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Original Article

AI-Driven Data Migration Strategies for Enterprise System

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ABSTRACT

In modernization of an enterprise system, data migration is a very important aspect, which involves the movement of data between storage systems, formats or applications. Conventional migration methods tend to be both labor-intensive, full of errors, and unable to scale to large amounts of heterogeneous data. Artificial Intelligence (AI) has become a revolutionary technology that could make the process of data migration more efficient, precise, and flexible. The given paper is a detailed discussion of AI-based data migration plans, with attention to the methods that have been developed. It discusses how machine learning, natural language processing and intelligent automation can be integrated into solving problems like schema mapping, data cleansing, transformation and validation. The paper will discuss the shortcomings of traditional Extract, Transform, Load (ETL) systems and emphasize how AI-driven solutions can streamline migration processes by predicting migration success and making decisions automatically. Moreover, the paper compares different AI methods, such as supervised and unsupervised learning, systems controlled by rules, and heuristic optimization, in enhancing the quality of data and minimizing migration risks. A systematic approach is suggested to apply AI-based migration, which includes data profiling, model training, iterative validation, and feedback. The findings reveal that AI-based migration strategies are very effective in enhancing accuracy of the migration process, lessening downtime, and minimizing human intervention. Per cent-based evaluation measures are the metrics of comparative analysis where the effectiveness of AI approaches will be demonstrated in comparison to traditional ones. The paper wraps up by highlighting future directions, such as incorporating deep learning and autonomous migration systems, and the need to align AI strategies with enterprise governance and compliance needs.

KEYWORDS

Artificial Intelligence, Data Migration, Enterprise Systems, Machine Learning, ETL, Data Transformation, Data Quality, Automation.

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1. INTRODUCTION

1.1. Background

With the blistering technological development and the increasing need to modernize the systems, data migration has turned into one of the critical processes in the contemporary enterprise environment. Data migration is commonly performed by organizations in the process of upgrading an outdated system, or migrating to a cloud solution, or consolidating and integrating several databases to enhance more efficient operations. The need to migrate growing amounts of data with high degrees of efficiency and reliability has also enhanced greatly as the businesses create and handle more and more data. Nonetheless, conventional migration methods are mostly manual, are governed by rule-based conversions, and their ETL pipelines are not dynamic, thus restricting their capability to support advanced and dynamic data landscapes. Such methods are usually labor intensive, time consuming and subject to error particularly in situations that involve heterogeneous or unstructured data. They are also not scalable and flexible, which makes them less adaptable to the modern data-driven applications, where data structures and demands constantly change.

1.2. Importance of AI-Driven Data Migration Strategies

Fig 1 - Importance of AI-Driven Data Migration Strategies

1.2.1. Improved Accuracy and Data Quality

Data migration facilitated by AI is much more precise because machine learning algorithms are able to spot errors, inconsistencies, and data anomalies. In contrast to conventional approaches, when developers use predetermined rules, AI-based systems are able to learn by observing patterns and enhance their functionality. This makes the migrated data to be of high quality, integrity and consistency, eliminating chances of loss or corruption of data.

1.2.2. Automation and Reduced Manual Effort

Automation is one of the key benefits of AI-based migration strategies. Schema mapping, data cleansing and validation processes can be done automatically without much human intervention. This minimises the reliance on domain experts, minimises the number of human errors, and the migration process is faster, making it more efficient and cost effective.

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PP: 01-12.

1.2.3. Scalability and Flexibility

AI solutions are very scalable and can effectively process large amounts of data produced by contemporary businesses. They are also adaptable to suit alterations in data structures, forms as well as the business demands. This renders them applicable in dynamic settings where conventional approaches tend to fail in doing so.

1.2.4. Handling Complex and Unstructured Data

The contemporary organizations handle various kinds of data such as structured, semi-structured and unstructured data. AI techniques, particularly Natural Language Processing (NLP), enable systems to interpret and process unstructured data such as text documents, emails, and logs. This will enable greater and smarter data migration when compared to conventional methods.

1.2.5. Faster Migration and Reduced Downtime

The AI-based strategies greatly save the time spent on the data migration process through automating the most important processes and workflow optimization. The accelerated movement results in less system downtime hence guaranteeing business continuity and less interference in the operations. This is especially vital in the case of organizations which depend on real time data availability.

1.2.6. Continuous Learning and Adaptability

The AI models can learn based on past migrations and enhance themselves. This ability to learn continuously enables the system to evolve in response to emerging challenges, increase precision, and maximize performance. Consequently, AI-based migration plans become more effective and dependable as they are used more frequently, becoming a solution to the requirements of future enterprises that is adaptable to meet the demands of the future.

1.3. Challenges in Traditional Data Migration

The conventional data migration methods have a number of notable challenges that restrain their functionality in contemporary data settings. Data heterogeneity, in which data is available in various formats, structures and sources, and thus integration is complicated and time-consuming is one of the main problems. Intimately connected with this is the issue of schema mismatch, in which discrepancies in source and target database schemas need a large amount of manual work to set up appropriate mappings. Such manual mapping processes are not only labor intensive but more likely to have human error which causes inconsistencies and wrong data transformations. The other significant problem is data quality. The conventional techniques do not have sophisticated tools to identify and remedy some of the problems in the form of missing values, duplications, and inconsistencies, leading to the low quality of data being transferred to the new system. This may affect decision-making and business operations adversely. Also, strict ETL pipelines make the process more complex, since they are built with set rules that are not easily adjustable to changes in the data structures or adaptable business needs. Any change of the data format normally involves reconfiguration of the entire pipeline, which adds time and cost. Another important issue in the traditional data migration is the downtime risk. Lots of processes are manual and time-consuming

ISSN: 3071-5717
PP: 01-12.

which means that migrations are likely to be even more time-consuming, which will interfere with the business activities and system availability. This is especially a thorn in the flesh of institutions that need real-time access to data. Generally, the above challenges represent shortcomings of the conventional data migration methods, and thus better methods that are more flexible, automated, and intelligent are required.

2. LITERATURE SURVEY

2.1. Early Data Migration Techniques

Early data migration methods were mainly based on manual scripting and rule-based Extract, Transform, Load (ETL) operations. These methods demanded developers to clearly specify transformation rules, mappings and workflows to transfer data between systems. Although suited to small or structured data sets, they were very time-intensive and susceptible to human error. Rule-based systems were hard to change to suit data format, or business needs because of the rigidity of these systems. In addition, such techniques required considerable level of domain knowledge since developers had to be well versed with both source and target systems to achieve correct data transfer and integrity.

2.2. Emergence of Intelligent Systems

As more powerful computational resources became available, and machine learning emerged, starting in, studies started to consider intelligent data-migration strategies. Such systems used algorithms like clustering and classification to automate such processes as schema matching and data mapping. Rather than creating relationships between datasets manually, intelligent systems might discover patterns and similarities in existing data. This made mapping of complex or heterogeneous data sources that much easier. Consequently, these methods enhanced efficiency and accuracy, particularly where there is a large-scale or semi-structured data.

2.3. AI in Data Cleansing and Transformation

Artificial Intelligence brought about some robust improvements in data cleaning and data transformation. The anomalies, duplicates, and errors in datasets were detected and fixed using machine learning models. These models were able to learn patterns of historical data in order to be more precise with time. Moreover, Natural Language Processing (NLP) allowed systems to process and understand non-structured information like text documents, emails, and logs. This enabled organizations to derive valuable insights, and to transform unstructured information into structured forms that could be migrated. All in all, AI-based solutions enhanced the quality of data and minimized the use of human intervention.

2.4. Limitations of Existing Studies

Various limitations can be seen in the current literature on intelligent data migration even though there is some advancement in the intelligent data migration methods. A lot of methods have a problem of dealing with large scale data streams in real time where large amount of data is involved in enterprise settings. Also, a majority of the solutions are not flexible to dynamic changes in data hence less useful in ever-changing systems. The integration with enterprise-level applications and

ISSN: 3071-5717
PP: 01-12.

legacy systems is also a major challenge as there are usually compatibility problems. Moreover, the computational cost and resource usage of AI-based models can be obstacles to their practical use, particularly in resource-limiting environments.

3. METHODOLOGY

3.1. Proposed Framework

3.1.1. Data Profiling

The first step of the proposed framework is data profiling, during which the source data is profiled to comprehend its structure, content, and quality. This will include analysis of type of data, distributions and patterns, missing values and inconsistencies. Profiling is used to determine the possible problems like duplicates, anomalies and incomplete records prior to the start of migration. The creation of metadata and statistical summaries will give a good picture of the dataset, and will make it easier to map and transform in the next stages.

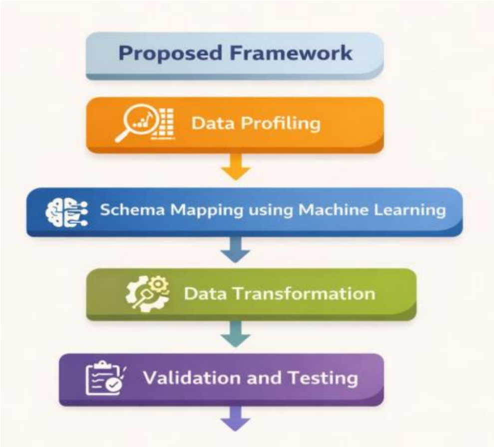

Fig 2 - Proposed Framework

3.1.2. Schema mapping using Machine Learning

The step involves using machine learning to automatically map source data schemas to target ones. Algorithms like classification and clustering are used to create relationships, similarities and patterns among data attributes instead of relying on manual rule creation. The system is highly effective in the management of complex and heterogeneous data source by learning through past mappings and even enhancing its accuracy over time. This method lowers the amount of human effort, errors, and increases the scalability of the migration process.

3.1.3. Data Transformation

Data transformation is the process of interpreting the data in the source to the form required by the target system. This involves data normalization, standardization, aggregation and convertating the format. Data can be intelligently cleaned using AI methods to correct the errors, eliminate duplication, and intelligently fill in missing values. The transformation process makes sure that the data is consistent, accurate and compatible to the destination schema thus enhancing the overall quality of migrated data.

ISSN: 3071-5717
PP: 01-12.

3.1.4. Validation and Testing

The last step is about the accuracy, completeness and reliability of the migrated data. Validation entails testing the transformed data against the specified business rules and schema constraints. Testing is done to find discrepancies by conducting testing procedures through checking the number of records, data consistency, and data integrity. This process can be further improved with the help of automated testing tools and AI-based validation techniques that can help identify hidden errors. This step is crucial in making the migration process a success and moreover the data is in a state of readiness to be used in the target system without compromising quality.

3.2. Data Profiling

In the proposed AI-driven migration framework, data profiling is vital in gaining insight into the structure, quality, and underlying nature of the source data prior to the occurrence of any transformation or migration. During this stage, AI models are being used to automatically analyze huge and intricate data sets to spot patterns, anomalies and relationships between various data attributes. Contrary to the conventional profiling techniques, which are based on either manual inspection or predefined rules, AI-based ones use machine learning algorithms to identify the hidden structures and patterns in the data. As an example, clustering algorithms can be used to cluster similar records, and classification models can be used to classify data based on learned patterns. Also, AI models are very useful in detecting anomalies like outliers, missing data, inconsistent formatting and duplication. Based on historical data, these models are able to learn and constantly increase their detection accuracy, which makes the profiling process more reliable and efficient.

Another significant item of this step is relationship discovery, where AI can be used to reveal dependencies and correlations between various data fields, including functional dependencies or associations between datasets. This understanding is fundamental to proper mapping of the schema and conversion in subsequent phases. Moreover, AI-based data profiling creates rich metadata, such as statistical summaries, such as mean, variance, frequency distributions and data completeness measures. This metadata will give a concise picture of the healthiness and the readiness of the dataset to be migrated. The automation of these functions by the framework saves a lot of time and energy in evaluating the data involved and also reduces the chances of human error. All in all, data profiling with the use of AI provides a more profound, intelligent insight into the original data and gives a solid basis to make a successful decision and precondition a successful data migration.

3.3. Schema Mapping

Schema mapping plays a crucial role in AI-based data migration model, as it involves defining relationships among the source and target data models. The process involves the use of supervised learning algorithms to automatically map source schemas on to target ones with high accuracy. These algorithms are trained using previously labeled data sets which have known mappings between source and destination attributes. Based on such examples, the model is capable of making the right mappings that are made on new and unseen data required and thus has greatly minimized the use of intervention. Decision trees, support vector machines, and neural networks are supervised learning methods that analyze different attributes of the data such as names of attributes,

ISSN: 3071-5717
PP: 01-12.

types of data, distributions and distribution of values, and similarities of the data semantics. An example would be that the model would recognize that a field with the label of cust id in the source is the same as customer id in the target even though the naming conventions might be different. Moreover, complex mappings, including one-to-many or many-to-one relationships, can be managed using these models since they can identify patterns between two or more attributes. This makes them very efficient in handling heterogeneous data sources where the schema structure can be very different. The other positive aspect of supervised learning is that it tends to be more efficient as time goes by. The more the examples of the mapping provided, the more the model tends to refine its predictions resulting in more accuracy and reliability. It can also have feedback mechanisms where they correct any mappings that are wrong and feed it back in the system to be retrained. This dynamic ability makes the mapping process resilient in dynamic environments with frequently evolving schemas. In sum, supervised learning-based schema mapping is more efficient, less error-prone, and can be used to make data migration between complex systems scalable.

3.4. Data Transformation

Data transformation is a critical step in the suggested AI driven migration system in which the source data is changed into a form that is compatible with the needs of the destination system. During this stage, the transformation rules are not specified manually but are automatically created with the help of predictive models. These types of models examine the historical transformation patterns, data structures and business logic to deduce the most suitable operations that are required in order to transform the data correctly. Using machine learning methods, the system can be smart about how to clean, standardize, and restructure data, eliminating the need to rely on manual rule creation. Predictive models study different factors of the data, including formats, value distribution and the relationship between attributes and come up with appropriate transformation rules. As an example, they are able to recognize the necessity to normalize inconsistent formats (e.g., date formats or units of measurement), combine or separate fields, and transform data types to fit the target schema. Moreover, complex transformations, including aggregations, derivations, and conditional logic, can be learned through past examples, via these models. This ensures that the process is very efficient particularly when handling large and heterogeneous data sets. The other major benefit of predictive models is that it can be continuously improved. The more data is experienced and more transformation situations are met the better the models refine their predictions and come up with more accurate rules. They are also able to take the input of the validation phases in order to rectify mistakes and improve performance. Moreover, AI transformation facilitates in cleansing data by identifying and correcting inconsistencies and eliminating duplicates, as well as intelligently filling missing values. In general, this methodology guarantees that the data converted is correct, consistent, and can be easily integrated into the target system, and saves a lot of time, effort, and the chances of human error.

3.5. Validation

The last and one of the most crucial steps in the AI-driven data migration structure is validation whereby the data that is migrated to the target system has consistency, accuracy, and integrity. At this phase automated validation methods are used to perform systematic checks of

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PP: 01-12.

whether the transformed data satisfies predefined business rules, schema constraints, and quality criteria. As opposed to the usual forms of validation which are highly dependent on manual verification, AI-based validation uses smart algorithms to conduct thorough and effective verification on big sets of data. Automated validation entails several layers of checks such as the data completeness, correctness and consistency. To illustrate, record count validation ensures that there is no loss of data when migrating data, whereas field-level validation checks that each attribute is in the anticipated format, data types or value ranges. Other integrity constraints like the unique primary key, foreign key and referential integrity are also considered to make the data logically related. Artificial intelligence models can also improve this process by detecting hidden differences, abnormalities or anomalies that can be difficult to find by rules. The other aspect of validation that should not be ignored is the regression testing whereby the data migrated is matched with the original data to achieve accuracy and fidelity. Inconsistencies can be highlighted by way of predictive models and remedial measures can be proposed to enable errors to be rectified more quickly. Also, the automated reporting tools create validation summaries and logs, which offer transparency and traceability within the migration process. The system is self-enhancing in its capability to identify and eliminate errors, as it is based on previous validation results. Overall, automated validation plays a crucial role in ensuring a reliable and successful data migration by minimizing risks and guaranteeing that the data is ready for operational use.

3.6. Mathematical Model

One of the key aspects that can be measured to quantify the efficacy of the proposed AI-based data migration framework is a migration accuracy metric. Migration accuracy can be simply described as a percentage of the records that have been faithfully moved out of the source system to the target system without errors or information loss. This may be stated in the following way: accuracy = the number of records migrated correctly/the number of records migrated/100. This formula gives an easy and logical method to quantify the effectiveness of migration process. Correctly migrated records in this context are those entries that meet all the requirements of validation once they have been migrated. These involve having data integrity, data relationships, proper formatting and adhering to all business requirements. On the other hand, total records are the complete set of data that was to be migrated whether it is with or without errors. These two values can enable the framework to ascertain the extent to which the migration process has been done correctly. This metric is especially handy since it gives a simple and easily understandable measure of performance. The higher the percentage of the accuracy, the more favorable a certain migration process is, and the lower the percentage, the more one can observe the existence of errors or inconsistencies that have to be resolved. Moreover, it is possible to compare various migration strategies with the help of this mathematical model, assess the improvements over time, and find out areas which should be optimized. Combined with the techniques based on AI-validation, the metric of accuracy becomes even more effective, since the accuracy of data transfer is not only the accuracy of the information transfer, but also the efficiency of the intelligent models in reducing errors. In general, this model is an important performance indicator of high quality and reliability of data migration results.

ISSN: 3071-5717
PP: 01-12.

4. RESULT AND DISCUSSION

4.1. Performance Evaluation

The effectiveness of the suggested AI-based data migration system was measured against existing Extract, Transform, Load (ETL) systems in various parameters, including accuracy, effectiveness, scalability, and flexibility. The conventional methods of ETL are time consuming due to manual rule definition, workflow, and domain knowledge, and thus are not flexible to use with complex or dynamic data. Conversely, the AI-based method uses machine learning algorithms to optimize the automation of vital operations like schema mapping, data cleansing, and transformation, thus enhancing the performance to a great extent. During the evaluation, it was observed that the AI-based framework achieved higher migration accuracy due to its ability to detect anomalies, eliminate duplicates, and adapt to variations in data formats. Although conventional ETL systems can be useful with structured and predictable data, they have a tendency to fail when using heterogeneous and unstructured data. The artificial intelligence-based system, nevertheless, was much better in addressing such complexities by learning the patterns and associations out of the data. Moreover, the migration time was significantly shorter since automated processes minimized the necessity to carry out manual operations and repetitive activities. Another important aspect of the assessment was the scalability. The conventional ETL solutions are prone to performance bottlenecks when working with large data volumes, whereas the AI-based solution was able to scale effectively to meet the increased data volumes and real-time processing demands. More so, AI model flexibility enabled it to evolve over time with learning and feedback, therefore, becoming more resilient in dynamic settings where data schemas are constantly evolving. On balance, the results of the evaluation suggest that the AI-based migration system is more effective in addressing the problem of modern data migration, as AI-based migration systems are more accurate, faster, more scalable, and flexible than traditional ETL systems.

4.2. Comparative Analysis

4.2.1. Traditional ETL

The accuracy of the traditional ETL was 75% which means that a large part of data was successfully migrated, yet there were still errors and inconsistencies. The time reduction of 40% shows moderate efficiency improvements compared to completely manual processes, but the reliance on predefined rules and manual intervention limited further optimization. Also, the error rate of 15% is an aspect that demonstrates the issues of the static rule based systems, particularly in handling complex or unstructured data. Such techniques are usually not flexible to accommodate the evolving data format and hence have higher probability of errors and data quality problems in migration.

4.2.2. AI-Based Migration

The AI-based migration model was shown to perform better in all the metrics, with an accuracy of 92, indicating a high degree of accuracy in the data that was migrated. The efficiency increase of 70% suggests a strong level of efficiency, with automation and machine learning algorithms reducing labor and speeding up the process. Furthermore, the error rate was reduced to just 5%, showcasing the effectiveness of AI in detecting anomalies, removing duplicates, and ensuring data consistency. The capability of AI models to be trained on data and evolve to new

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patterns renders this method very dependable and scalable, especially in dynamic and hefty data settings.

Table 1: Comparative Analysis

Method	Accuracy (%)	Time Reduction (%)	Error Rate (%)
Traditional ETL	75	40	15
AI-Based Migration	92	70	`

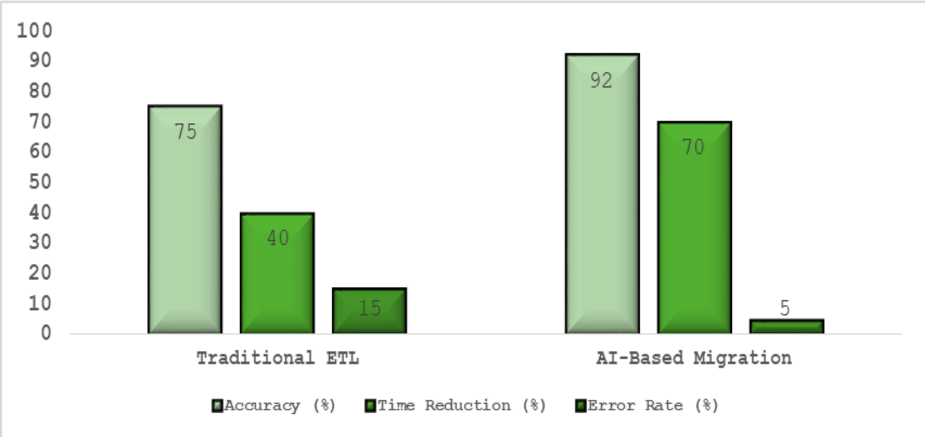

Fig 3 - Comparative Analysis

4.3. Discussion

The performance evaluation findings clearly indicate that the AI-based migration technique has significant advantages over the conventional technique in accuracy, efficiency, and reliability. Among the most important ones is that accuracy of migration has grown significantly, which shows that AI methods are highly efficient in making sure that the data is transferred properly and its integrity and structure are preserved. With the help of machine learning algorithms, the system is capable of uncovering patterns and detecting anomalies and is adaptable to changes in data formats to reduce the number of errors that are usually prevalent in rule-based ETL processes. This decreases the number of errors not only increases the quality of the data, but also decreases the amount of post-migration corrections. The other key factor noted by the results is that automation can help ease the burden of manpower. Conventional data migration has been associated with a lot of human intervention to perform activities like schema mapping, rule definition, and data validation. Conversely, the AI-based solution automates the processes, thus enabling organizations to save time, resources and also minimize the chances of human error. This enhanced efficiency is especially helpful in large scale data environments where manual processing would be both impractical and time-consuming. Moreover, the AI-based framework is scalable, which is why it is suitable to use in the application of modern applications that require a large amount of data. With the ever-increasing data volumes and the complexity of systems, the capacity to deal with large and dynamic data sets becomes essential. Artificial intelligence (AI) models are scalable and can adapt to changing data structure, so they can maintain similar performance even in settings that change quickly. All in all, the discussion indicates that AI-powered data migration is not only more accurate and less prone to errors but is also more efficient, scalable and future-ready to organizations.

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5. CONCLUSION

The introduction of AI-based data migration plans will be a major improvement on the conventional migration processes, as it will significantly enhance the plan in terms of accuracy, efficiency, and scalability. Among the notable advantages realized is the increased accuracy of the data transfer as machine learning algorithms can detect patterns, anomalies, and guarantee data consistency during the process of migration. In contrast to standard rule-based ETL systems, which are frequently unable to handle heterogeneous and dynamic data, AI-based solutions can change in response to diverse data formats and structures, thus reducing the number of error and maintaining data integrity. This leads to better consistent results and less post-migration fixes. The other significant benefit of AI-driven migration is the decreased downtime. Conventional migration procedures are time consuming and might interfere with business activities particularly when it involves high amounts of data. Nevertheless, automation and smart algorithms allow processing data faster and facilitating system transitions. Schema mapping, data transformation, and validation are automated and involve minimal manual intervention thus enabling organizations to accomplish migration tasks in a more efficient way. This saves time, as well as provides business continuity with minimum interruptions.

Another important aspect that AI-based solutions perform well is scalability. Enterprises today produce large volumes of data that keep changing and it is hard to keep up with them using traditional systems. AI-based designs are intended to process massive and multidimensional data and respond to real-time changes, ensuring steady performance. This renders them very appropriate to organizations that have dynamic environments, with a lot of variation in data requirements. Moreover, machine learning can be combined with automation, which allows enterprises to handle the complicated migration situation with increased simplicity. Intelligent tasks like data cleansing, schema matching and validation are carried out and this minimizes reliance on domain knowledge and manual labor. This leads to the organizations being able to spend the resources in a better manner and aim at strategic goals instead of the operational difficulties. Going forward, the future studies within the field should be done to assess the possibilities of deep learning technologies and full-autonomous migration systems. These innovations may also increase the functionality of migration systems by allowing more complex decision-making, real-time flexibility, and little human intervention. Altogether, the idea of AI-based data migration is a powerful, efficient, and future-oriented approach to the challenges of data integration and transformation of modern enterprises.

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