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# Research on Application Pathways and Practices of Intelligent Financial Technologies Empowering International Tax Compliance Management

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## Abstract

The digitalization of cross-border business has dispersed tax-relevant information across enterprise resource planning systems, electronic invoices, banking transactions, country-by-country reports, and account information exchange records, making manual review increasingly difficult when data are frequent, heterogeneous, and distributed across jurisdictions. Intelligent financial technologies can organize these records by means of data standardization, entity matching, anomaly detection, risk scoring, and audit prioritization, converting fragmented tax information into identifiable risk features and directing higher-risk cases to professional review; this process supports transaction verification, profit-shifting detection, and more selective allocation of audit resources within one connected compliance workflow. The practical value of such technologies depends on the quality of source data, the stability of analytical models, and the role of professional judgment, so reliable use requires a traceable relationship among original records, extracted risk features, model outputs, and review outcomes, allowing screening results to remain explainable and suitable for later recalibration under changing cross-border reporting conditions.

## Keywords

Intelligent financial technologies; international tax compliance; risk identification; machine learning; cross-border tax management

## Introduction

Cross-border transactions, settlement activities, and tax reporting are now increasingly recorded in digital systems, while compliance information has expanded beyond tax returns to include electronic invoices, accounting records, cross-border account information, and country-by-country reporting data; digital tax administration has consequently placed greater emphasis on data linkage, continuous verification, and anomaly identification [1]. Differences in field definitions, entity identifiers, reporting periods, and currency treatment still make cross-system comparison difficult, and manual review may delay the recognition of risks when related-party transactions, profit allocation, and international cash flows interact within the same case. Intelligent financial technologies offer a practical response by converting dispersed records into comparable inputs, detecting transactions that depart from expected patterns, and assigning a clearer order of priority for audit work and professional review.

## 1. Technical Foundations for Embedding Intelligent Financial Technologies in International Tax Compliance Management

### 1.1 Multi-Source Tax Data Integration and Feature Modeling

International tax compliance relies on general ledger records, electronic invoices, banking transactions, related-party information, country-by-country reports, and cross-border account data, yet these sources often differ in entity

identifiers, accounting periods, currencies, and tax fields; intelligent financial systems therefore require a unified data dictionary for field mapping and entity resolution based on taxpayer IDs, account information, corporate names, and counterparty relationships [2]. After basic cleaning, risk features can be extracted from revenue, profit margins, tax burdens, related-party transaction ratios, fund flows, and transaction frequency, while missing values, outliers, and currency-conversion errors need to be handled before the data enter analytical models. Standardized features provide a comparable input space for later anomaly detection, and their stability directly affects the reliability of risk scores and the consistency of assessments across reporting periods.

### 1.2 Intelligent Risk Identification and Audit Resource Allocation

Once the feature set has been prepared, machine-learning models can estimate taxpayer risk from historical filings, transaction behavior, and previous audit outcomes, then rank cases according to risk scores, potential tax exposure, and case complexity [3]. Neural networks are suited to nonlinear relationships among multiple variables, while unsupervised anomaly-detection methods can identify unusual transactions when labeled cases are limited; model performance should be examined with precision, recall, false-positive rates, and class imbalance in mind so that poorly calibrated thresholds do not generate excessive low-value alerts. Audit resources can then be directed toward cases with higher estimated risk and greater potential impact, after which tax professionals review the transaction context, filing basis, and evidential completeness before the case proceeds to formal compliance assessment.

## 2. Application Pathways of Intelligent Financial Technologies in International Tax Compliance Management

### 2.1 Cross-Border Tax Data Access and Standardized Validation

Cross-border tax records enter compliance systems from ERP ledgers, electronic invoices, bank payment files, tax returns, and counterparty records, so the first operational task is to establish a stable correspondence among tax identifiers, invoice numbers, transaction dates, currency codes, account entries, and reporting periods; schema mapping converts source fields into a common record format, while entity matching links the same taxpayer or counterparty across systems and preserves the original source identifier for later verification. Once records are aligned, rule-based checks compare invoice value, settlement amount, booked revenue or expense, declared tax base, applicable tax rate, and currency-conversion result at transaction level, with inconsistencies assigned exception codes according to their type and materiality rather than being mixed into a single warning category. Electronic invoicing is especially useful at this stage because structured invoice fields support repeated machine matching against accounting and filing records, allowing unmatched documents, duplicate entries, date mismatches, and value discrepancies to be isolated before they enter later risk analysis [4].

### 2.2 Anomalous Transaction Detection and Profit-Shifting Monitoring

Cross-border risk analysis requires indicators that describe whether reported profit remains reasonably aligned with operating activity across jurisdictions, so country-by-country reporting fields such as revenue, profit before tax, income tax, employee numbers, and tangible assets can be converted into ratios including profit-to-revenue, tax-to-profit, profit-per-employee, and profit-to-tangible-assets; these measures are then examined together with related-party transaction intensity, transaction frequency, and the concentration of reported earnings. Statistical deviation measures or unsupervised detection methods can assign an anomaly score to observations that depart materially from their peer or historical range, after which the score is combined with transaction value, cross-border exposure, and data completeness to produce a ranked risk record rather than a binary judgment. A high score signals the need for closer examination of the commercial functions, asset location, transaction counterparties, and reported allocation of profit, while the underlying CbCR fields remain available for tracing why a case entered the review queue [5].

### 2.3 Intelligent Compliance Decisions and Audit Workflow Coordination

Model output becomes operational only when risk scores are converted into differentiated review actions, and a practical workflow may classify low-risk records for routine monitoring, medium-risk records for additional documentary checks, and high-risk records for specialist review; case priority can then be determined from model score, estimated tax exposure, evidence completeness, transaction complexity, and the persistence of anomalies across reporting periods. Tax professionals examine contracts, filing positions, related-party relationships, payment

evidence, and earlier compliance records before deciding whether a case should proceed to extended verification or audit, while the final disposition is returned to the analytical layer as labeled feedback for threshold adjustment and later model calibration. As shown in Figure 1, the operating chain links the data-source, data-processing, intelligent-analysis, compliance-decision, and feedback layers, while data quality, explainability, human review, and model monitoring run alongside the chain as control functions; this arrangement keeps model screening, risk ranking, professional judgment, and audit decisions traceable within the same workflow [6].

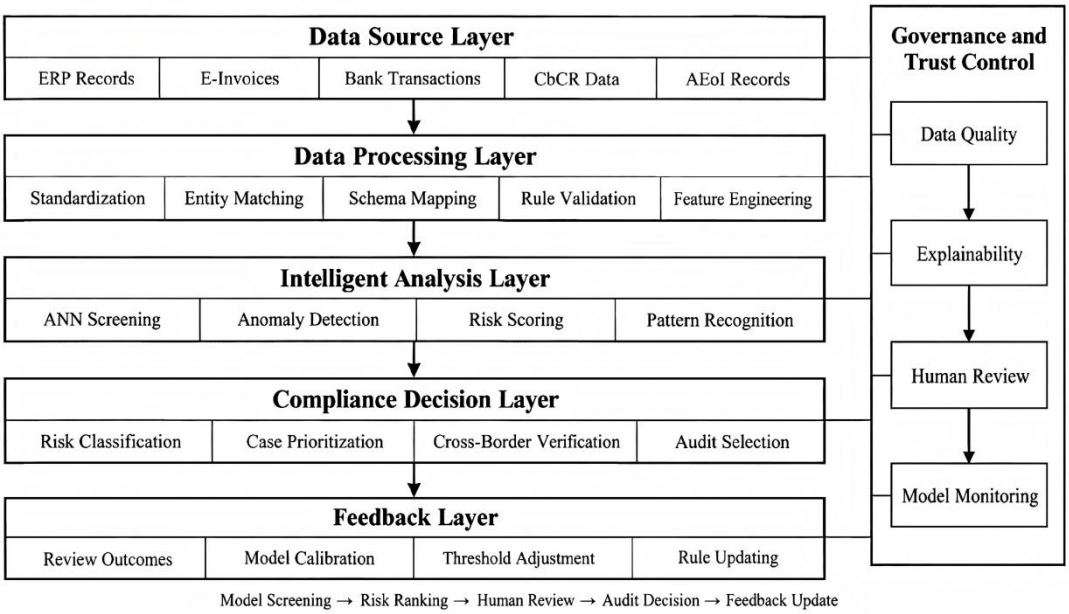


**Figure 1. Layered architecture of intelligent financial technologies for international tax compliance management.**

## 3. Empirical Validation and Compliance Control of Intelligent Financial Technology Applications

### 3.1 Empirical Comparison Across Tax Compliance Applications

The empirical assessment covers three operational settings—audit-lead identification, audit-case reallocation, and cross-border account information exchange—which correspond to classification, case ranking, and reporting verification. As shown in Table 1, the California dataset contains 93,413 tax records from 8,647 restaurant businesses over ten years; its ANN classifier achieved 40.1% precision, 58.7% recall, and an F1-score of 0.42, while the audit-gain regressor reported an MAE of USD 155,490, and the Italian audit setting used actual tax-return and audit records to reorder candidate cases [7-9].

**Table 1. Empirical validation results of intelligent technologies in tax compliance**

| Application scenario | Data scale/Setting | Analytical method | Verified result |
|---|---|---|---|
| California audit-lead selection | 93,413 tax records; 8,647 restaurant businesses; 10 years | Artificial Neural Network | Precision 40.1%; Recall 58.7%; F1 = 0.42; MAE = USD 155,490 |
| Italian audit-case reallocation | Administrative tax-return and audit data for sole proprietorships | Machine-Learning Audit Selection | Replacing 10% of low-predicted-value audits increased detected evasion by up to 39% and recovered evasion by 29% |
| Swiss cross-border information exchange | About 107,000 taxpayers; approximately 2% of taxpayers | AEoI + Difference-in-Differences | CHF 37.6 billion in previously hidden wealth disclosed; reported wealth increased by roughly 50% |

These outcomes should be used according to the function of each indicator: the California results test screening accuracy, the Italian results measure case-ranking performance under a fixed audit volume, and the Swiss data capture reporting changes following cross-border information matching. Replacing the least promising 10% of Italian audits with algorithm-selected cases raised detected evasion by as much as 39% and recovered evasion by 29%,

while the Swiss AEoI setting involved around 107,000 taxpayers, disclosed CHF 37.6 billion of previously hidden wealth, and was associated with an average increase of roughly 50% in reported wealth among participants.

### 3.2 Reliability Testing of Model Outputs

Model validation should separate classification performance from monetary prediction: an audit-lead file records true positives, false positives, true negatives, and false negatives for each completed case, from which precision, recall, and the F1-score are calculated so that class imbalance is not concealed by overall accuracy. Monetary estimates require a separate record containing predicted audit gain and actual audit gain for each audited case, with their differences used to calculate MAE; cases can then be grouped by risk score and checked against realized audit yield, keeping the probability of a productive audit distinct from the expected monetary amount.

Operational validation should proceed across reporting periods, with earlier observations retained for training and a later period reserved as an out-of-time sample; the review then compares score distributions, the precision-recall relationship, and actual outcomes among highly ranked cases. Persistent false positives within the upper-risk range require a return to input fields, missing-value treatment, categorical encoding, and entity-matching records before the classification threshold is recalibrated on validation data. Each adjustment should retain the model version, feature set, training period, validation period, and threshold so that the analytical conditions attached to an individual case remain reproducible.

### 3.3 Operational Control of Cross-Border Compliance Cases

Each case entering professional review should receive a separate case record containing the source record ID, entity identifier, reporting period, risk score, triggered feature, model version, and review status, with every flagged feature linked back to the original filing field. When a flag arises from a mismatch between reported profit and operating scale, reviewers return to revenue, profit before tax, employee counts, tangible assets, and related transaction records, then examine business functions, counterparties, asset locations, contractual terms, and payment evidence before assigning a status such as confirmed, unresolved, or false positive.

Completed cases are maintained in a score–review result–audit outcome file: confirmed cases proceed to further verification, false positives enter a dedicated error set, and cases later identified during audit but missed by the model are added to the false-negative set. At each reporting cycle, reviewers inspect missing-field rates, currency-conversion records, entity-matching outputs, and the distribution of risk scores; material changes in the input structure trigger model retraining, while the previous model version and its audit outcomes remain available as a benchmark. This record structure allows threshold changes, feature revisions, and case-ranking decisions to be traced to the exact data and model version used at the time.

## 4. Conclusion

Intelligent financial technologies connect data access, risk identification, case ranking, and professional review within an integrated international tax compliance workflow. Once multi-source tax records are aligned by field mapping, entity matching, and rule validation, they can support anomalous transaction screening, profit-shifting detection, and audit prioritization, while verified administrative data show measurable performance in audit-lead identification, audit reallocation, and cross-border information exchange. Operational use still requires a clear link among source records, input features, model versions, risk scores, and review outcomes, together with regular checks for false positives, false negatives, and data drift. Further deployment should concentrate on cross-jurisdictional data compatibility, model stability, and professional review so that analytical outputs remain explainable, reproducible, and traceable when incorporated into tax compliance decisions.

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