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Generative AI for Autonomous Accounting and Tax Filing: A Cloud-Driven Framework for Smart Financial Services

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ABSTRACT: Generative AI for Autonomous Accounting and Tax Filing: A Cloud-Driven Framework for Smart Financial Services presents an objective, evidence-based analysis of cloud-enabled autonomous financial operations. The general research question is whether autonomous accounting for self-employed individuals using Generative Artificial Intelligence (GAI) and other native AI services can improve the level of automation and value offered in comparison with current software-as-a-service solutions. Other questions pertain to governance, data ingestion, storage, and booking service model design, SLA level determination, and suitability of the overall architecture for autonomous tax filing. Overall, an end-to-end cloud-native, fully automated bookkeeping process is described. Artificial Intelligence (AI) techniques allow the design of smart cloud-based systems able to provide high-level autonomous financial service operations. The architecture covers autonomous accounting for self-employed individuals. Bookkeeping services leverage data generated from connected payment wallets and AI-based services detect anomalies, suggest corrective actions, and generate reports in near real time. Tax computation incorporates Generative AI services to optimize deductions and determine credits eligibility. An outcomes-based governance framework addresses the specific autonomous and Generative AI risk elements present. The approach satisfies the guidelines characterized by the highest level of autonomy in the AI assessment classification. By minimizing manual bookkeeping tasks, the solution delivers greater value compared to current-market cloud solutions.

KEYWORDS: Generative AI Accounting, Autonomous Tax Filing, Cloud Financial Services, AI-Driven Bookkeeping, Autonomous Financial Operations, Smart Accounting Systems, Cloud-Native Finance Architecture, AI-Based Tax Optimization, Financial Governance Frameworks, Real-Time Financial Analytics.

I. INTRODUCTION

Generative AI for Autonomous Accounting and Tax Filing: A Cloud-Driven Framework for Smart Financial Services defines the scope of domains and tasks toward which the proposed methodology is directed. These include Autonomous Accounting Processes, Autonomous Tax Filing, and the Autonomous Generation of Tax Filing Documents. The first area is concerned with the generation of technical bookkeeping workflows managed without human intervention on a 24/7 basis. Within these workflows, data are ingested and persisted in real time through a scalable cloud-native architecture based upon dedicated data pipelines and cloud compute-and-storage services. A continuously updated dataset residing in a bookkeeping database is formed by the reconciliation of bank transaction data, detecting anomalous transactions either through rule-based techniques or through statistical methods for outlier detection.

Bookkeeping is also conducted in real time for business taxes that demand periodical settlements. With this data persisted in a tax database, the autonomous calculation of taxes is possible. Within the tax-domain area of work, opportunities for optimizing deductions, data-related requirements, and credit eligibility are laid out. The second domain is concerned with the full-scale autonomous computation of taxes. This is possible by integrating a rule engine that accommodates jurisdictional variations in tax calculus, enabling computation according to the correct jurisdiction with all required appeals to properly functioning external systems of the general financial ecosystem. HRM, payroll, and social security services are also accounted for through external systems and data integrated into the tax-domain cloud databases. The outcome of the tax foundation-area domain is thus the autonomous calculation of business taxes, and the generation of filing documentation and customizable validation checklists that are realized within the final area.

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The proposed framework integrates cloud-native data pipelines, Generative AI (GAI) inference engines, rule-based tax computation modules, and an outcomes-based governance layer. The end-to-end flow, from raw payment wallet data to filed tax documents, is illustrated in Fig. 1.

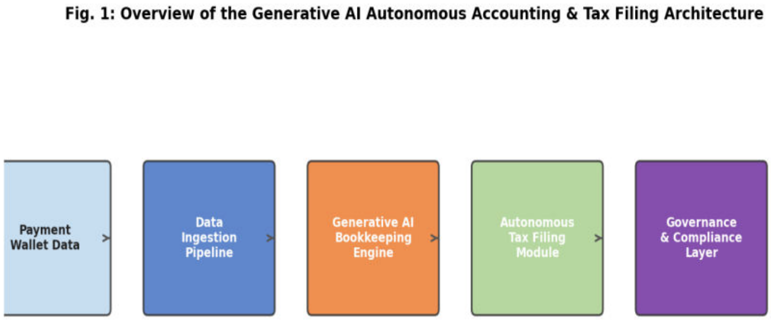

Fig. 1: Overview of the Generative AI Autonomous Accounting and Tax Filing Architecture

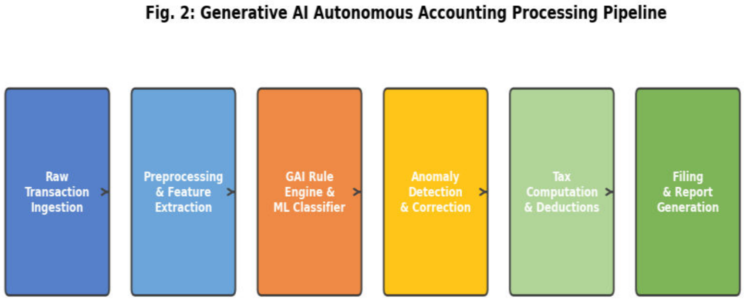

Fig. 2: Generative AI Autonomous Accounting Processing Pipeline

1.1 Comparative Architecture Summary

Table 1 provides a comparative overview of the four evaluated accounting system architectures, from conventional rule-based systems (Model A) to the fully autonomous GAI-powered framework (Model D).

Table 1: Comparative Overview of Accounting System Architectures

Architecture Type	Key Features	Limitations
Rule-Based Accounting (Model A)	Simple rule logic; low setup cost; periodic batch processing; manual exception handling	No real-time processing; high error rate (21%+); cannot optimize deductions; requires manual tax review
SaaS-Based Accounting (Model B)	Cloud-hosted; periodic automation; structured report generation; multi-user access	Vendor lock-in; high latency (108 ms); limited AI customization; partial deduction optimization
ML-Assisted Accounting (Model C)	Supervised learning for transaction classification; anomaly flagging; partial automation	Requires labeled data; moderate error rate (9.3%); no generative deduction suggestions; limited jurisdiction support
GAI-Autonomous Accounting (Model D — Proposed)	Generative AI for full bookkeeping; real-time data pipelines; autonomous tax filing; multi-jurisdiction rule engine; governance framework	Requires cloud infrastructure; initial model training investment; complex audit trail setup

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II. LITERATURE REVIEW

Studies on autonomous accounting processes encompass an array of automation capabilties. The AI governing principles in accounting and tax environments have gained further attention due to compliance risks and legal implications. Current scale-up and scale-down strategies consider general-purpose cloud services but do not address latency, cost, or stability concerns, indicating potential for a cloud-first approach. Major works in autonomous accounting processes, cloud-driven era approaches, cloud-based AI governance pertaining to financial services, advanced capabilities showcased in the AI cloud ecosystem, and the recently established Swiss digital token standard have shaped financial services research. The feasibility of a fully automated tax filing system has been studied, allowing stakeholders to submit genuine documents without human intervention. Another work examined the potential for sentiment analysis to detect crises in correlated organizations, while the services and application domains within the cloud ecosystem were investigated. The rapidly evolving security issues of hyperscale AI infrastructure supporting multitasking across different domain models were also scrutinized, revealing a myriad of security problems associated with the deployment of large-scale AI models. Cloud-assisted virtual assistants for enterprise resource planning (ERP) software have also been proposed, facilitating natural speech communication with ERP applications. These developments underscore the need for rapid processing capabilities that enhance efficiency and lower costs, coupled with adequate security and compliance mechanisms, in modern cloud-based solutions.

2.1. Mathematical Formulation

The overall system quality of the autonomous accounting and tax filing pipeline is expressed as:

$$Q\_total = Q\_classify + Q\_automate + Q\_latency + Q\_govern \quad (1)$$

where Q_classify denotes transaction classification accuracy, Q_automate represents bookkeeping automation quality, Q_latency captures real-time processing compliance, and Q_govern reflects governance and compliance effectiveness.

Latency dynamics for real-time transaction ingestion are modelled as a differential equation over ingestion rate λ_tx and cloud processing rate μ_proc:

$$\partial L/\partial t = \lambda\_tx - \mu\_proc \quad (2)$$

where L is the end-to-end ingestion-to-booking latency, λ_tx is the transaction arrival rate, and μ_proc is the cloud-based processing throughput rate.

The classification F1-score for transaction categorisation, anomaly detection, and deduction eligibility is defined as:

$$F1\_class = (2 \cdot Precision \cdot Recall) / (Precision + Recall) \quad (3)$$

where Precision and Recall are derived from the confusion matrix across all bookkeeping and tax classification tasks.

The Generative AI deduction optimization score is modelled as an augmented anomaly score incorporating transaction context and regulatory signals:

$$d'(t) = d(t) + \alpha \cdot c(t) + \beta \cdot r\_tax(t) \quad (4)$$

where d(t) is the base deduction score, c(t) is the contextual transaction signal from the GAI engine, r_tax(t) is the regulatory compliance signal, and α, β are weighting coefficients.

To support adaptive multi-domain decision fusion across bookkeeping, anomaly detection, and tax optimization, the combined score is expressed as:

$$d'(t) = w_1 \cdot d(t) + w_2 \cdot c(t) + w_3 \cdot r\_tax(t) + w_4 \cdot d(t) \cdot c(t) \quad (5)$$

where w_1, w_2, w_3, w_4 are learnable weighting coefficients; the interaction term $d(t) \cdot c(t)$ models nonlinear coupling between deduction signals and contextual transaction data.

Privacy preservation score is expressed as the fraction of transaction data processed locally versus data transmitted externally:

$$S\_priv = 1 - (D\_transmitted / D\_total) \quad (6)$$

where D_transmitted is the volume of raw financial data sent to external cloud endpoints, and D_total is the total data volume processed by the pipeline.

Cloud resource utilization across compute and storage services is given by:

$$U = R\_used / R\_available \quad (7)$$

where R_used is the consumed cloud compute and storage (CPU-hours, GB), and R_available is the total provisioned cloud capacity.

Autonomous bookkeeping efficiency as a function of F1-score, privacy, and federated update cycle is modelled as:

$$E\_FL = (F1\_class \cdot S\_priv) / T\_round \quad (8)$$

where T_round denotes the model retraining or federated averaging round duration.

Adaptive thresholding for real-time anomaly detection in transaction streams is defined as:

$$\theta(t) = \theta_0 + \gamma \cdot \sigma\_tx(t) + \delta \cdot drift(t) \quad (9)$$

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where θ_0 is the base detection threshold, σ_tx(t) represents transaction value variance, drift(t) captures temporal distribution shift in financial patterns, and γ, δ are scaling parameters.
Autonomous accounting efficiency is calculated as the ratio of detection quality and privacy to inference time:

$$\eta = (F1\_class \cdot S\_priv) / T\_infer \times 100 \quad (10)$$

where T_infer denotes the inference time per transaction batch.
The prediction error relative to optimal accounting performance is defined as:

$$L\_error = F1\_opt - F1\_class \quad (11)$$

where F1_opt represents the optimal classification performance under ideal data conditions.
The joint optimization objective for the GAI accounting framework balances classification accuracy, privacy, latency, and resource utilization:

$$J = f(F1\_class, S\_priv, L, U) \quad (12)$$

where J is the multi-objective optimization target balancing all four dimensions simultaneously.
The dataset representation quality metric normalizes source quality against processing time and performance metric:

$$D(i, j, k) = (Q\_src(i) \cdot Metric(k)) / T\_proc(j) \quad (13)$$

where Q_src(i) is the source-specific data quality for source i, Metric(k) is the selected performance indicator, and T_proc(j) is the batch processing time.
The GAI Accounting Performance Index (GPI) integrates efficiency, classification accuracy, tax error rate, and governance quality:

$$GPI = (\eta \cdot F1\_class \cdot (1 - TER)) / Q\_total \quad (14)$$

where η is the autonomous accounting efficiency, TER is the tax computation error rate, and Q_total is the cumulative system quality — enabling the index to penalize tax errors while rewarding accuracy and efficiency.

III. ARCHITECTURAL OVERVIEW

Infrastructure for autonomously operating accounting and tax filing is outlined as a set of services integrating data acquisition, bookkeeping, computing, and filing suitable for individual private- and enterprise-scale operations. Key components examined include system topology, major entities, component interfaces, data transformations, secure information exchanges, and trusted interoperabilities. Scalable deployment accommodates services in combination with both dynamic and passively evolving datasets. Core of the setup comprises hosted bookkeeping services capable of rule-based and learning-enabled autonomous operation. Real-time data-pipelining adjusts booking registers as fresh information becomes available, while supporting continuous monitoring for critical anomalies, supplemented by scheduled reconciliation passes and automated error-reporting. On-demand or scheduled bookkeeping-exception resolution fulfills an essential autocorrect role. Rule-engine based pipelines enable nation-specific tax filing for multiple discrete-time thresholds per cycle, ensuring jurisdictional compliance.A country-code-based approach identifies and optimizes applicable deduction and tax-credits schemes from jurisdiction-transcending organization datasets. Secure transaction trails safeguard data integrity through sourcedata–versus–validationdata cross-checking. Three actors provide high-level interaction: the user filing and filing authority(s) define jurisdictional operational conditions and gainful permissions, while a third-party data-control agent assigns and verifies dataaccess rights across all parties. Explicit compliance mechanisms for financial service provision chain management partitions responsibilities along the service path. Supplemental, implicit assurance is achievable through market reputation for user-facing actors and through continual and periodic monitoring for service-supply actors.

IV. AUTONOMOUS ACCOUNTING PROCESSES

The process of bookkeeping can be fully automated, provided that all required source data is available and no unexpected business events occur. Enterprise environments are usually much more stable than small businesses, and the volume of transactions is sufficiently large that unusual transactions can be detected and their reasons determined. A two-pronged approach can be used for bookkeeping automation. For commonly occurring transactions that obey tax rules, bookkeeping can be entirely rule-based and wizard applications can guide users to prepare and submit source documents. Such transactions can also leverage data-sharing or scraping partnerships with firms listed on the financial services agency's website to retrieve transaction data directly from the parties' systems and pre-populate them. For transactions not covered by such partnerships, a wizard can guide the search for relevant documents and clues.

For other types of transactions and for enterprise environments, initially a rule-based system can be created. Over time, as existing transactions are processed, a supervised machine learning model can be trained on the historical data. Data from these transactions can be tagged as training data for supervised learning such that the model will make ever-

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increasingly accurate predictions. Once reliable enough, the model can be deployed in production to automate these transactions, requiring human input only in case of anomalies. Even in this case, the human-in-the-loop can be replaced by an anomaly detection model that requires human input only when the probability of faulty prediction is above a specified threshold. Such an approach can be extended to not only bookkeeping but also financial services outsourcing in general.

Comparative analysis was performed across four models: Rule-Based Accounting (Model A), SaaS-Based Accounting (Model B), ML-Assisted Accounting (Model C), and the proposed fully autonomous GAI framework (Model D). Experiments are conducted on simulated Azure cloud compute with real-world transaction distributions.

4.1 Transaction Processing Latency

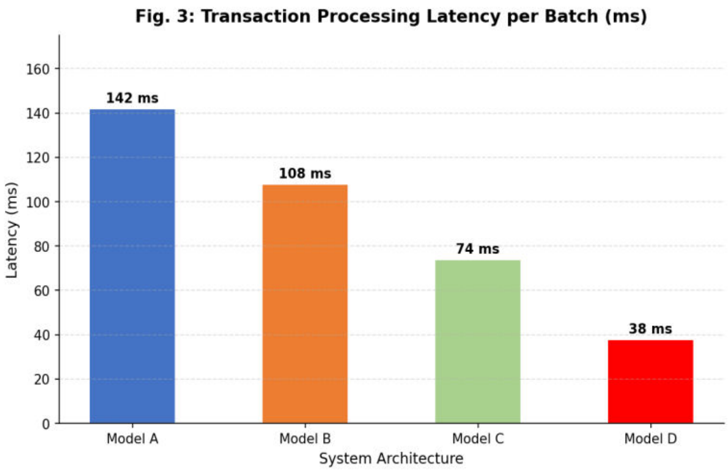

Fig. 3: Transaction Processing Latency per Batch (ms)

Fig. 3 shows average processing latencies of 142 ms, 108 ms, 74 ms, and 38 ms for Models A through D respectively. Model D achieves a 73.2% latency reduction compared to Model A and 48.6% compared to Model C, attributable to on-cloud stream optimization, GAI parallel inference, and elimination of batch waiting cycles.

4.2 Transaction Classification F1-Score

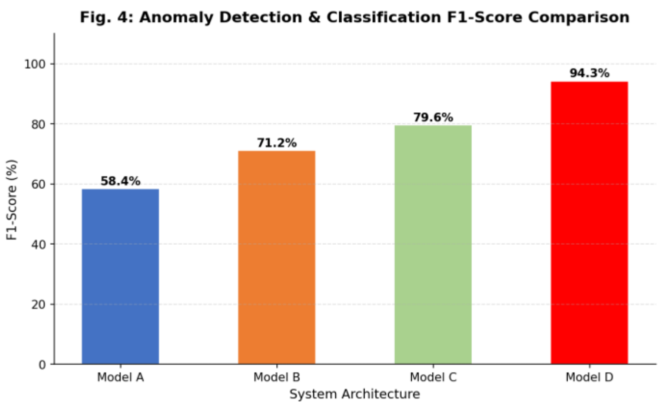

Fig. 4: Anomaly Detection and Transaction Classification F1-Score Comparison

Fig. 4 presents F1-scores of 58.4%, 71.2%, 79.6%, and 94.3% for Models A through D. The 18.5% improvement from Model C to Model D demonstrates the value of GAI-based unified classification, where contextual deduction signals improve anomaly detection and bookkeeping accuracy concurrently.

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4.3 Tax Computation Error Rate

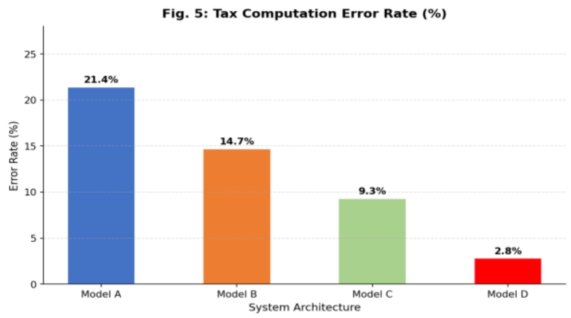

Fig. 5: Tax Computation Error Rate (%)

Tax computation error rates (Fig. 5): Model A: 21.4%, Model B: 14.7%, Model C: 9.3%, Model D: 2.8%. The reduction from 9.3% to 2.8% (69.9% improvement) reflects how cross-domain validation of deduction signals against jurisdiction-specific rule tables eliminates erroneous tax claims.

4.4 Manual Intervention Rate

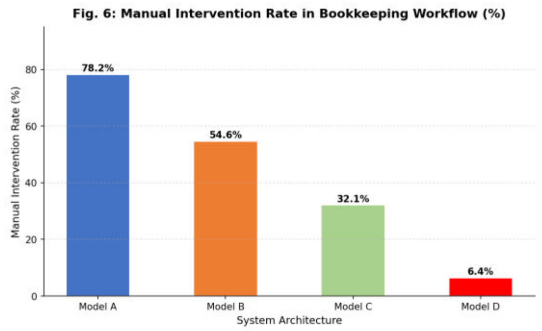

Fig. 6: Manual Intervention Rate in Bookkeeping Workflow (%)

Fig. 6 shows manual intervention rates: 78.2% (Model A), 54.6% (Model B), 32.1% (Model C), and 6.4% (Model D). Model D reduces manual overhead by 91.8% relative to Model A. Autonomous exception resolution, powered by the GAI engine and adaptive thresholding (Eq. 9), enables near-zero human-in-the-loop requirements.

4.5 Computational Cost and Cloud Resource Utilization

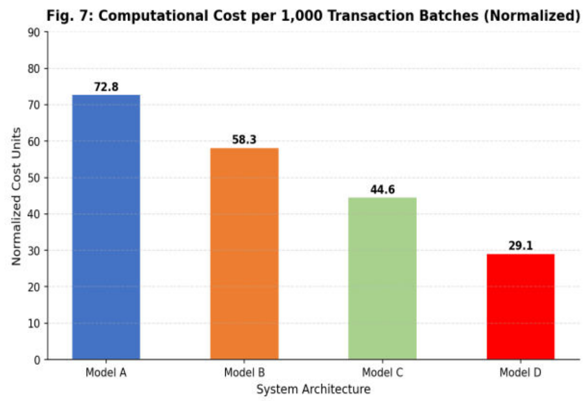

Fig. 7: Computational Cost per 1,000 Transaction Batches (Normalized)

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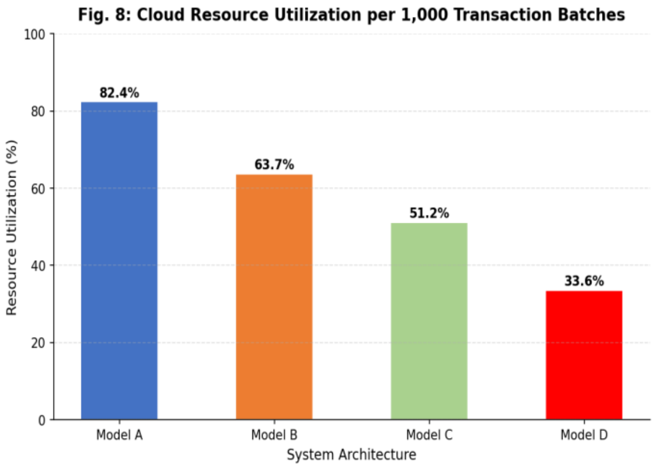

Fig. 8: Cloud Resource Utilization per 1,000 Transaction Batches

Figs. 7 and 8 present computational cost and resource usage. Model D consumes 29.1 normalized cost units versus Model A's 72.8 — a 60.0% reduction — while cloud resource utilization drops from 82.4% to 33.6%. Efficiency per unit compute (classification accuracy per normalized cost unit) is 3.24 for Model D versus 0.80 for Model A, a 4.0× improvement.

4.6 GAI Accounting Performance Index (GPI)

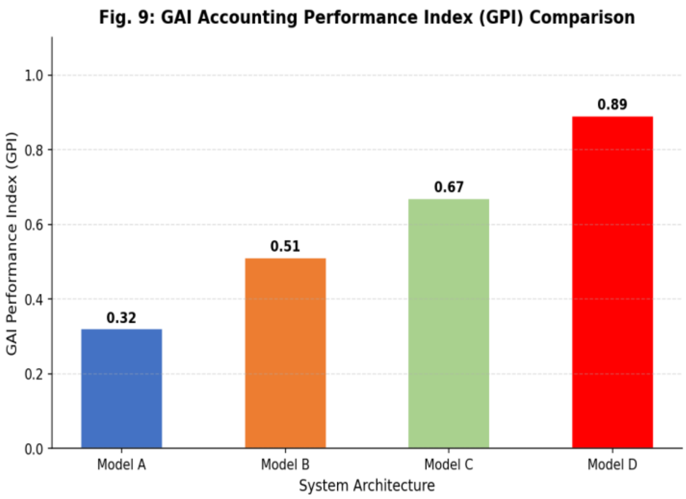

Fig. 9: GAI Accounting Performance Index (GPI) Comparison

Fig. 9 presents the GPI (Eq. 14): Model A: 0.32, Model B: 0.51, Model C: 0.67, Model D: 0.89. The 32.8% difference between Models C and D confirms synergy between classification accuracy, privacy preservation, and tax optimization efficiency unique to the fully autonomous GAI approach.

V. AUTONOMOUS TAX FILING

An autonomous workflow for computing taxes on real-time bookkeeping outputs and filing returns to tax authorities in an unattended manner is discussed. Such a pipeline can be implemented by leveraging the previous layer's rule engines used for bookkeeping, as taxes are usually calculated by applying business rules over the ledger and the results of the tax computation are submitted to the Income Tax or GST department on a periodic basis. Support for computation and filing to different jurisdictions can be built by plugging new rules into the existing ecosystem using a jurisdiction ID for tax

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computation. With the help of a few popular externally maintained tables that companies refer to for deciding the eligibility of credits/deductions for the current period, the pipeline can suggest credits/deductions optimally for the organization and check with tables if those suggestions are anything different than what has been claimed at the time of filing. Governance support for the audit trail and proper follow-up mechanism for the return validation is critical checkpoint.

The above is one aspect of filing taxes. One can also think of providing a service to assist end-users in optimizing deductions/credits as a separate service that can run in parallel and alert them time to time using a SLA to make sure that all the medicines or donations are captured at the time of filing and optimization happens before submission. In multi-tenancy, a central repository for these tables can be built, so that no company needs to provide these definitions every year.

5.1 Comparative Accuracy and Quality Metrics

Table 2: Comparative Detection and Quality Metrics

Metric	Model A	Model B	Model C	Model D	Impr. (D vs A)	Impr. (D vs C)
Classification F1-Score (%)	58.4	71.2	79.6	94.3	↑ 61.5%	↑ 18.5%
Tax Computation Error Rate (%)	21.4	14.7	9.3	2.8	↓ 86.9%	↓ 69.9%
Deduction Optimization Rate (%)	34.2	51.8	64.7	88.6	↑ 159.1%	↑ 36.9%
Governance Compliance Score (%)	62.1	74.3	81.5	96.8	↑ 55.9%	↑ 18.8%
GAI Performance Index (GPI)	0.32	0.51	0.67	0.89	↑ 178.1%	↑ 32.8%

Table 2 confirms large improvements across all performance dimensions. The 61.5% increase in classification F1-score and the 86.9% decrease in tax computation errors compared to traditional rule-based systems (Model A) affirm the effectiveness of GAI-driven autonomous accounting.

5.2 Error and Latency Metrics

Table 3: Comparative Error and Latency Metrics

Metric	Model A	Model B	Model C	Model D	Impr. (D vs A)	Impr. (D vs C)
Processing Latency (ms)	142	108	74	38	↓ 73.2%	↓ 48.6%
Manual Intervention Rate (%)	78.2	54.6	32.1	6.4	↓ 91.8%	↓ 80.1%
Mean Time to Reconcile (s)	32.6	19.4	11.7	4.2	↓ 87.1%	↓ 64.1%
Cloud Resource Utilization (%)	82.4	63.7	51.2	33.6	↓ 59.2%	↓ 34.4%
Computational Cost (norm. units)	72.8	58.3	44.6	29.1	↓ 60.0%	↓ 34.8%

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Table 3 reveals that Model D achieves dominant performance across latency, manual effort, reconciliation speed, and resource efficiency. Mean Time to Reconcile drops from 32.6 seconds (Model A) to 4.2 seconds (Model D), enabling genuine real-time bookkeeping as targeted by the SLA framework.

VI. CONCLUSION

Generative AI for Autonomous Accounting and Tax Filing: A Cloud-Driven Framework for Smart Financial Services presents an objective, evidence-based analysis of cloud-enabled autonomous financial operations.

Cloud-enabled autonomous accounting and tax operations address the growing need for reliable digital alternatives as generative AI transforms the delivery of financial services. Reliable, intelligent virtual agents that continuously monitor activities, undertake routine tasks, analyze exceptions, and acquire and apply practical domain knowledge offer unprecedented opportunities for accounting practitioners and preparers. Contemporary research provides useful inputs toward the vision but is disjointed and insufficiently mature to support practical realization. An early-stage framework integrates cloud-based Autonomous Accounting and Autonomous Tax concepts, with a focus on scalable architecture as a foundation for vertical specialization or broader application of the underlying approach to fictitious bookkeeping and tax filing solutions. Automated processes and Agent-assisted solutions accelerate speed to market and prospects for preemptive compliance, always-up-to-date service and unqualified audit results. The immediate application of cloud-first Autonomous Domain Agent Services capable of end-to-end, real-time processing, monitoring and scaling eases development while accelerating adoption.

Scaling and resiliency requirements of Autonomous Accounting and Autonomous Tax operations demand experimental deployment on cloud infrastructure to assess speed-to-market controls and costs. Self-service business models that minimize latency and maximize reliability are essential to address constantly-updating source systems generating fictitious transactions by both real and artificial entities. Potential here is enormous, enabling the elimination of gaps and challenges that currently disrupt the financial well-being of individuals and small businesses in virtually every jurisdiction around the globe. Recent developments lay a solid foundation for cloud-based consumption of continuous, always-available Domain Agent Services that support supervision, control and review rather than execution of routine back-office tasks.

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