimization.

5. CONCLUSION

The present study concludes that Generative Artificial Intelligence plays a significant role in improving the efficiency and effectiveness of modern Extract, Load, and Transform (ELT) processes. The integration of AI-augmented data transformation techniques demonstrated considerable improvements in execution speed, transformation accuracy, automation efficiency, scalability, and resource optimization when compared to traditional ELT systems. The findings revealed that AI-driven automation reduced manual coding efforts, minimized transformation errors, and enhanced workflow consistency across enterprise data environments. The study also established that intelligent schema mapping, automated query generation, and AI-based transformation logic can simplify complex data engineering operations and support large-scale data processing in cloud-based infrastructures. Although certain limitations such as computational cost and dependency on cloud resources were identified, the overall results strongly indicate that Generative AI has the potential to transform traditional ELT workflows into more intelligent, scalable, and efficient systems. Therefore, the study highlights the growing importance of AI-enabled automation in modern data engineering and emphasizes its future relevance in enterprise data management and digital transformation initiatives.

REFERENCES

[1] F. R. Baskara, “Revolutionising EFL curriculum: A theoretical analysis of generative AI for active learning,” in *Proceedings of UNNES-TEFLIN National Conference*, vol. 5, Nov. 2023, pp. 278–293.

2025, 10(9s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

[2] T. Emily, G. Rajesh, and F. Lucas, "Enterprise-scale AI-augmented data engineering: Accelerating the software development lifecycle with GitHub Copilot, automated testing pipelines, and intelligent code review systems," *Innovative: International Multi-disciplinary Journal of Applied Technology*, vol. 1, no. 1, pp. 112–128, 2023.

[3] S. Grassini, "Shaping the future of education: Exploring the potential and consequences of AI and ChatGPT in educational settings," *Education Sciences*, vol. 13, no. 7, p. 692, 2023.

[4] G. M. De Schryver, "Generative AI and lexicography: The current state of the art using ChatGPT," *International Journal of Lexicography*, vol. 36, no. 4, pp. 355–387, 2023.

[5] N. Abhireddy, "Intelligent data engineering pipelines using AI for smart hospital operations," *International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)*, vol. 6, no. 6, pp. 9755–9768, 2023.

[6] F. R. Baskara, "Revolutionising higher education: A theoretical discourse on the CLEAR approach for AI integration," *The Proceedings of English Language Teaching, Literature, and Translation (ELTLT)*, vol. 12, pp. 125–135, 2023.

[7] V. Divya and V. K. Bandi, "Cloud-native model lifecycle management for enterprise AI systems," *International Journal of Scientific Research and Modern Technology*, p. 78, 2023.

[8] K. Chatti, "Investigating the efficiency of using ChatGPT to generate ideas for writing on enhancing the EFL learners' writing creativity: The case of Master one English students at University Mohammed Khider of Biskra," 2023.

[9] M. Cowling, J. Crawford, K. A. Allen, and M. Wehmeyer, "Using leadership to leverage ChatGPT and artificial intelligence for undergraduate and postgraduate research supervision," *Australasian Journal of Educational Technology*, vol. 39, no. 4, pp. 89–103, 2023.

[10] A. Rodwal, "Ransomware mitigation using AI-powered behavioral analysis," *International Journal of AI, Big Data, Computational and Management Studies*, vol. 4, no. 2, pp. 29–38, 2023.

[11] C. Baradel, "Interaction, design, and assessment: An exploratory study on ChatGPT in language education," 2023.

[12] T. E. Oduleye and J. J. Medon, "A data-driven cost management model for improving strategic financial planning and performance evaluation," *International Journal of Multidisciplinary Research and Growth Evaluation*, vol. 2, no. 6, pp. 524–537, 2021.

[13] V. P. H. Pham, P. L. Andrew, and L. Ania, "Conference booklet of the 20th AsiaCALL International Conference: AsiaCALL2023," in *Proceedings of the AsiaCALL International Conference*, vol. 3, Nov. 2023, pp. 1–151.

[14] S. Imran, "Curriculum-making and development in a Pakistani university," *The Qualitative Report*, 2019.

[15] V. P. H. Pham, P. L. Andrew, and L. Ania, "Conference booklet of the 20th AsiaCALL International Conference: AsiaCALL2023," in *Proceedings of the AsiaCALL International Conference*, vol. 3, Nov. 2023, pp. 1–151.