WCRG Global Research
WORLD COMET RESEARCH GROUP

International Journal of Artificial Intelligence & Digital Transformation
Vol. 5, No. 2, 2022
Doi: 10.67228/30713315/IJAIDT-2022PII9A1N
PP. 01-12

Original Article

Transformer-Based Architectures for Intelligent ETL Processes

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Received: 11-06-2022 Revised: 11-24-2022 Accepted: 12-01-2022 Published: 12-03-2022

ABSTRACT

Traditional Extract, Transform, Load (ETL) processes are fundamental to data integration and management, yet they often struggle with scalability, adaptability, and semantic understanding of diverse data sources. This paper explores the application of Transformer-based architectures to design intelligent ETL pipelines capable of automating complex data transformation tasks, handling schema drift, and improving data quality through contextual semantic analysis. We propose a modular ETL framework powered by state-of-the-art Transformer models such as BERT and T5, and demonstrate how these models enhance schema inference, data mapping, and transformation logic. Comparative evaluations show significant improvements in accuracy and adaptability over traditional ETL systems. The paper also discusses challenges, limitations, and directions for future research in the convergence of AI and data engineering.

KEYWORDS

Transformer Architecture, ETL, Data Engineering, Semantic Data Integration, Intelligent Data Pipelines, Schema Inference, Data Transformation, BERT, T5, Big Data.

ISSN: 3071-3315
PP: 01-12.

1. INTRODUCTION

1.1. Overview of Traditional ETL Processes

ETL (Extract, Transform, Load) processes form the backbone of traditional data warehousing and business intelligence systems. The ETL workflow involves extracting data from various sources often in heterogeneous formats transforming that data into a common schema or model, and then loading it into a data warehouse, data lake, or other analytical systems. This process is typically rule-based, rigid, and orchestrated using predefined workflows. The transformation phase, in particular, is highly manual, requiring significant input from data engineers to write and maintain complex scripts for tasks such as schema mapping, data cleansing, and format standardization. While traditional ETL has served enterprises well for decades, the growing complexity, volume, and velocity of data in modern ecosystems have begun to outstrip its capabilities.

1.2. Challenges with Legacy ETL Tools

Despite their widespread use, legacy ETL tools like Informatica, Talend, and Apache Nifi exhibit several limitations. First, they lack scalability in the face of big data and cloud-native architectures, often struggling with the ingestion and transformation of petabyte-scale datasets in real time. Second, their workflows are static, offering limited flexibility in adapting to changes such as schema drift, evolving data sources, and unstructured or semi-structured formats like JSON or XML. Third, most traditional tools operate without any learning capabilities; they cannot infer patterns, recognize context, or make intelligent decisions about data transformation without manual configuration. These limitations make it increasingly difficult for organizations to keep up with the dynamic and heterogeneous nature of modern data environments.

1.3. Rise of AI in Data Engineering

In response to the growing complexity of data pipelines, the field of data engineering is undergoing a paradigm shift with the integration of Artificial Intelligence (AI) and Machine Learning (ML). AI-driven ETL frameworks aim to automate schema mapping, anomaly detection, data validation, and transformation logic by learning from existing data patterns and contextual cues. Transformer models, which have revolutionized natural language processing (NLP), are now being repurposed to understand, represent, and transform structured and semi-structured data. The ability of these models to grasp semantics and context makes them ideal candidates for intelligent ETL applications. Their use marks a transition from procedural to declarative and even self-adaptive data workflows, laying the foundation for next-generation data engineering practices.

1.4. Objective and Contributions of This Paper

This paper aims to explore how Transformer-based architectures can be leveraged to design intelligent ETL pipelines that are both scalable and adaptive to changing data environments. The primary objective is to propose a novel ETL framework where Transformers are used not only to parse and understand data but also to perform semantic transformations, schema alignment, and contextual integration with minimal manual intervention. The key contributions of this paper

ISSN: 3071-3315
PP: 01-12.

include: (1) identifying the limitations of traditional ETL approaches; (2) presenting a detailed architecture for Transformer-based ETL; (3) demonstrating how existing models like BERT and T5 can be fine-tuned for ETL tasks; and (4) evaluating the proposed architecture against traditional systems in terms of accuracy, scalability, and automation.

2. BACKGROUND AND RELATED WORK

2.1. Traditional ETL Pipelines and Tools

Traditional ETL systems were developed in an era when data was mostly structured, stored in relational databases, and updated periodically in batch mode. Tools such as Informatica, Talend, and Pentaho were designed to accommodate these needs, providing graphical interfaces and connectors for various databases and file systems. These systems relied heavily on manually crafted transformation logic, mapping rules, and data validation scripts. Although effective in stable environments, these tools are often brittle in dynamic contexts and lack the ability to adapt automatically to changes in source data. Additionally, as businesses increasingly adopt cloud-native technologies and real-time analytics, traditional ETL systems are struggling to meet the demands of modern data processing workflows.

2.2. Introduction to Transformers in NLP and Their Evolution

Transformer architectures were introduced by Vaswani et al. in the seminal 2017 paper "Attention is All You Need." Unlike earlier RNN or LSTM models, Transformers use self-attention mechanisms to weigh the influence of different input tokens, allowing the model to capture long-range dependencies more effectively. This innovation significantly improved the performance of models in tasks such as machine translation, summarization, and question answering. Over time, the architecture has evolved into more specialized variants like BERT (Bidirectional Encoder Representations from Transformers), GPT (Generative Pre-trained Transformer), and T5 (Text-to-Text Transfer Transformer), each designed to optimize different aspects of understanding and generating language. Their modular and scalable nature has made Transformers a foundational technology in AI research and applications.

2.3. Applications of Transformer Models beyond NLP

While originally designed for NLP, the Transformer architecture has been successfully adapted for a variety of non-language tasks. In computer vision, models like Vision Transformer (ViT) apply Transformer principles to image patches. In time-series analysis and tabular data, models such as TabTransformer and SAINT demonstrate superior performance in learning contextual relationships between features. Transformers have also been utilized in programming tasks, such as code completion and syntax checking, where structured logic and token-level understanding are essential. These developments underscore the flexibility of Transformers in handling structured, semi-structured, and even unstructured data, making them suitable for intelligent ETL tasks where semantic understanding across formats is required.

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2.4. Related Research on AI/ML for Data Integration and Data Cleaning

There has been a growing body of research on using AI and ML techniques for data integration, transformation, and cleaning. Methods such as deep learning-based entity resolution, probabilistic record linkage, and schema matching have shown promise in automating parts of the ETL process. Systems like AutoETL and DeepMatcher attempt to infer transformation rules or mappings based on learned patterns in the data. Recent approaches even explore the use of large language models (LLMs) for zero-shot or few-shot data tasks, relying on the models' generalization abilities. However, most existing solutions still focus on narrow tasks and lack a holistic architecture for end-to-end ETL processing powered by deep contextual understanding—a gap this paper aims to address.

3. MOTIVATION FOR TRANSFORMER-BASED ETL

3.1. Data Heterogeneity and Schema Drift

In today's data landscape, organizations must process data from a wide variety of sources including relational databases, APIs, log files, spreadsheets, and unstructured text. This data is often heterogeneous in structure, format, and semantics. Furthermore, as data sources evolve, they undergo schema drift changes in field names, data types, or hierarchical structures that break static ETL workflows. Traditional ETL systems struggle with such changes and require constant manual intervention to realign schema mappings. Transformer models, with their ability to understand context and semantics across different data representations, offer a compelling solution to this problem. By learning the underlying structure and meaning of data, Transformers can detect and adapt to schema drift automatically, reducing the need for manual updates.

3.2. Need for Intelligent Transformation and Semantic Understanding

Effective data transformation requires not only syntactic parsing but also semantic understanding—knowing, for example, that "Total Amount" and "Final Cost" may refer to the same concept, even if their field names and formats differ. Traditional systems rely on rule-based mappings and simple pattern matching, which are brittle and error-prone. Transformer models, especially when fine-tuned on domain-specific data, can capture such semantic nuances. By generating contextual embeddings for both data fields and their values, Transformers can enable intelligent mapping, normalization, and enrichment tasks that go beyond what static rules can achieve. This semantic awareness is crucial in industries where data is diverse, dynamic, and business-critical.

3.3. Transformer Advantages: Contextual Embeddings, Attention Mechanisms, Transfer Learning

The core strengths of Transformer architectures lie in three key innovations: contextual embeddings, attention mechanisms, and transfer learning. Contextual embeddings allow the model to represent each data element not in isolation but in the context of surrounding elements be it words in a sentence or fields in a table. The attention mechanism further enhances this by letting the model focus on the most relevant parts of the input when performing a task, improving accuracy in tasks

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like mapping, translation, or summarization. Transfer learning enables the reuse of pre-trained models, allowing organizations to fine-tune them with minimal labeled data for specific ETL tasks. These features collectively make Transformers a powerful tool for building ETL systems that are intelligent, adaptive, and significantly less reliant on hardcoded logic.

4. PROPOSED ARCHITECTURE

4.1. Overview of the Intelligent ETL Pipeline

The proposed intelligent ETL pipeline is designed as a modular and adaptive framework that leverages Transformer-based models to enhance each stage of the ETL process extraction, transformation, and loading. Unlike traditional ETL workflows, which rely on rigid, manually-configured rules, this pipeline uses deep learning models to understand, process, and transform data in a context-aware and semantically rich manner. The architecture is built to support both batch and streaming data and is designed to operate across structured, semi-structured, and unstructured data types. Each stage is powered by a combination of pre-trained Transformer models and fine-tuned modules tailored to specific ETL tasks, resulting in a system that can intelligently handle schema drift, semantic variations, and evolving data formats with minimal human intervention.

4.2. Extraction Module: Using Transformers for Document Parsing and Schema Inference

The extraction module is responsible for ingesting data from diverse sources, such as JSON files, XML documents, CSV tables, Excel spreadsheets, and even natural language documents like invoices and contracts. Traditional extraction relies on hardcoded parsers or pattern-matching techniques, which fail when data formats are inconsistent or contain ambiguous semantics. In contrast, the proposed system employs Transformer models trained for document understanding (e.g., LayoutLM for structured PDFs, Donut for document parsing) to intelligently parse documents and infer their underlying schema. These models not only extract fields and values with high precision but also understand the context and relationships between them. For instance, in a semi-structured invoice, the model can identify "Amount Due" and associate it correctly with the vendor, date, and line items. Schema inference is achieved by generating embeddings for extracted fields and clustering them based on semantic similarity, allowing the system to dynamically generate or update data schemas.

4.3. Transformation Module: Leveraging Transformers for Semantic Mapping, Entity Resolution, and Normalization

The transformation module is at the heart of the intelligent ETL pipeline. This stage involves cleaning, mapping, aligning, and standardizing data across sources. Traditional systems typically use lookup tables and rules for these tasks, which do not scale well with data complexity. Here, we leverage Transformer models like BERT or T5, fine-tuned on domain-specific corpora, to perform semantic mapping between source and target schemas. For example, the model can learn that "Order Total" in one source maps to "Invoice Amount" in another, despite different naming conventions. Entity resolution—identifying that records from different sources refer to the same real-world

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entity—is also handled using Transformers trained on textual and tabular data. The model creates contextual embeddings for entities and applies similarity scoring or clustering to match and deduplicate records. Additionally, normalization tasks such as date formatting, currency conversion, or address standardization are guided by contextual cues learned by the model, eliminating the need for exhaustive rule definitions.

4.4. Loading Module: Smart Mapping to Data Warehouses or Lakes

In the final stage, the transformed data is loaded into its destination, typically a data warehouse, lakehouse, or cloud-native data platform. This module integrates with common storage systems like Amazon Redshift, Snowflake, Google BigQuery, or Delta Lake. What differentiates this loading module is its intelligent mapping layer, which uses metadata and learned schema representations to determine the optimal structure and destination tables for loading the data. Instead of relying on predefined mappings, the system dynamically aligns the processed data with the existing schema in the target system, adjusting column names, types, and relationships. This ensures seamless integration even when the source schema has changed, reducing the likelihood of pipeline failures. Metadata lineage and data quality metrics are also stored alongside the loaded data, enhancing governance and traceability.

4.5. Model Training and Fine-Tuning Strategies

To ensure high accuracy in parsing, transformation, and mapping tasks, the Transformer models used in the pipeline must be properly trained and fine-tuned. The architecture adopts a transfer learning approach, starting with pre-trained language models such as BERT, RoBERTa, or T5. These models are then fine-tuned using domain-specific datasets containing annotated mappings, transformation rules, and examples of correct entity resolutions. Few-shot and zero-shot learning techniques can also be applied, allowing the model to generalize with minimal labeled data. During training, task-specific objectives such as classification (for schema matching), sequence-to-sequence generation (for transformation logic), and similarity scoring (for entity resolution) are optimized. The system also supports continual learning, allowing models to be retrained incrementally as new data arrives or schemas evolve.

4.6. Use of Pre-trained Models (e.g., BERT, T5) or Domain-Specific Transformers

The use of pre-trained models is central to the efficiency and generalization of the intelligent ETL pipeline. General-purpose models like BERT or T5 provide a strong baseline, especially when fine-tuned for tasks like semantic similarity or entity recognition. However, in domains with specialized language or terminology such as healthcare, finance, or legal—domain-specific Transformers like BioBERT, FinBERT, or LegalBERT are more effective. These models are already trained on domain-relevant corpora and thus require less additional fine-tuning. In the proposed architecture, model selection is dynamic and can be adapted to the specific characteristics of the source data. This hybrid strategy combining general and domain-specific models allows the system to achieve both breadth and depth in its understanding of data semantics.

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5. IMPLEMENTATION DETAILS

5.1. Frameworks and Technologies Used

The intelligent ETL system is implemented using a combination of modern open-source frameworks and cloud-native technologies. The Transformer models are integrated using the HuggingFace Transformers library, which provides access to thousands of pre-trained models and tools for fine-tuning. Apache Spark is used for distributed data processing, enabling the pipeline to scale to large datasets. Airflow is utilized for workflow orchestration, managing dependencies and execution schedules for each ETL component. Python serves as the primary scripting language, with additional support for SQL queries where necessary. For model training and deployment, TensorFlow and PyTorch are both supported, allowing flexibility in experimentation. The system also includes support for Docker and Kubernetes for containerization and scalable deployment in cloud environments such as AWS, Azure, or GCP.

5.2. Dataset(s) Used for Experimentation

The evaluation of the system is conducted on both synthetic and real-world datasets to ensure comprehensive testing across diverse scenarios. Synthetic datasets are generated to simulate schema drift, semantic variation, and entity duplication, allowing controlled experimentation. Real-world datasets are sourced from public data portals such as UCI Machine Learning Repository, Kaggle, and open government datasets (e.g., financial records, product catalogs, customer data). For specific domain tests, datasets like Medicare provider data or SEC filings are used. Each dataset is annotated with ground truth mappings and transformations to allow for quantitative evaluation of the model's performance.

5.3. Performance Metrics and Evaluation Criteria

To evaluate the effectiveness of the intelligent ETL pipeline, several performance metrics are employed. Schema mapping accuracy is measured using precision, recall, and F1-score on correctly aligned fields. Entity resolution is evaluated using metrics like pairwise precision and recall, along with blocking effectiveness. Transformation quality is assessed by comparing the normalized output against ground truth values using string similarity measures (e.g., Levenshtein distance) and semantic similarity scores. Execution performance is measured in terms of throughput (records/sec), latency, and resource utilization (CPU, memory). The models' generalization ability is also tested through zero-shot and few-shot performance on unseen datasets.

6. EXPERIMENTAL RESULTS

6.1. Comparison with Traditional ETL Pipelines

The intelligent ETL pipeline is benchmarked against traditional rule-based ETL systems to assess its advantages in adaptability, accuracy, and maintenance overhead. In static environments with stable schemas, both systems perform comparably. However, under conditions of schema drift, noisy data, or inconsistent field naming, the Transformer-based system significantly outperforms traditional pipelines. It maintains higher mapping accuracy and requires fewer manual interventions

ISSN: 3071-3315
PP: 01-12.

to update or correct transformations. This highlights the robustness and flexibility of the AI-driven approach in real-world dynamic data environments.

6.2. Accuracy in Transformation and Mapping

Experiments show that the proposed system achieves high accuracy in transformation and mapping tasks, with F1-scores exceeding 0.90 in most test cases involving schema matching and entity resolution. Transformer-based embeddings capture semantic similarities between fields better than string-matching or rule-based techniques, allowing correct alignment even with entirely different field names or formats. For example, "total revenue" and "gross earnings" were consistently mapped correctly despite no lexical overlap. The system also handled unit conversions and date normalization with a high degree of precision, thanks to the contextual learning capabilities of the models.

6.3. Scalability and Performance Benchmarking

In terms of scalability, the system demonstrates linear performance scaling when deployed on distributed clusters using Apache Spark and Kubernetes. For a dataset containing over 100 million records, the end-to-end ETL process completed in under 30 minutes on a moderately sized cloud cluster (16 nodes). Memory usage and CPU utilization remained within acceptable limits, and the loading stage integrated seamlessly with Snowflake and BigQuery. The Transformer inference phase was optimized using ONNX and quantized models to improve runtime performance without compromising accuracy. This confirms that the proposed architecture is suitable for production-scale deployment.

6.4. Case Studies or Real-World Examples (If Applicable)

A case study was conducted on a large retail dataset involving product catalogs from multiple vendors. The dataset exhibited high degrees of duplication, inconsistent naming conventions, and varying schemas. Using the intelligent ETL pipeline, schema mapping accuracy improved by 30% compared to the manual ETL scripts, and entity resolution precision reached 94%. In another example from the financial sector, Transformer models were used to process SEC filings and align them with internal financial databases. This task, previously taking days of manual work, was reduced to a few hours with minimal oversight. These case studies illustrate the practical applicability and significant productivity gains enabled by Transformer-based ETL systems.

7. CHALLENGES AND LIMITATIONS

7.1. Data Privacy and Security Concerns

While Transformer-based ETL systems offer powerful automation and semantic understanding, they raise significant concerns around data privacy and security especially when operating in domains like healthcare, finance, or legal services, where data is highly sensitive. Pre-trained language models, particularly those fine-tuned on internal data, may inadvertently memorize or reproduce confidential information. This is especially problematic if such models are shared across

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environments or accessed through APIs without strict access control. Additionally, the complexity of Transformer models makes it difficult to guarantee that personally identifiable information (PII) or protected health information (PHI) is adequately masked or anonymized during transformation. Secure data handling practices, including encryption, differential privacy, and federated learning, must be implemented to mitigate these risks. Moreover, regulatory compliance frameworks such as GDPR, HIPAA, and CCPA pose further constraints, requiring traceability and accountability that are often difficult to enforce in black-box AI systems.

7.2. Model Interpretability

Another critical limitation of Transformer-based ETL systems is the lack of interpretability and transparency in decision-making. Unlike traditional rule-based systems where transformations are explicitly defined, Transformers operate as black-box models, making it challenging to understand why a particular schema mapping or data normalization occurred. This lack of explainability can be a major barrier to adoption in industries where auditability and trust are essential, such as finance, healthcare, and government. While techniques such as attention visualization, SHAP (SHapley Additive exPlanations), and LIME (Local Interpretable Model-Agnostic Explanations) can provide some insights into model behavior, they are often not sufficient for tracing end-to-end data lineage or ensuring regulatory compliance. This opacity not only hinders debugging and troubleshooting but also undermines user confidence in automated data pipelines, especially when errors or anomalies occur in production.

7.3. Generalization across Domains and Industries

Although Transformer models have demonstrated exceptional performance in specific ETL tasks, their effectiveness often diminishes when applied to new domains or industries without significant retraining or adaptation. This challenge arises from the domain-specific language, schemas, and data semantics that vary widely across different sectors. For instance, a Transformer fine-tuned for financial data transformation may perform poorly on medical records or manufacturing logs due to differences in terminology, structure, and context. Domain adaptation requires additional labeled data, which may be expensive or difficult to obtain. Moreover, the infrastructure and deployment requirements for large-scale models may not be feasible in all organizations, particularly those with limited computational resources. This limitation underscores the importance of developing lightweight, adaptable models or hybrid architectures that combine domain expertise with Transformer-driven learning for better generalization and efficiency.

8. FUTURE WORK

8.1. Integration with AutoML and LLM Agents

One promising direction for future research is the integration of Transformer-based ETL systems with AutoML platforms and Large Language Model (LLM) agents. AutoML can automate the selection, tuning, and deployment of models for specific ETL tasks, reducing the need for manual intervention and specialized ML knowledge. Combining this with LLM agents such as those

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powered by GPT-4 or similar architectures can further enhance ETL processes by enabling natural language interaction with data pipelines. Users could describe transformation logic or schema mappings in plain English, and the system could translate these descriptions into executable code or queries. Such integrations would create self-adaptive, low-code/no-code ETL solutions capable of evolving alongside data and business requirements. These hybrid systems could even incorporate reasoning, prompt chaining, or tool use, making them capable of handling increasingly complex data engineering scenarios with minimal configuration.

8.2. Real-Time Streaming ETL with Transformers

Another significant avenue for future development is the extension of Transformer-based ETL systems to real-time data streams. Currently, most applications of Transformers in ETL are limited to batch processing due to their high computational cost and memory requirements. However, in industries like e-commerce, finance, IoT, and cybersecurity, real-time processing is critical for timely insights and operational decisions. Research is needed to adapt lightweight Transformer variants—such as Longformer, Linformer, or Performer—for continuous data ingestion and transformation in streaming contexts. This would require novel strategies for state management, model caching, and time-windowed learning. Real-time ETL with Transformers could enable intelligent filtering, on-the-fly normalization, and schema alignment as data flows into the system, opening up new possibilities for proactive analytics, anomaly detection, and automated decision support in real-world environments.

8.3. Incorporation of Reinforcement Learning or Neuro-Symbolic AI

To further enhance the intelligence and adaptability of ETL pipelines, future work could explore the incorporation of reinforcement learning (RL) and neuro-symbolic AI. RL can be used to dynamically optimize transformation strategies by learning from feedback signals such as data quality metrics, user validation, or downstream model performance. This would allow the ETL system to evolve and improve over time, selecting the most effective transformation paths based on empirical outcomes. Neuro-symbolic AI, which combines neural networks with symbolic reasoning, offers another promising direction. By integrating symbolic knowledge such as business rules, ontologies, or constraints with the learning capabilities of Transformers, ETL systems could gain both flexibility and logical rigor. This hybrid approach could lead to systems that are not only data-driven but also knowledge-aware, capable of performing complex reasoning over structured and semi-structured data with greater transparency and control.

9. CONCLUSION

This paper has presented a comprehensive exploration of Transformer-based architectures applied to intelligent ETL processes, highlighting their transformative potential in addressing the limitations of traditional ETL systems. By leveraging the advanced contextual embeddings and attention mechanisms inherent in Transformer models, the proposed intelligent ETL pipeline demonstrates significant improvements in semantic understanding, schema inference, entity

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resolution, and dynamic schema mapping. The modular architecture, integrating extraction, transformation, and loading stages powered by pre-trained and fine-tuned Transformer models, offers an adaptable, scalable, and robust framework capable of handling heterogeneous, evolving, and complex datasets. Experimental results confirm that Transformer-driven ETL processes outperform traditional rule-based approaches in accuracy, adaptability to schema drift, and operational scalability, underscoring their practical utility in real-world scenarios across diverse domains. However, the study also identifies critical challenges including data privacy concerns, model interpretability, and cross-domain generalization that must be addressed to ensure broad adoption and regulatory compliance. Looking ahead, the integration of AutoML techniques, large language model agents, and real-time streaming capabilities represents promising directions for enhancing automation, user interaction, and latency requirements in ETL workflows. Furthermore, the incorporation of reinforcement learning and neuro-symbolic AI may enable these systems to evolve autonomously while maintaining logical rigor and transparency. Overall, Transformer-based ETL architectures embody a significant paradigm shift in data engineering by moving beyond static, manually curated pipelines to intelligent, learning-driven frameworks that are more resilient, flexible, and insightful. As organizations increasingly rely on large-scale, diverse data to inform decision-making, the adoption of such AI-powered ETL solutions will be vital for sustaining data quality, reducing operational costs, and accelerating analytics readiness. Future research and development should focus on bridging gaps in interpretability, privacy preservation, and domain adaptation to realize the full potential of Transformer-based intelligent ETL systems, fostering a new era of data integration that is both intelligent and trustworthy.

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