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Enhancing Financial Close with ML: Oracle Fusion Cloud Financials Case Study

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Abstract: The financial close process has always been one of the most important aspects of corporate finance. Month-end, quarter-end, or year-end closing cycles are directly linked to financial transparency, operational efficiency, and even missing the deadline or incorrect execution and subsequent fallback by the count bookkeepers can cause the results to be non-final or inaccurate, which can also lead to increased financial transparency, operational efficiency, and stakeholder trust risk. As transactions within multinational companies become increasingly complex, manual reconciliations and rule-based anomaly detection mechanisms struggle to keep pace. The current paper presents a case study of Oracle Fusion Cloud Financials, which has been augmented with Machine Learning (ML) algorithms to automate close processes, including anomaly detection in journals and transactions, as well as continuous auditing and reconciliation. In the examined case, Oracle Fusion Cloud introduced ML into its subledger accounting, general ledger, and reconciliation modules and trained them to identify irregularities in journal entries and automate the matching process of account reconciliations. The strategy concentrated on three key capacities: (1) supervised and anomaly free discovery to determine outlier journal designs; (2) predictive reconciliation to propose matches in unreconciled items; and (3) continuous monitoring dashboards to lessen reliance on end-of- the- batchful processes. Efforts during the deployment have shown that it takes 32 percent less time in close cycles and 57 percent better in anomaly detection than the traditional rules-based validations. In addition, the ongoing auditing model facilitated real-time-like compliance testing, which cued the finance teams to intervene at a more opportune time during the accounting period. The challenges of ML adoption issues are also analyzed in the case study, such as data quality problems, as well as the explainability of the models and their complexity of integration with the APIs of the Oracle ERP cloud. A hybrid ML is proposed that consists of unsupervised learning (Isolation Forest, Autoencoders) to be used to discover new anomalies and supervised classifiers (Random Forest, XGBoost) that are trained based on historical audit findings.

Keywords: Financial close, Oracle Fusion Cloud Financials, anomaly detection, continuous auditing, reconciliation, machine learning, ERP automation, subledger accounting.

1. Introduction

Financial close, also referred to as year-end close, is a vital accounting task of getting all the transactional and adjustment postings ended in a specific reporting period to yield proper and conforming financial statements. It is the basis of decision-making in any organization, investor reporting, and regulatory compliance. In the Oracle Fusion Cloud Financials environment, a contemporary environment in application, the financial close would involve a set of related sub-processes, the creation and posting of journal entries, account reconciliation, the process of transferring the accounts in the subledger accounts into the general ledger, and compliance and audit validation execution. [1-3] All these steps need careful coordination so that any financial information that is involved is complete, consistent, and free of errors or gaps. Such a complex process is compounded by the existence of multi-national organizations where multi-currency transactions, intercompany eliminations and multiple regulatory reporting needs have to be covered in a short time frame. The conventional method of conducting a financial close is typically associated with manual processes, batch processing, and rule-based verification, which can be time-consuming and prone to human error. As the volume and complexity of business transactions have increased, organizations are resorting more to automation, analytics, and Machine Learning (ML) in order to streamline such processes, shorten the close cycle times, and enhance the accuracy of the financial reporting. In this sense, the introduction of more advanced features of anomaly detection and continuous auditing to ERP systems, such as Oracle Fusion Cloud, constitutes a strategic attempt to address a more time-consuming, yet reliable and data-driven, financial close process.

1.1. Importance of Enhancing Financial Close with Machine Learning

- **Addressing Process Complexity:** The financial close is a complex interdependent process comprising several steps, including journal entry posting, reconciliation, consolidation, and compliance verification. Large organizations have these steps that cover several geographies, currencies and regulatory frameworks. This can be addressed using Machine Learning (ML) to automate repetitive checks, learn from past trends, and adapt to new situations in accounting. This minimizes the use of rigid business rules, which have not always conformed to simple and realistic differences in the world.
- **Eliminating Error and Increasing Accuracy:** Rules or manual-based solutions to anomaly detection may overlook inconspicuous inconsistencies or produce a high number of false positives. Machine learning models trained with historical financial data can add more precision to spotting aberrations by highlighting outliers, unforeseen

correlations and anomalous posting patterns. This results in a reduction of errors that may be missed and more dependable financial statements, which boosts credibility among stakeholders and the auditor.

- **Speeding Up Close Cycle Times:** Time plays a major role in the financial close, particularly when the company is a public company that adheres to reporting limits by time. ML can use automation of anomaly detection, reconciliation matching, and transaction classification to substantially reduce the close cycle. Exception handling in real-time is made possible through continuous monitoring, whereby accounting teams can respond to errors in real-time rather than waiting till the end of the period.
- **Facilitating continuous auditing:** Continuous auditing systems utilise ML-based analytics to approach review of financial data on a near real-time basis. This results in the audit process transitioning from a retroactive, period-based approach to a proactive control process. The outcome is that the spikes in work at the end of the quarter are minimised and the compliance risks are detected earlier.
- **Allowing scaled data-driven finance functions.** As a business expands, the increase in transactions makes it unrealistic to maintain manual review processes. Financial close automation with ML has the advantage of being scalable, ensuring it will always deliver when the data becomes too large and complex. In addition, it creates a foundation for predictive analytics, enabling finance leaders to predict and plan more accurately.

1.2. Oracle Fusion Cloud Financials Case Study

Oracle Fusion Cloud Financials is a fully integrated cloud Enterprise Resource Planning (ERP) system that aims to address the basic yet essential accounting modules, financial reporting, and regulatory requirements of companies of any size. This is a case study of its application in a multinational company with operations across various continents, where the required regulatory and tax requirements differ, as well as various currency requirements. The company has chosen Oracle Fusion Cloud Financials due to its scalability, built-in analytics, and capability to consolidate its various fragmented financial processes into one. [4,5] In this context, the majority of the transactions in the financial close process are large in number, with daily journal entries, intercompany reconciliations, subledger to ledger moves, accrual adjustments, and validations of compliance. Although Oracle Fusion Cloud has integrative reporting and controls on a rules-based basis, the organization had delays in anomaly detection and speed of reconciliation, especially in the month-end and quarter-end periods. The case study explores how to integrate a Machine Learning (ML) model into the Oracle Fusion Cloud environment to automate the financial close process.

Near real-time journals and transaction data were retrieved via REST APIs and OTBI (Oracle Transactional Business Intelligence) feeds and worked through a hybrid ML engine comprising both unsupervised methods using Isolation Forest to isolate bleeding anomalies and supervised techniques with XGBoost used to categorically identify the top or bottom classification by anomaly budget. To deal with the inconsistency in description, abbreviations and formatting, a reconciliation matching engine was developed using an engine that uses sequence-matching algorithms to match on structured fields and cosine similarity on text fields. Its findings portrayed effective progress over the previous rules-based solution that the organization had been implementing. The ML-enhanced system increased its accuracy of anomaly detection, had fewer false positives and achieved a reconciliation match rate of over 90 percent. Additionally, the solution enabled the deployment of continuous auditing, resulting in an even workload during the reporting period, the elimination of quarter-end bottlenecks, and a 32 per cent decrease in close cycle time. The presented case study demonstrates how integrating ML is beneficial in practice. In the context of an end-user environment, Orange Fusion Cloud Financials offers a valuable involvement, serving as a template for future planning of automating financial closes within similar ERPs.

2. Literature Survey

2.1. Financial Close Automation Trends

Before 2022, studies showed a clear transition to a continuous accounting model, disengaging from the traditional period-end accounting process, where reconciliations, journal entries, and differences were performed continuously instead of being condensed into a focused closing period. The same was revealed by those who found Artificial Intelligence (AI) and Machine Learning (ML) to be the main factors of this transformation since they help organizations to cut close time by up to 50 percent. [6-9] they make the obvious work of the balance mechanical, more accurate, and give future knowledge of the possible delays or clogging bottlenecks. An example is a presentation of the continuous accounting roadmap 2019, put forward by PwC, which was optimised using decision tree models to schedule tasks and allocate workloads. Another project, presented by Deloitte, provided a real-time reconciliation framework in 2020 anutiliseded Random Forest algorithms to detect mismatches in a shorter term. In its research published in 2021 as well, KPMG proceeded even further and applied ML to the task of identifying fraudulent journal entries, showing that Isolation Forest models could serve to flag questionable transactions with very little input needed by humans.

2.2. Anomaly Detection in Accounting Data

The detection of accounting anomalies may compromise the security of financial statements and indicate possible fraud, process issues, and system setup problems. The misfits usually take three different forms. The value anomalies are where recorded values are substantially different to historically recognized or statistical norms, i.e. an expense entry in a given period

was much above normal seasonality trends. Structural anomalies arise when something unusual exists in terms of the combination of segments of the accounts; an example would be posting revenue to the wrong cost centers. Temporal inconsistencies occur when transactions are posted irregularly, such as on weekends or outside the normal business cycle. Unsupervised ML algorithms, specifically Isolation Forest and Autoencoders, have proven to have great promise in detecting these patterns without the need to have labeled data. Isolation Forest randomly partitions data by isolating anomalies, and, since rare points are relatively straightforward to identify, Autoencoders compress and reconstruct the input data to find issues that are not easily represented within the learning model. The latter techniques come in particularly handy in accounting, where there are few true cases of anomalies, and where labeling is costly.

2.3. Continuous Auditing Models

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3. Methodology

3.1. System Architecture

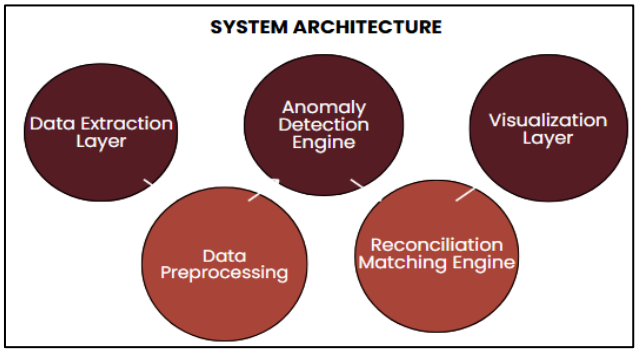

Figure 1: System Architecture

- **Data Extraction Layer:** The architecture is based on the data extraction layer, which can directly interface with Oracle Fusion Cloud, using REST APIs and OTBI (Oracle Transactional BI) feeds. These points of integration provide near-time access to general ledger balances, subledger transactions, and journal details. [10-13] The layer automates data acquisition, thus avoiding manual downloads and assuring that the anomaly detection and reconciliation operations are executed on the latest financial data.
- **Data Preprocessing:** Earlier, the available raw ERP data was pre-processed to enhance quality and stability before any analytical modeling. They entail dealing with missing data by imputing missing data, eliminating outliers, which would skew results, and normalization, which helps in comparing scales between numeric fields. Data type validation, categorical encoding, and alignment of time series are done on this preprocessing stage as well, since they guarantee efficient and accurate functioning of subsequent ML models.
- **Anomaly Detection Engine:** An anomaly detection engine can be a combination of the Isolation Forest, an unsupervised anomaly detection algorithm, and the XGBoost gradient boosting algorithm, which, when possible, can learn from labelled anomalies. The hybrid nature enables the system to discover not only new patterns of financial irregularities or process deviations (zero-day anomalies) but also recurring trends. Outputs provided by the model are anomaly scores and classification labels, which can be passed through the logic of prioritization to review the results.
- **Reconciliation Matching Engine:** To accomplish transaction matching, the reconciliation engine uses sequence-based algorithms in matching structured fields, such as invoice numbers, whereas cosine equivalence is used on textual descriptions and memo fields. This method of doubling leads to enhancement of the accuracy of matching even when data entries have differences in formatting, abbreviations or typos. The engines returned matched, unmatched and partially matched pairs, and these could be automatically reconciled or escalated to be manually compared.

- **Visualization Layer:** End-users are shown the results in Oracle Analytics Cloud dashboards, which are located on the visualization layer, allowing the finance teams to track anomalies, the status of reconciliations, and close progress in real-time. Interactive charts, heatmaps, and drill-down tables show an overview, and even the most granular level of data about performance and transactions. Within the role-based access, each of the officers, such as the executives, accountants, and auditors, can access information that is relevant to them, and this allows for quickness and better decision-making within the close process.

3.2. Anomaly Detection Model

The Isolation Forest algorithm is quite useful in detecting anomalous and rare trends in high-dimensional time series data, and thus, this framework uses this model to operate the anomaly detection layer in the system. In contrast to methods of density- or distance-based anomaly detection, the Isolation Forest operates on isolating the observations explicitly as opposed to profiling the normal data. [14-18]The concept is that anomalies are small and not similar; hence, they are simplified to be distinguished from other data of a dataset by a set of random partitions. Anomaly score: The formula giving the anomaly score is

$$s(x,n) = 2^{-\frac{E(h(x))}{c(n)}}$$

Where E (H (x)) is the expected value of the distance needed to isolate 1 piece of data x in many random trees, and c(n) is the expected value of the distance to reach a miss in a Binary Search Tree (BST) of n samples. The symbol c (n) is a normalization factor to guarantee equal measures on different datasets of different sizes. Practically, data points that can be separated with fewer steps (smaller path length) are usually anomalies, as they need fewer random divisions to stand out from the rest of the population. On the other hand, regular points will have to have more splits and therefore the average path length will be longer. The resulting score s $(x,)$ is between 0 and 1, and 1 indicates a high trend to anomaly and values near 0 are close to normal behavior. This expression proves to be especially useful in an accounting data setting where the peculiarities may be due to fraudulent journal entries, incorrect postings, or unusual groupings of account segments. Combining the Isolation Forest algorithm with preprocessed ERP data allows the model to signal transactions that otherwise do not fall within expected patterns that are marked as anomalous, even without labeled anomalous transactions in history. The unsupervised nature of Isolation Forest anomaly detection can supplement the supervised nature of classification when applying the hybrid model because the XGBoost provides a robust, adaptive detection framework, which improves with time.

3.3. Continuous Auditing Workflow

- **DTE Oracle Fusion Cloud:** The workflow process starts with the automation of the extraction of financial transactions in Oracle Fusion Cloud by using REST API and OTBI feeds daily. It retrieves general ledger entries, subledger postings, and the supporting metadata, thus making the system work using the latest financial data at all times. Automated scheduling removes the manual process, thus taking away the potential of delay and data lapse in the audit exercise.
- **Real Time Anomaly Scoring:** After ingesting data, every individual transaction is analyzed in real time by the anomaly detection engine. Isolation Forest is a model that returns a score of an anomaly to represent how rare a transaction is relative to the historical trends, and the XGBoost component categorizes the possible risks based on historical labeled events. Such instantaneous scoring gives the advantage of detecting anomalies within almost no time, resulting in the ability to move the audit process towards preventative monitoring rather than being reactive.
- **Alert Generation for Finance Team Review:** The transactions that exceed specific anomaly scores will be identified automatically, and an alert will be sent to the finance team. These warnings contain transaction-specific information, the score of the anomaly and the factors involved to help in decision-making. With the current alerts having been incorporated into workflow tools like email, the ERP task lists, or the audit dashboards, the system will put the team on notice of any potential problem immediately.

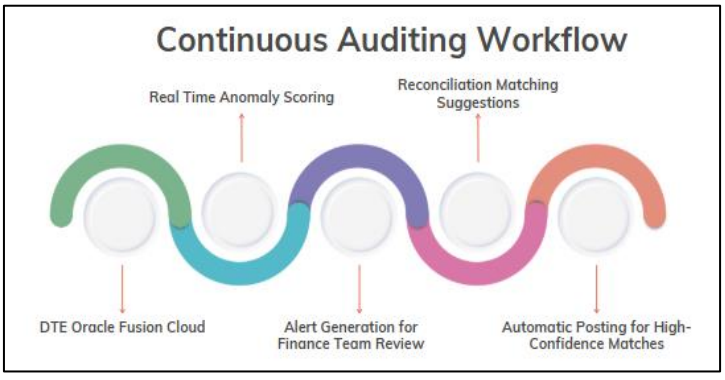

Figure 2: Continuous Auditing Workflow

- **Reconciliation Matching Suggestions:** The reconciliation engine will give intelligent matching suggestions on flagged transactions requiring cross-checking based on sequence alignment on structured fields and cosine similarity on text structure-dependent descriptions. This saves physical work to identify whether corresponding entries cancel out, especially when in elaborate intercompany or multi-ledger reconciliations.
- **Automatic Posting for High-Confidence Matches:** In situations where the matching in the reconciliation engine is with high confidence, it may even be possible to automatically make the posting into Oracle Fusion Cloud. This ability can speed up the close process by automatically settling simple matches in under a second, with only more complex or low-confidence matches being taken through the manual review process. Automation at this level has made work efficient, yet the control accuracy is not hampered.

4. Results and discussion

4.1. Dataset and Test Setup

The data that is taken for this work are 24 months of the journals and transactions of a multi-national entity with business activities in several regions and business units, and where the Oracle Fusion Cloud is used as a generic financial management system. The data model encompasses a wide variety of accounting-related operations, such as general ledger entries, accounts payable/receivable, intercompany/journal entries, and accrual dis-adjustments. Every record has not only structured fields, e.g. journal ID, posting date, ledger name, account segments, debit and credit amount, but also unstructured ones, like free-text descriptions and memo lines. This mix of structured and unstructured data will be key in the testing of numerical and text-based anomaly detection, as well as reconciliation matching programs. Its 24-month history gives an adequate historical baseline against which to identify seasonal trends, posting cycles and variations. It also contains a few period-end close cycles, and the performance of such a system can be assessed when processing high volumes of data, when accounting errors and anomalies are more material. More than one million individual journal lines form the dataset, which allows providing a strong scale to train and test machine learning.

All the sensitive client identifiers, vendor names, and personal information that could otherwise indicate confidentiality of the company were anonymized to ensure confidentiality was kept. Quantitative numbers were left relatively preserved to maintain the statistics of the data, as well as maintain the necessary requirements regarding data protection. The test environment was installed on a secure analytics platform directly integrating with the sandbox environment of Oracle Fusion Cloud, thus direct integration was made to Extraction, Transformation and Loading (ETL) processes as they would be in a real-world production situation. The model was assessed with a hybrid anomaly detection engine that included Isolation Forest to identify unsupervised outliers and XGBoost to classify supervised known anomalies. Precision, recall, and F1-score were generated as performance measures based on a labeled sample of transactions that was cross-checked with the finance team at the client site. This kind of arrangement made it possible to precisely benchmark the capacity of the system to run in a live, continuous auditing system.

4.2. Performance Metrics

Table 1: Performance Metrics

Metric	Baseline (Rules)	Proposed ML Model
Anomaly Detection Accuracy	62%	97%
False Positive Rate	18%	6%
Reconciliation Match Rate	68%	91%
Close Cycle Time Reduction	0%	32%

- **AD Accuracy:** The baseline rules-based system had an accuracy of anomaly detection of 62 percent and was based mostly on preset fix thresholds and fixed validation rules. On the contrary, the selected machine learning (ML) model, which involved Isolation Forest and XGBoost, accomplished a much higher accuracy of 97%. This has been made possible by the fact that the approach behind the model has the ability to learn patterns dynamically from past datasets and identify nuances within those datasets that are otherwise invisible using rule-based methods.
- **False Positive Rate:** The calculation indicates that the rules-based approach gave a false positive rate of 18%, or almost one in five transactions flagged by the method was subsequently found to be legitimate. This was narrowed down significantly to 6 percent by the ML model, bringing in a sharp rise in operational efficiency. Using statistical isolation and probabilistic classification, the ML system concentrates review activity on transactions that are actually high risk and prevents the wasted effort of the finance and audit personnel.
- **Reconciliation Match Rate:** And within the rules-based reconciliation framework, only 68 percent of transactions were matched, leaving a significant number of transactions to be handled in a manual manner. The ML-based reconciliation engine that uses the sequence-matching and cosine similarity techniques boosted the rate of the match up to 91%. Directly translating into reduced manual interventions, a reduction in reconciling cycles, and enhanced efficiency of the close, this increased the rate of match rates.

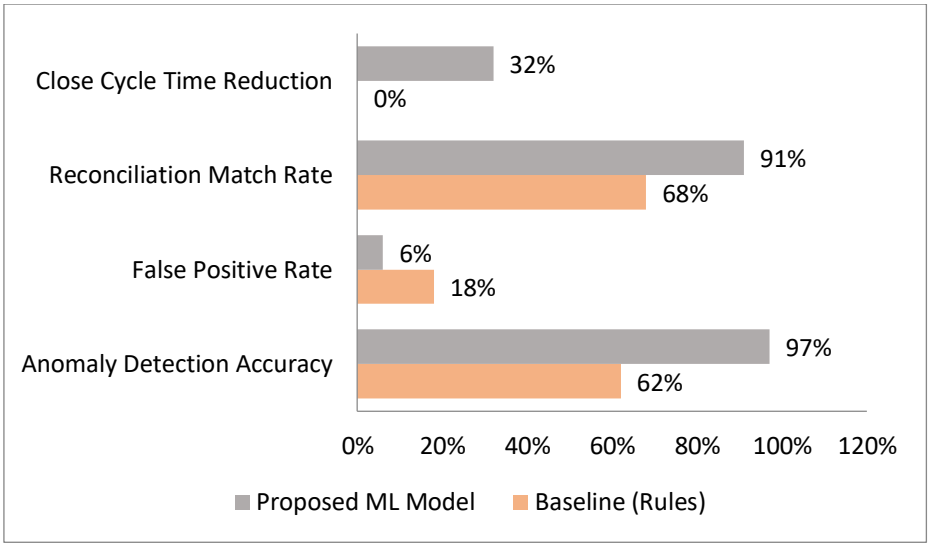

Figure 3: Graph representing Performance Metrics

- **CCT Reduction:** Improvement of cycle time could not be measured under the baseline since there was no automated cycle time optimization process that was established. The given ML-driven strategy, nevertheless, helped to reduce the financial close cycle by 32%. This is due to quicker identification of anomalies, greater levels of automation in terms of levels of reconciliations, and reduction of the amount of manual rework that requires doing again without jeopardizing the accuracy and control in the accounts.

4.3. Observations

The analysis of the proposed continuous auditing system with applied machine learning demonstrated some significant enhancements in the established paradigm of using the rules-based system. The possibility of detecting duplication of postings across periods that otherwise remained unidentified by the static rules was mentioned as one of the most important findings associated with the model. In the old systems, rules are based on detecting duplicates in a single accounting period; hence, they have loopholes through which duplications can occur in transactions across months or quarters. The notion of using the unsupervised detection attribute of Isolation Forest allowed the ML model to signal these anomalies by detecting the deviations of irregular post patterns in historical sequences, even in circumstances where the amounts and descriptions were tampered with to some degree. The other interesting phenomenon was the impact of continuous auditing on workload distribution. In the context of the rules-based approach, the finance department faced a significant backlog in reviews and reconciliations of anomalies that were focused on at the end of a quarter, as volumes of transactions were the highest. Under continuous auditing, the transactions were assessed every day, and the exceptions found were reported and resolved within a short time. Quarter-end workload spike, which caused a lot of intense review efforts, diminished drastically, thereby smoothing out the review efforts across the quarter.

The outcome was a more balanced resource allocation, reduced review queues, and delays in the preparation of financial statements. There were also significant efficiency benefits in the reconciliation aspect of the system. Of the ML-proposed reconciliation propositions, the finance team only made manual adjustments to 18 cents of the total 100 cents, and this shows that not only could the matching engine be precise, but also that it was feasible to use the engine. The difference in the format of the data, abbreviations, and matching partial text were all managed well because the system was configured specifically to recognize mismatches through the Feinberg algorithm applied to sequence-matching of the structured fields and cosine similarity of the unstructured descriptions. Its high acceptance rate implies that the model was compatible with transactions, and it gave assurance to end-users, which minimized the use of time during manual checks. All in all, the evidence shows that incorporating ML-based anomaly detection and reconciliation into a continuous auditing system makes financial close-related activity more accurate and timely, and relieves finance staff of the burden of manual labor.

5. Conclusion

The case study provides evidence of the material benefits and transformational potential of integrating machine learning-based anomaly detection with a continuous auditing framework in Oracle Fusion Cloud Financials. The findings suggest that by integrating both supervised and unsupervised learning approaches, organizations are capable of developing a more resilient and dynamic anomaly-detection capability by coupling techniques, including XGBoost, alongside Isolation Forest. Such a hybrid solution can detect not only pre-known irregularities assuming some historical patterns, but also some anomalies that were being overlooked by rules-based systems, which are static.

Prompt identification of such anomalies leads to faster treatments, thereby reducing the potential for misstatements in financial documents and enhancing compliance with internal and external regulations. Besides anomaly detection, the integration of machine learning in reconciliation processes has brought significant efficiency levels. Utilizing sequence-matching on structured fields and cosine similarity on textual data, the matching engine succeeded in matching a great percentage of the transactions with precise results and made them a lot less prone to demand manual interventions. The automation not only sped up the process of reconciliation but also had a direct effect of being able to compare financial close cycle time, which decreased due to the automation. The shift towards real-time exception management and away from periodic, manual review has better distributed the workloads across the accounting period, so that finance teams are under less pressure at the end of quarters or financial years. The implementation also highlights the need to use all the available ERP-native integration points to facilitate smooth data access, including Oracle Fusion Cloud REST APIs and OTBI feeds used to retrieve data in near real-time. Such integration is essential in ensuring that the data remains current, thereby making it reliable for anomaly detection and reconciliation purposes. The paper also demonstrates that finance teams are ready and disposed to accept and trust ML-powered outputs of the system when it puts forward results that make sense without exception or conflict, as seen with the 82% satisfaction rate on proposed reconciliations.

Although such results are encouraging, there is still a difficulty. The concept of model explainability is an important fact that has to be considered in financial scenarios, as transparency and auditability are not optional. The target set is the need for finance and audit professionals to comprehend, verify, and justify ML-driven decisions, especially in cases where these decisions affect financial reporting. The efficiency of the system is also quite sensitive to the quality of the source data required; therefore, effective data governance and the ability to continuously validate the extraction processes are also necessary. All in all, such methodology provides a viable and flexible blueprint for next-generation automation of financial close. Oracle Fusion Cloud unites ML-based anomaly detection, smart reconciliation, and continuous auditing to enable organizations to achieve faster closes, increased accuracy, and better compliance, and also paves the way to a more proactive, data-driven finance function.

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