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INTELLIGENT LEGACY-TO-CLOUD ERP TRANSFORMATION USING AUTOMATED DATA MIGRATION AND VALIDATION

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ABSTRACT

Enterprise Resource Planning systems form the operational foundation of many organizations by integrating finance, procurement, inventory, manufacturing, human resources, customer operations, supply-chain processes, and regulatory reporting. However, numerous enterprises continue to depend on legacy ERP platforms characterized by tightly coupled architectures, obsolete technologies, fragmented databases, customized schemas, manual interfaces, limited scalability, and expensive maintenance. Migrating these environments to cloud-based ERP platforms is complex because decades of operational data may contain inconsistent formats, duplicate entities, missing attributes, obsolete codes, undocumented dependencies, incompatible master-data structures, and business-critical historical records. This paper proposes an intelligent legacy-to-cloud ERP transformation framework using automated data migration and validation. The proposed methodology integrates legacy-system discovery, metadata extraction, dependency analysis, data profiling, schema mapping, semantic transformation, duplicate detection, anomaly identification, data-quality scoring, automated cleansing, incremental migration, reconciliation, business-rule validation, referential-integrity verification, API-based integration, secure credential management, cloud deployment, and post-migration monitoring. Machine-learning techniques are incorporated to identify mapping candidates, anomalous records, duplicate entities, and high-risk migration objects. The framework maintains traceability between legacy source records and cloud targets so that transformed data can be audited and reconciled. A staged migration model combines pilot migration, historical backfill, incremental synchronization, controlled cutover, rollback readiness, and continuous validation. Representative evaluation indicates that the proposed framework can improve mapping accuracy, reduce duplicate records, increase validation coverage, decrease migration defects, shorten reconciliation effort, and reduce business disruption compared with predominantly manual migration approaches. The framework provides a practical foundation for ERP modernization, cloud transformation, intelligent data engineering, automated validation, enterprise integration, and scalable digital operations.

Keywords: ERP Modernization, Legacy-to-Cloud Migration, Automated Data Migration, Data Validation, Machine Learning, Cloud ERP, Data Quality, Enterprise Transformation, Schema Mapping, Intelligent Automation.

I. INTRODUCTION

Enterprise Resource Planning (ERP) systems have become indispensable for managing finance, procurement, inventory, manufacturing, supply chain, customer relationship management, and human resource operations within modern enterprises. Over the past several decades, many organizations have accumulated complex legacy ERP environments containing customized business logic, fragmented databases, obsolete technologies, inconsistent master data, undocumented interfaces, and tightly coupled applications. These limitations increase operational costs, reduce scalability, hinder

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business agility, and make digital transformation increasingly difficult. Consequently, migrating legacy ERP systems to cloud-based platforms has become a strategic initiative for organizations seeking improved flexibility, operational efficiency, and long-term sustainability **[1], [2]**.

Legacy-to-cloud ERP transformation involves more than transferring databases from one platform to another. Enterprise information contains heterogeneous schemas, duplicate records, inconsistent business rules, historical transactions, customized workflows, and numerous interdependent relationships that must be preserved throughout migration. Conventional Extract–Transform–Load (ETL) approaches often emphasize technical data movement while providing limited support for semantic validation, automated mapping, dependency analysis, anomaly detection, and continuous reconciliation. Intelligent migration frameworks therefore employ metadata analysis, machine learning, automated validation, and rule-driven transformation to improve migration accuracy and reduce operational risk **[3], [4]**.

Recent advances in cloud computing, intelligent automation, Application Programming Interfaces (APIs), business process management, and enterprise integration have significantly improved ERP modernization capabilities. Cloud-native architectures provide scalable infrastructure, containerized deployment, elastic resource allocation, and service-oriented integration, while machine learning assists in schema matching, duplicate detection, anomaly identification, and automated validation. These technologies enable organizations to modernize ERP platforms with reduced downtime, improved data quality, enhanced governance, and greater operational transparency **[5], [6]**.

Security and governance remain fundamental requirements during ERP transformation because migration pipelines process sensitive financial records, customer information, supplier databases, employee data, regulatory documents, and business-critical operational information. Secure authentication, protected API communication, role-based access control, encrypted data transfer, audit trails, and continuous monitoring ensure that enterprise information remains protected throughout migration. Intelligent governance also supports rollback planning, staged deployment, business continuity, and post-migration validation to minimize disruption during cloud transformation **[7], [8]**.

Although previous studies have independently investigated enterprise integration, cloud migration, business process management, API-driven communication, and intelligent automation, relatively few provide a unified framework integrating automated metadata extraction, machine learning-assisted schema mapping, secure API communication, intelligent validation, anomaly detection, cloud-native deployment, reconciliation, and continuous migration governance. Therefore, this research proposes an **Intelligent Legacy-to-Cloud ERP Transformation Framework Using Automated Data Migration and Validation** that combines intelligent data discovery, automated transformation, secure enterprise integration, predictive validation, cloud-native orchestration, and continuous quality monitoring to improve migration accuracy, operational reliability, enterprise security, and digital transformation efficiency **[9], [10]**.

II. LITERATURE SURVEY

Davenport (1998) examined enterprise systems and demonstrated that ERP platforms integrate organizational functions through centralized information management. The study emphasized that successful ERP implementation requires standardized business processes, reliable enterprise data, and coordinated organizational change. These concepts remain fundamental for

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intelligent legacy-to-cloud ERP transformation projects **[11]**.

Markus and Tanis (2000) presented the enterprise systems lifecycle model covering ERP adoption, implementation, stabilization, and operational success. Their work demonstrated that ERP transformation is a continuous organizational process rather than a single software deployment activity. This lifecycle perspective supports phased migration and continuous validation within cloud ERP modernization **[12]**.

Nah, Lau, and Kuang (2001) investigated critical success factors for enterprise system implementation and identified executive support, governance, project planning, organizational readiness, and business-process alignment as essential elements of successful ERP deployment. These principles remain highly relevant for intelligent ERP migration and cloud transformation initiatives **[13]**.

Themistocleous, Irani, and Love (2001) investigated enterprise application integration challenges associated with heterogeneous information systems. Their research highlighted interoperability issues, incompatible interfaces, and inconsistent data structures within enterprise environments. These findings support the need for intelligent API-based integration and automated schema transformation during legacy-to-cloud ERP migration **[14]**.

Proper and Grefen (2012) discussed enterprise architecture as a governance framework for aligning organizational objectives with information technology infrastructure. Their work demonstrated that structured architectural governance improves interoperability, modernization planning, and enterprise transformation, supporting intelligent ERP migration strategies **[15]**.

Hailpern and Tarr (2006) investigated model-driven software modernization and demonstrated that abstraction models significantly improve software transformation, maintainability, and migration planning. Their concepts support intelligent metadata extraction, automated mapping generation, and repeatable ERP modernization workflows **[16]**.

Jamshidi, Ahmad, and Pahl (2013) conducted a systematic review of cloud migration research and identified migration assessment, planning, execution, and validation as essential phases of successful cloud adoption. Their work provides an important foundation for intelligent ERP transformation methodologies that integrate automated migration and continuous validation **[17]**.

Erl, Puttini, and Mahmood (2013) discussed cloud computing architecture, service models, virtualization, scalability, and enterprise cloud adoption. Their research demonstrated how cloud-native infrastructure improves resource utilization, operational flexibility, and enterprise scalability, providing valuable concepts for cloud ERP deployment and modernization **[18]**.

Gummadi (2020) proposed API design and implementation using RAML and OpenAPI specifications. The study demonstrated that standardized APIs improve interoperability, consistency, and reliable communication among distributed enterprise systems. These concepts are directly applicable to legacy-to-cloud ERP transformation where API-driven integration coordinates migration services, cloud ERP platforms, validation engines, and enterprise applications **[19]**.

Kumar Adabala (2021) proposed a smart data migration framework for ERP modernization emphasizing structured migration planning, intelligent transformation, and modernization-oriented governance. The study highlighted the importance of systematic migration processes for improving enterprise reliability during digital transformation. The proposed framework extends this work by incorporating automated metadata discovery, machine learning-assisted schema

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mapping, anomaly detection, cloud-native orchestration, secure API lifecycle management, intelligent validation, staged migration, reconciliation, and continuous post-migration monitoring **[20]**.

III. PROPOSED METHODOLOGY

The proposed methodology establishes an intelligent legacy-to-cloud ERP transformation framework in which data migration, validation, integration, and operational transition are managed through a unified lifecycle. The methodology is based on the principle that ERP transformation cannot be treated as a simple extract-transform-load operation because enterprise records contain complex semantic relationships, historical dependencies, custom extensions, business rules, regulatory constraints, and operational significance. Therefore, the framework combines deterministic validation with machine-learning-assisted analysis and controlled human review.

The first stage performs legacy landscape discovery. ERP applications, databases, interfaces, batch jobs, reports, custom modules, external systems, file exchanges, and integration dependencies are identified. Each component is classified according to business criticality, data ownership, technology, operational schedule, and migration relevance. This stage reduces the risk of discovering hidden dependencies during cutover.

The second stage performs automated metadata extraction. Table definitions, columns, data types, keys, indexes, relationships, stored procedures, views, file layouts, and interface schemas are collected where access permits. Metadata is stored in a centralized migration repository. Automated extraction reduces dependence on outdated documentation.

The third stage creates a migration knowledge model. Source entities, target entities, business domains, dependencies, data owners, transformation rules, and validation policies are connected. The knowledge model provides a continuously updated representation of migration state. It supports impact analysis when a mapping or source structure changes.

The fourth stage classifies data domains. Customer, supplier, product, employee, financial, inventory, procurement, manufacturing, order, asset, and historical transaction data are separated according to business meaning. Domain classification is important because different data types require different validation and migration strategies.

The fifth stage performs data profiling. Each source dataset is analyzed for completeness, uniqueness, value distribution, invalid formats, unexpected values, duplicate rates, null patterns, range violations, and referential inconsistencies. Profiling results establish a baseline before transformation. The framework avoids assuming that legacy data is correct merely because it has existed for many years.

The sixth stage assigns data-quality risk. Datasets with high duplication, missing mandatory values, inconsistent codes, weak referential integrity, or undocumented semantics receive higher migration risk. Business criticality is also considered. A small financial table may require more rigorous validation than a much larger low-impact archive.

The seventh stage identifies personally sensitive and regulated information. Data classification determines encryption, masking, access, residency, retention, and validation requirements. Migration logs avoid exposing unnecessary sensitive values. Access to high-risk datasets is restricted according to role.

The eighth stage performs schema matching. Source fields and target fields are compared using names, data types, descriptions, value patterns, reference relationships, and historical mappings. Machine-learning-assisted similarity analysis generates candidate mappings. The system does

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not automatically approve uncertain semantic mappings.

The ninth stage performs semantic mapping. Technical similarity is supplemented with business meaning. A source field named customer status may not correspond directly to a target field with a similar name if code definitions differ. Data stewards review high-impact mappings and approve transformation logic.

The tenth stage introduces mapping confidence. Every candidate mapping receives a confidence category based on metadata similarity, value compatibility, relationship evidence, and prior approved patterns. High-confidence low-risk mappings can proceed through automated validation, while uncertain mappings require human review.

The eleventh stage establishes canonical transformation rules. Date formats, currency representations, units, identifiers, addresses, code sets, status values, and text encodings are standardized. Transformation rules are version controlled and traceable. Changes are reviewed because one transformation can affect millions of records.

The twelfth stage performs automated data cleansing. Invalid whitespace, inconsistent casing, malformed dates, obsolete codes, duplicate formatting, and selected missing values are treated according to approved rules. The framework does not silently invent business-critical information. Records requiring uncertain correction are routed to exception handling.

The thirteenth stage performs duplicate detection. Exact matching identifies identical records, while machine-learning-assisted similarity detects probable duplicates with spelling variation, abbreviation, address differences, or incomplete identifiers. Duplicate resolution considers business rules because two similar records may represent distinct entities.

The fourteenth stage performs anomaly detection. Statistical and machine-learning methods identify records that differ substantially from historical patterns or comparable groups. Examples include unusual transaction values, impossible date sequences, rare code combinations, and inconsistent quantities. Anomalies are prioritized for review rather than automatically deleted.

The fifteenth stage validates referential integrity. Parent-child relationships are checked before migration. Transactions referencing missing customers, products, suppliers, accounts, or organizational units are identified. Resolution can involve correction, approved placeholder strategy, archival treatment, or exclusion according to governance.

The sixteenth stage establishes business-rule validation. Technical schema conformity is insufficient for ERP data. Rules verify conditions such as valid accounting periods, allowed status transitions, consistent currency relationships, quantity constraints, organizational assignments, and transaction dependencies. Business rules are defined with domain owners.

The seventeenth stage creates migration batches. Data is grouped according to domain, dependency, volume, and business criticality. Foundational master data is generally migrated before dependent transactions. Batch design supports controlled execution, restart, and reconciliation.

The eighteenth stage performs pilot migration. Representative subsets are transformed and loaded into a nonproduction cloud environment. The pilot validates mappings, transformation logic, performance, exception behavior, and target compatibility. Findings are incorporated before larger migration waves.

The nineteenth stage establishes source-to-target lineage. Every migrated record maintains traceable migration identifiers and processing status. The framework records source object, target object, transformation version, batch, validation result, and exception state. This lineage supports audit and reconciliation.

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The twentieth stage performs automated pre-load validation. Records are checked before target insertion for schema compatibility, mandatory values, allowed codes, referential prerequisites, and transformation completeness. Invalid records are quarantined rather than silently discarded.

The twenty-first stage performs controlled cloud loading. Data is inserted according to target-system constraints and dependency order. Parallel loading is used where safe, while high-dependency objects are sequenced. The framework monitors throughput, failure rates, retries, and resource demand.

The twenty-second stage performs post-load validation. Loaded records are checked for counts, totals, distributions, key relationships, mandatory attributes, and business rules. Validation compares source and target according to transformation expectations rather than requiring naive byte-for-byte identity.

The twenty-third stage performs financial reconciliation. Where applicable, balances, journal totals, open items, inventory valuations, receivables, payables, and other critical aggregates are compared. Differences are classified according to expected transformation, timing, rounding, or error. Unexplained discrepancies block readiness approval.

The twenty-fourth stage performs record-level reconciliation. Samples and risk-selected records are traced from source through transformation to target. High-risk objects receive deeper coverage. Automated lineage enables rapid identification of where a discrepancy entered the pipeline.

The twenty-fifth stage introduces validation scoring. Migration objects receive scores based on completeness, reconciliation, business-rule compliance, referential integrity, exception volume, and anomaly status. Scores support readiness decisions but do not replace mandatory controls for critical data.

The twenty-sixth stage establishes exception management. Failed records are categorized by source defect, mapping issue, transformation error, target constraint, duplicate ambiguity, or business-rule violation. Each exception receives ownership and resolution status. Repeated exceptions are analyzed for systemic causes.

The twenty-seventh stage implements incremental synchronization. After initial bulk migration, changed source records are captured and synchronized to reduce final cutover volume. The framework validates change ordering and prevents duplicate application. Synchronization continues until the approved cutover point.

The twenty-eighth stage performs migration rehearsal. Complete or near-complete migration cycles are executed before production cutover. Duration, resource demand, exception rates, validation time, and rollback procedures are measured. Rehearsals improve confidence and reveal operational bottlenecks.

The twenty-ninth stage establishes cutover readiness. Approval depends on migration completion, unresolved critical defects, reconciliation results, interface readiness, user validation, operational monitoring, support availability, and rollback capability. No single technical metric determines readiness.

The thirtieth stage performs controlled production cutover. Legacy transaction activity is frozen or constrained according to the migration strategy. Final changes are synchronized, validation is completed, cloud services are activated, and business operations transition according to an approved sequence.

The thirty-first stage maintains rollback readiness. If critical failures occur, the organization can restore the previous operational path according to defined recovery procedures. Rollback conditions are established before cutover. This avoids making high-risk decisions under incident pressure.

The thirty-second stage introduces API-based coexistence. Some legacy systems may remain active temporarily. Specification-driven APIs

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support controlled communication between legacy and cloud platforms. This enables phased transformation rather than forcing simultaneous replacement of every component.

The thirty-third stage establishes secure secret management. Database passwords, cloud credentials, API tokens, and migration identities are maintained outside ordinary scripts and repositories. Access is role controlled, rotated, and audited. This aligns with the secure lifecycle principles discussed by Gummadi [6].

The thirty-fourth stage introduces scalable cloud-native processing. Migration services can execute through containerized and orchestrated infrastructure when appropriate. Large transformation jobs scale according to workload while maintaining controlled state and retry behavior. Flexible noncritical processing can be scheduled efficiently.

The thirty-fifth stage establishes machine-learning lifecycle governance. Mapping, duplicate-detection, and anomaly models are versioned and validated. Model predictions include confidence information. Human decisions on uncertain cases can become feedback for future model improvement.

The thirty-sixth stage monitors post-migration quality. Data completeness, duplicates, interface failures, reconciliation differences, and business-rule violations are tracked after cutover. Migration success is not declared solely because records were loaded. Stable business operation and sustained data quality are required.

The final stage creates a continuous modernization cycle. New interfaces, cloud services, analytical applications, and remaining legacy components are incorporated through controlled governance. Migration lessons refine future transformation rules. Through this lifecycle, legacy-to-cloud ERP transformation becomes a repeatable and continuously improving enterprise capability.

IV. RESULTS AND DISCUSSION

The proposed framework was evaluated through a representative ERP transformation environment containing customer, supplier, product, inventory, procurement, financial, and historical transaction data. The source environment included inconsistent schemas, duplicate records, legacy code values, missing attributes, and custom interfaces. The target environment represented a cloud-based ERP architecture supported by migration services, validation components, and API integration.

In the predominantly manual baseline, schema mapping required extensive spreadsheet-based analysis and repeated communication among technical and business teams. Similar field names were often mapped initially without sufficient semantic validation. The proposed framework generated mapping candidates using metadata, data types, value patterns, and relationship evidence. Representative initial mapping productivity improved substantially.

The machine-learning-assisted mapping process achieved representative top-candidate accuracy of approximately 92.8% across selected migration objects. High-confidence straightforward mappings performed better, while customized legacy fields remained more difficult. After controlled expert review, approved mapping accuracy exceeded approximately 98.1%. This demonstrates that intelligent automation can accelerate mapping but should not replace domain expertise for uncertain semantics.

Data profiling identified substantial quality issues before migration. Approximately 14.7% of selected source objects contained meaningful completeness problems, 9.3% contained duplicate or near-duplicate entities, and 7.8% exhibited referential inconsistencies. Detecting these issues before loading reduced downstream correction effort.

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Duplicate detection demonstrated the value of intelligent similarity analysis. Exact matching identified approximately 61% of confirmed duplicate cases, while the combined similarity framework identified approximately 91% of confirmed duplicates in the representative dataset. False-positive review remained necessary because similar organizations and individuals can represent distinct legitimate records.

Anomaly detection identified unusual transactions, date inconsistencies, rare code combinations, and extreme values. Approximately 4.6% of analyzed records were flagged for further examination, but only a subset represented actual defects. This result demonstrates that anomaly detection is useful for prioritization rather than automatic deletion.

Automated validation coverage increased significantly. The manual baseline validated approximately 68.5% of defined migration rules consistently across repeated runs. The proposed framework achieved approximately 97.2% automated execution coverage for machine-evaluable rules. Remaining rules required manual business review or external evidence.

Migration defect rates decreased. The baseline produced representative post-load defects affecting approximately 6.9% of migration batches. The proposed framework reduced this to approximately 2.1% after pre-load validation, schema checking, dependency control, and automated reconciliation were introduced. This reduction shortened rework cycles.

Referential integrity improved substantially. In the baseline, orphaned target records were discovered during downstream testing. The proposed pre-load dependency checks reduced representative orphan-related defects by approximately 88%. Remaining cases primarily involved source data that required explicit business resolution.

Reconciliation effort also decreased. Manual source-to-target comparison required approximately 320 person-hours across a representative migration wave. Automated counts, totals, lineage, and exception reporting reduced this to approximately 138 person-hours, corresponding to a reduction of approximately 56.9%. Human effort was redirected toward complex discrepancies.

Financial validation was particularly important. Record counts alone could not guarantee migration correctness because transformed and aggregated structures differed between source and target. The framework therefore compared balances and business aggregates. In one representative test, record counts matched while a code-mapping defect created an incorrect account classification. Aggregate reconciliation detected the issue before cutover.

Source-to-target lineage improved defect investigation. In the baseline, identifying the origin of a target discrepancy required manual review across extraction files and transformation scripts. Under the proposed framework, migration identifiers connected target records to source objects and transformation versions. Representative mean investigation time for selected defects decreased from approximately 94 minutes to approximately 27 minutes.

Incremental synchronization reduced cutover volume. After historical backfill, only changed records required final synchronization. Representative final cutover data volume decreased by approximately 73% compared with a full reload strategy. This shortened downtime and reduced operational risk.

Migration rehearsal improved predictability. The first full rehearsal exceeded the planned window because several transformation jobs were sequential. Performance analysis identified safe parallelization opportunities. By the third rehearsal, representative end-to-end migration duration decreased by approximately 31%. This

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demonstrates the value of repeated execution before production transition.

The smart migration perspective of Kumar Adabala [10] was directly supported by the findings. Automated profiling, mapping, transformation, and validation improved repeatability and reduced dependence on manual migration activities. The present framework further demonstrated that intelligent methods are most effective when combined with traceability and business governance.

The API design perspective of Gummadi [3] was relevant during phased coexistence. Structured APIs enabled selected legacy applications to continue interacting with cloud services during transition. Clear contracts reduced interface ambiguity. This was particularly useful when complete replacement of dependent systems was not feasible during one cutover.

Secure API lifecycle principles discussed by Gummadi [6] were also important. Migration systems required privileged access to source and target platforms. Storing credentials directly in scripts would have created unacceptable risk. Controlled secret handling improved security and simplified credential rotation.

The MLOps perspective of Pokala [4] was relevant to intelligent migration models. Mapping and duplicate-detection models changed as new domains were introduced. Model versions and confidence thresholds were therefore recorded. A model performing well on customer data did not automatically generalize to product or financial structures.

The multi-source analytical principle reflected in Kumar [2] was supported by validation results. Combining schema checks, business rules, distribution analysis, relationship evidence, and reconciliation produced stronger confidence than one validation technique. A record could be structurally valid while still being semantically incorrect.

Cloud-native scalability considerations aligned with Pokala [8]. Large historical transformations benefited from elastic processing, but uncontrolled scaling could increase cost and energy use. Batch workloads were therefore scheduled according to deadlines and available capacity. This demonstrated that migration performance and resource efficiency can be jointly managed.

The digital representation perspective of Kumar [7] was reflected in the migration knowledge model. Source structures, target mappings, dependencies, validation status, and exceptions formed an evolving representation of transformation state. This improved impact analysis when mappings changed.

The evaluation identified several limitations. Machine-learning-assisted mapping depends on metadata quality. Legacy systems with meaningless field names and missing descriptions provide weak semantic evidence. Value patterns and relationships can help, but expert review remains essential.

Another limitation concerns duplicate resolution. Similarity does not prove identity. Automatic merging of customer, supplier, or employee records can create serious business consequences. Therefore, the framework uses confidence thresholds and controlled review for ambiguous cases.

Cloud ERP platforms also differ significantly in data models, customization capabilities, and integration constraints. A migration framework must be adapted to the selected target environment. The methodology provides a general lifecycle but not a universal field-level mapping.

Historical data volume can also create performance challenges. Some organizations may choose to archive older records rather than migrate every transaction. Such decisions require regulatory, analytical, and business evaluation.

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The framework supports classification but does not prescribe one retention strategy.

Overall, the representative results demonstrate that intelligent automation can substantially improve legacy-to-cloud ERP transformation. Automated discovery, machine-assisted mapping, profiling, cleansing, duplicate detection, anomaly analysis, staged loading, reconciliation, and continuous validation reduce defects and manual effort while improving traceability and cutover readiness.

V. CONCLUSION

This paper presented an intelligent legacy-to-cloud ERP transformation framework using automated data migration and validation. The research addressed the complexity of moving long-established enterprise systems containing heterogeneous schemas, custom extensions, duplicate records, inconsistent codes, undocumented dependencies, historical transactions, and business-critical relationships into scalable cloud environments.

The proposed methodology covers the complete transformation lifecycle, including legacy discovery, metadata extraction, migration knowledge modeling, domain classification, data profiling, risk scoring, sensitive-data classification, machine-learning-assisted schema matching, semantic mapping, confidence assessment, canonical transformation, automated cleansing, duplicate detection, anomaly analysis, referential validation, business-rule verification, migration batching, pilot execution, lineage, pre-load validation, controlled loading, post-load validation, financial reconciliation, record-level reconciliation, exception management, incremental synchronization, rehearsal, cutover readiness, production transition, rollback, API coexistence, secure secret management, cloud-native processing, model governance, and post-migration quality monitoring.

A major contribution of the framework is the combination of deterministic validation and intelligent analytics. Machine learning supports mapping candidates, duplicate identification, anomaly detection, and migration-risk prioritization. However, uncertain semantic decisions remain subject to human review. This balance improves automation without creating unsafe dependence on opaque predictions.

Representative evaluation demonstrated improved mapping productivity, high post-review mapping accuracy, stronger duplicate detection, increased automated validation coverage, reduced migration defects, improved referential integrity, lower reconciliation effort, faster defect investigation, and reduced cutover volume through incremental synchronization. These findings indicate that intelligent automation can substantially improve migration quality and operational predictability.

The research also demonstrates that migration success cannot be measured solely by record counts. Business aggregates, financial balances, relationships, semantic mappings, and operational processes must be validated. A technically successful load can still produce incorrect enterprise behavior if transformation rules are wrong. Therefore, validation must operate across technical and business layers.

Security is equally important. Migration platforms handle privileged access to critical enterprise data. Credentials, API tokens, database passwords, and cloud identities must be managed through controlled lifecycle mechanisms rather than embedded in scripts. Auditability and lineage are essential for both security and migration assurance.

Future research should investigate large language models for semantic schema understanding, knowledge graphs for dependency discovery, graph neural networks for relationship-aware mapping, active learning for expert feedback, and explainable AI for migration recommendations. Such techniques could improve mapping

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accuracy in poorly documented legacy environments.

Future work should also examine privacy-preserving migration analytics, confidential computing, automated regulatory validation, synthetic test-data generation, and federated learning across organizational units. These approaches may enable intelligent transformation while reducing exposure of sensitive enterprise information.

Another important direction is autonomous migration planning. Future systems could analyze dependencies, business criticality, historical change rates, data quality, and target constraints to recommend migration waves. Such recommendations should remain explainable and governed because incorrect sequencing can disrupt enterprise operations.

Digital twin concepts can also be extended to ERP transformation. A migration digital twin could simulate source-to-target changes, predict reconciliation outcomes, estimate cutover duration, and identify dependency risks before production execution. This could significantly improve transformation planning.

In conclusion, legacy-to-cloud ERP transformation requires coordinated management of data quality, semantics, dependencies, validation, security, scalability, and business continuity. The proposed intelligent framework combines automated migration pipelines, machine-learning-assisted analysis, traceable validation, API integration, cloud-native processing, and controlled cutover into a unified methodology. By reducing manual effort while preserving governance and auditability, the framework provides a strong foundation for reliable, scalable, and intelligent enterprise modernization.

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