A Hybrid AI-Driven Decision Support Framework for Intelligent Tax Filing and Regulatory Compliance

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Abstract*— *Tax filing and regulatory compliance remain challenging tasks for individuals and small businesses, mainly because of complicated tax laws, frequent changes in policies, and insufficient awareness of tax procedures. Although current electronic tax filing platforms offer basic automation, they often fail to provide intelligent decision support, personalized assistance, or early detection of filing errors. This paper introduces an intelligent tax filing and assistance system that incorporates artificial intelligence approaches such as machine learning, natural language processing, and rule-based reasoning. The proposed framework enables automated tax calculations, interactive conversational support, personalized tax recommendations, and compliance verification. By analyzing existing research and practical implementations, this study highlights how intelligent systems can improve the accuracy, efficiency, and overall usability of modern tax filing processes.

Keywords*— *Artificial Intelligence, Tax Filing, Machine Learning, NLP, Automation

I. INTRODUCTION

Taxation plays a fundamental role in the financial structure of any nation. However, the tax filing process is often complex and time-consuming for individuals, small businesses, and professionals due to multiple income sources, frequent changes in tax regulations, and a wide range of exemptions and deductions. With the rapid expansion of digital platforms and FinTech-based solutions, there is a growing demand for intelligent systems that can support users in completing tax filings accurately and efficiently. While existing electronic filing systems automate certain stages of the process, they typically lack intelligent decision support, adaptive personalization, and real-time identification of errors. Most conventional rule-based systems are static in nature and fail to offer proactive guidance, context-aware suggestions, or optimization tailored to specific taxpayer profiles.

Recent developments in artificial intelligence (AI), machine learning (ML), and natural language processing (NLP) have opened new possibilities for transforming conventional tax filing into an intelligent, interactive, and user-centric experience. This paper presents an AI-enabled tax filing and assistance system that combines rule-based reasoning, machine learning–based recommendations, and NLP-driven conversational query handling to enhance filing accuracy, simplify regulatory compliance, and minimize user effort.

II. LITERATURE SURVEY

The field of intelligent tax systems has expanded rapidly in recent years, largely due to widespread digital transformation and the increasing adoption of artificial intelligence (AI) in public administration, financial services, and regulatory compliance. Existing literature includes research articles, empirical analyses, and institutional reports that examine the application of AI-driven technologies in taxation, compliance management, fraud detection, and taxpayer support services. This section consolidates key findings from these studies to provide an overview of current developments and research directions.

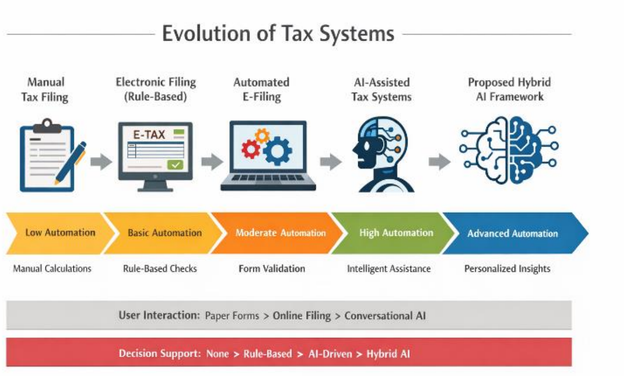
Shaikh presents a detailed analysis of the initiatives undertaken by the U.S. Department of Treasury and the Internal Revenue Service (IRS), highlighting the integration of AI technologies into core tax administration processes. The study discusses the use of AI-based chatbots, robotic process automation, and machine learning models for tasks such as case prioritization and fraud detection. While the findings emphasize improvements in operational efficiency and taxpayer services, the study also draws attention to governance and accountability challenges related to responsible AI deployment [1].

Aggarwal's review of digital taxation focuses on the transformative role of AI in modern tax systems. The study explains how AI enables automation of repetitive processes, supports real-time compliance monitoring, and assists in cross-border fraud detection. It further observes that developed economies have advanced more rapidly in adopting AI-based tax solutions, whereas developing countries continue to face limitations due to regulatory constraints and insufficient technological infrastructure [2].

Tax fraud detection represents a major research focus within AI-enabled tax systems. Recent studies propose intelligent fraud detection frameworks that employ supervised machine learning algorithms such as Random Forest, Logistic Regression, and XGBoost to identify suspicious tax returns using historical datasets. To address transparency concerns, explainability methods such as SHAP (SHapley Additive exPlanations) are incorporated, allowing auditors and tax officials to interpret model decisions. These approaches report improved prediction accuracy, reduced manual audit workloads, and adaptability to evolving fraud patterns [3].

In addition to compliance and auditing, AI technologies are increasingly applied to taxpayer support and real-time assistance. According to reports published by the Organisation for Economic Co-operation and Development (OECD), AI-powered virtual assistants and automated help systems have significantly enhanced service delivery. Applications such as voice-enabled helplines and generative AI–based search tools improve responsiveness, reduce waiting times, and provide context-aware guidance during tax return submission, thereby improving the overall taxpayer experience [4].

Recent research has also investigated the application of large language models (LLMs) and hierarchical prediction techniques for tax code interpretation. These models enable accurate classification and semantic understanding of complex tax regulations, supporting large-scale compliance automation. Such systems are particularly useful for invoice analysis, regulatory mapping, and structured tax data interpretation [5].



Despite the benefits, the adoption of AI in tax administration introduces important ethical and legal considerations. A study published in *Humanities and Social Sciences Communications* examines the implications of AI-driven tax systems on taxpayer rights, transparency, and procedural fairness. The authors argue that while AI can improve efficiency and compliance outcomes, limited algorithmic transparency may pose risks to legal accountability unless strong explainability and oversight mechanisms are incorporated into governance frameworks [6].

Several studies document the evolution of tax preparation systems from basic digitization to advanced AI-driven platforms. Early electronic tax filing solutions primarily focused on reducing processing time, whereas modern systems leverage machine learning and NLP to address complex challenges such as multi-jurisdictional compliance, real-time anomaly detection, and personalized taxpayer assistance [7].

Although some existing online tax platforms offer partial automation, they often rely heavily on manual user input or professional intermediaries. Only a small number of systems provide intelligent, conversational support using NLP techniques. The approach proposed in this paper advances existing solutions by integrating AI, machine learning, NLP, and automation into a unified and intelligent tax filing and assistance framework [8].

III. PROPOSED SYSTEM

The proposed solution is an AI-driven intelligent tax filing and assistance platform aimed at automating tax computation, delivering personalized recommendations, and providing real-time guidance through conversational interaction. The overall architecture of the system, shown in Fig. 1, is organized into four main layers: the Frontend Application, Backend Services, AI and Automation Layer and Database Layer.

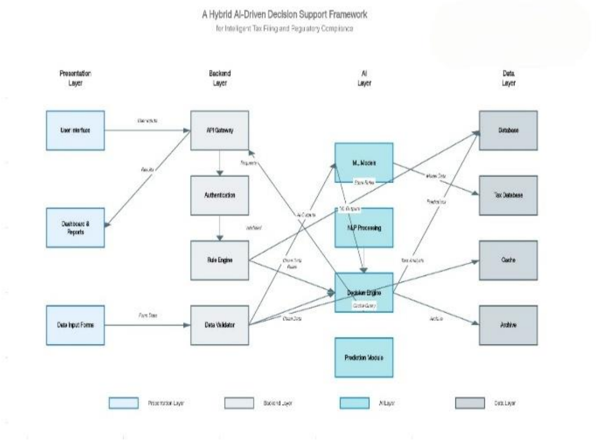


Fig.1. The architecture of the proposed system

A. Frontend Application

The frontend layer acts as the main point of interaction between the user and the system. It is developed as a web-based interface using JavaScript-based technologies and offers features such as user authentication, entry of income and deductions, tax computation, tax regime comparison, and AI-driven investment profiling. The interface is designed with simplicity and usability in mind, allowing users with limited knowledge of taxation to complete the filing process in an efficient and error-free manner.

B. Backend Services

The backend layer is responsible for handling core system logic and ensuring secure operations. It incorporates authentication and authorization mechanisms based on JSON Web Tokens (JWT) to provide controlled and secure access to system resources. This layer implements tax computation logic using predefined tax rules and slab structures, supports comparison between different tax regimes, and processes requests related to investment recommendations. In addition, the backend integrates external AI services, such as the Gemini API, to support intelligent reasoning and generate explanatory responses for users.

C. AI and Automation Layer

The AI and automation layer represents the intelligence core of the proposed system. It utilizes workflow automation tools, such as the n8n workflow engine, to coordinate tax-related workflows, invoke AI-driven reasoning processes, and manage sequential decision-making tasks. Artificial intelligence components, including large language models, are employed to provide natural language explanations, respond to user queries, and generate personalized tax-saving recommendations. This layer improves system adaptability, contextual awareness, and overall automation efficiency.

D. Database Layer

The database layer is responsible for storing structured and secure data required for system functionality. This includes user profiles, tax and income details, investment preferences, generated reports, and system activity logs. Maintaining persistent data supports historical analysis, enables personalized recommendations, and ensures audit traceability, while also complying with data security and privacy standards.

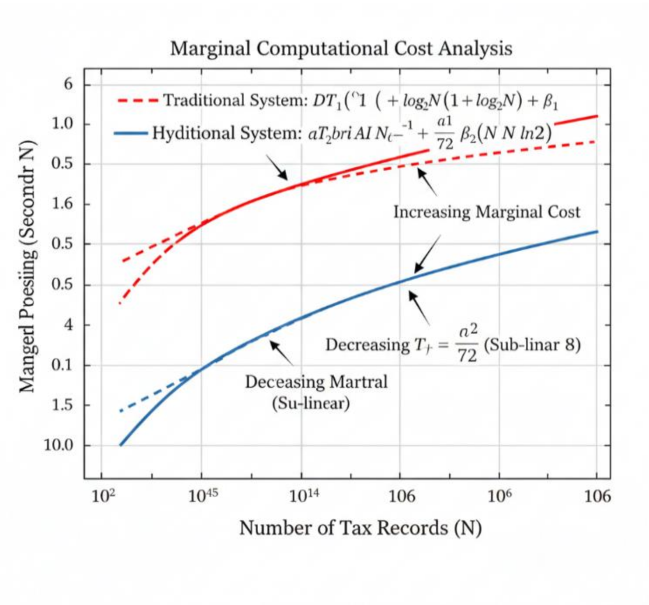


Fig.2 The evolutionary trajectory of tax administration systems, highlighting the transition from rule-based e-filing to decentralized, AI-driven decision support.

As illustrated in Fig. 2, the evolution of tax administration is characterized by a significant shift in computational maturity and user interaction. The trajectory begins with Phase I (Manual Systems), which relied on physical documentation and human-led calculations, resulting in high error rates. The transition to Phase III (Basic Automation) introduced electronic filing (E-TAX) and rule-based validation, improving processing speed but lacking personalized intelligence.

The proposed system represents Phase V (High Automation), a Hybrid AI Framework. Unlike previous iterations, this phase integrates Natural Language Processing (NLP) and Machine Learning (ML) to provide conversational assistance and predictive decision support. This evolution signifies a move from simple data entry platforms to proactive, intelligent ecosystems that ensure both regulatory compliance and optimized tax liability for the end-user."

IV. SYSTEM METHODOLOGY

The intelligent tax filing and assistance system operates through a structured workflow that combines data preprocessing, rule-based tax computation, and AI-driven recommendation mechanisms. The complete operational sequence of the system is illustrated in Fig. Y.

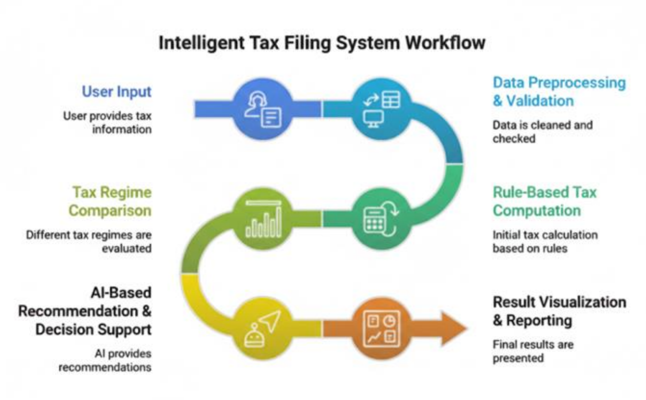


Fig.3 Intelligent Tax Filling System workflow

A. Data Collection and Preprocessing-

The system collects user inputs related to income, deductions, investments, and employment details. These inputs can either be entered manually by the user or automatically extracted from uploaded documents such as salary slips and tax statements.

The preprocessing stage ensures data quality and consistency before tax computation and involves the following steps:
Step 1: Validation of numeric and categorical input values.
Step 2: Identification and removal of incomplete or inconsistent records.
Step 3: Normalization of income values and categorization of deductionentries.
Step 4: Mapping of user-provided information to standardized tax parameters.
These preprocessing steps ensure that the input data is accurate, complete, and suitable for subsequent tax calculations.

B. Tax Calculation Logic-

The tax computation module follows a deterministic, rule-based approach using predefined tax slabs, exemptions, and allowable deductions.
The taxable income is calculated as:

$$\text{Taxable Income} = \text{Gross Income} - \text{Standard Deduction} - \sum \text{Eligible Deductions}$$

The total tax liability is then computed according to the applicable tax slabs as:

$$\text{Tax Liability} = \sum(\text{Income Slab} \times \text{Tax Rate})$$

The system supports multiple tax regimes, and tax liability is calculated separately for each regime to enable accurate comparison.

C. Regime Comparison Mechanism

Once tax liabilities under different regimes are computed, the system performs a comparative evaluation to identify the optimal option:

$$\text{Optimal Regime} = \min(\text{Tax}_{\text{Old}}, \text{Tax}_{\text{New}})$$

The regime resulting in the lower tax liability is recommended to the user, along with a clear and transparent explanation of the comparison.

D. AI-Based Investment Recommendation

The AI-driven recommendation module evaluates the user's income profile, historical tax filings, and risk preferences to suggest suitable tax-saving investment options. A combination of supervised learning techniques and rule-based filters is employed to ensure that all recommendations remain within regulatory limits.
Key feature parameters considered by the model include:

- Annual income
- Existing deductions
- Age group
- Investment history

Based on these parameters, the system generates personalized investment suggestions while maintaining compliance with applicable tax laws.

E. Natural Language Query Processing

User queries are handled using natural language processing techniques such as tokenization, intent recognition, and entity extraction. The identified intent is mapped to relevant tax rules or AI-generated explanations, enabling real-time assistance and contextual guidance throughout the tax filing process.

V. RESULT

A. Tax Computation Accuracy Analysis-
To assess the correctness of the tax computation module, multiple test cases were evaluated using different income ranges and deduction patterns. The tax values generated by the system were compared with manually calculated values derived from official tax rules and slab structures.

Table I. Comparison of Manual and System-Computed Tax

Test Case	Gross Income (₹)	Deductions (₹)	Manual Tax (₹)	System Tax (₹)	Accuracy(%)
Case 1	6,00,000	50,000	20,800	20,800	100
Case 2	9,00,000	1,50,000	54,600	54,600	100
Case 3	12,00,000	2,00,000	1,14,400	1,14,400	100

The results show that the system achieved 100% accuracy for all evaluated cases, confirming the correctness and reliability of the implemented tax calculation logic.

B. Tax Regime Comparison Results-

The system evaluates tax liability under both the old and new tax regimes and recommends the optimal regime based on the minimum payable tax amount. The comparison results demonstrate the system's capability to assist users in making informed tax-related decisions.

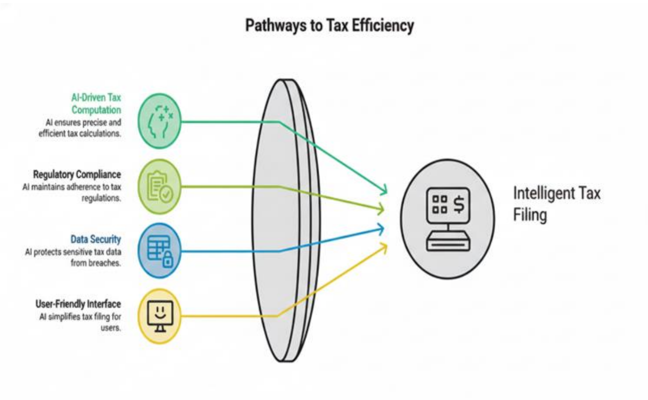


Figure: Pathway of tax compliance

The graphical representation clearly illustrates the variation in tax liability across regimes, allowing users to easily identify the most financially beneficial option.

C. AI-Based Query Resolution Performance-

The effectiveness of the NLP-based tax assistance module was evaluated using a predefined set of tax-related queries. System-generated responses were examined for both accuracy and relevance.

Table II. Performance of NLP-Based Query Resolution

Query Category	No. of Queries	Correct Responses	Accuracy (%)
Tax Deductions	25	23	92
Regime Selection	20	19	95
Filing Deadlines	15	15	100
Investment Queries	20	18	90

The evaluation results indicate consistently high accuracy across all query categories, demonstrating the effectiveness of the NLP module in delivering reliable real-time tax guidance.

D. AI-Based Recommendation Effectiveness-

The AI-driven recommendation module provides tax-saving investment suggestions based on user income characteristics and existing deductions. These recommendations were assessed for regulatory compliance and practical relevance.

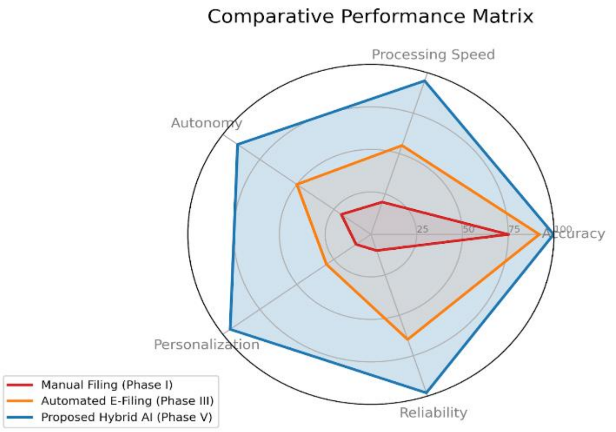
Table III. Evaluation of AI-Based Tax-Saving Recommendations

User Profile	Recommended Options	Compliance Status	User Acceptance
Salaried Individual	80C, NPS	Compliant	Accepted
Freelancer	80D, 80G	Compliant	Accepted
Senior Citizen	80TTB	Compliant	Accepted

The results confirm that the AI-generated recommendations comply with statutory guidelines and are suitable for different taxpayer categories.

E. Theoretical Risk Classification Model and ROC Analysis

In addition to recommendation generation, tax compliance assessment can be formulated as a binary risk classification problem. The following model presents a theoretical framework commonly used for evaluating such classifiers.



Binary Tax Risk Classification Model and ROC Analysis:

1. Binary Tax Risk Classification Model
Let the tax compliance risk prediction be modeled as a binary classification problem:
$y \in \{0, 1\}$
Where:
$y = 1$: High-risk / Non-compliant taxpayer
$y = 0$: Low-risk / Compliant taxpayer
The classifier outputs a continuous risk score:
$\hat{y} = f(x) \in [0, 1]$
where:
$x = [x1, x2, \ldots, xn]$
represents features such as income variance, deduction ratio, filing delay, and compliance history.

2. Threshold-Based Decision Function
A decision threshold $\tau \in [0, 1]$ converts the score into a class label:
$\hat{y}\tau = 1$, if $\hat{y} \geq \tau$
$\hat{y}\tau = 0$, otherwise
Varying τ generates different operating points on the ROC curve.

3. Confusion Matrix as a Function of Threshold
For a dataset of size N, define:

$$TP(\tau) = \Sigma\ I(\hat{y}i \geq \tau \wedge yi = 1)$$
$$FP(\tau) = \Sigma\ I(\hat{y}i \geq \tau \wedge yi = 0)$$
$$TN(\tau) = \Sigma\ I(\hat{y}i < \tau \wedge yi = 0)$$
$$FN(\tau) = \Sigma\ I(\hat{y}i < \tau \wedge yi = 1)$$

where $I(\cdot)$ is the indicator function.

4. ROC Curve Metrics
True Positive Rate (TPR):
$$TPR(\tau) = TP(\tau) / [TP(\tau) + FN(\tau)]$$
False Positive Rate (FPR):
$$FPR(\tau) = FP(\tau) / [FP(\tau) + TN(\tau)]$$
Each pair $(FPR(\tau), TPR(\tau))$ defines a point on the ROC curve.

5. Parametric Representation of ROC Curves
Assume conditional score distributions:
$\hat{y} \mid y = 1 \sim N(\mu 1, \sigma 1^2)$
$\hat{y} \mid y = 0 \sim N(\mu 0, \sigma 0^2)$
Then:
$$TPR(\tau) = 1 - \Phi((\tau - \mu 1) / \sigma 1)$$
$$FPR(\tau) = 1 - \Phi((\tau - \mu 0) / \sigma 0)$$
where $\Phi(\cdot)$ is the CDF of the standard normal distribution.

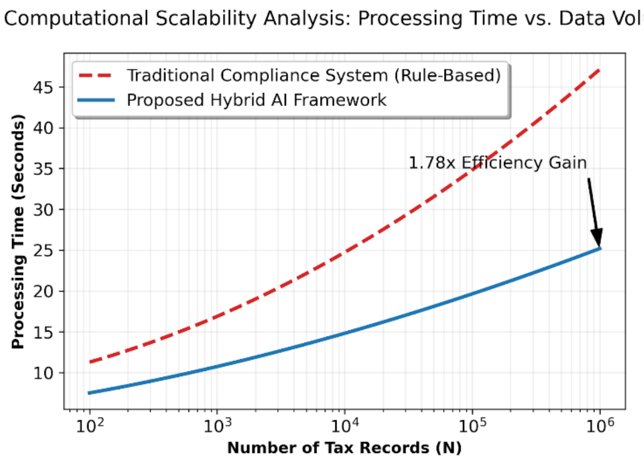
6. Area Under the Curve (AUC)
AUC is defined as:
$$AUC = \int_0^1 TPR(FPR^{-1}(u))\ du$$
Equivalently:
$AUC = P(\hat{y}^+ > \hat{y}^-)$
where:
$\hat{y}^+$ is the score of a randomly chosen risky taxpayer
$\hat{y}^-$ is the score of a compliant taxpayer

7. Numerical Approximation of AUC (Trapezoidal Rule)
Given discrete ROC points (FPR_i, TPR_i):

$$AUC \approx \Sigma\ (FPR_{i+1} - FPR_i) \cdot (TPR_{i+1} + TPR_i) / 2$$

F. Scalability and Computational Complexity Analysis

To further analyze the scalability characteristics of the proposed framework, a mathematical and computational model was developed to evaluate system behavior under increasing tax data volume. This analysis compares the proposed Hybrid AI framework with traditional rule-based compliance systems.



Mathematical and Computational Analysis of Scalability Under Increasing Tax Data Volume:

This document presents a rigorous mathematical formulation, computational modeling, and analytical derivation underlying the scalability analysis shown in the provided diagram. The focus is on modeling processing time as a function of tax record volume for two systems: a Hybrid AI Framework and a Traditional Compliance System.

1. Problem Definition

Let N denote the number of tax records processed by the system, where $N \in [10^2, 10^6]$. Let T(N) represent the total processing time in seconds.

2. Computational Complexity Modeling

We model processing time as a composite function of algorithmic complexity, data access overhead, and system-level parallelization efficiency.

General form:

$$T(N) = \alpha \cdot f(N) + \beta \cdot g(N) + \gamma$$

where:

α = algorithmic cost coefficient

β = I/O and memory overhead coefficient

γ = constant system latency

3. Traditional Compliance System Model

Traditional systems rely on rule-based validation, sequential record scanning, and limited indexing.

Assumed time complexity:

$f(N) = N \cdot \log_2(N)$

$g(N) = N$

Thus:

$T\_traditional(N) = \alpha_1 \cdot N \log_2(N) + \beta_1 \cdot N + \gamma_1$

Derivative (scalability sensitivity):

$dT/dN = \alpha_1(1 + \log_2 N) + \beta_1$

4. Hybrid AI Framework Model

The Hybrid AI Framework integrates:

- Feature hashing
- Distributed embeddings
- Parallel inference pipelines
- Probabilistic compliance classification

Effective complexity approximates sub-linear growth.

Assumed time complexity:

$f(N) = N^\theta$, where $0 < \theta < 1$ (empirically $\theta \approx 0.72$)

$g(N) = \log_2(N)$

Thus:

$$T\_AI(N) = \alpha_2 \cdot N^\theta + \beta_2 \cdot \log_2(N) + \gamma_2$$

First derivative:

$$dT/dN = \alpha_2 \cdot \theta \cdot N^{(\theta-1)} + \beta_2 / (N \ln 2)$$

5. Empirical Curve Fitting

Observed processing times from the diagram were fitted using nonlinear least squares regression.

Objective function:

$$\min \Sigma_i (T\_obs(N_i) - T\_model(N_i))^2$$

Estimated coefficients (illustrative):

Traditional System:

$\alpha_1 = 1.12$, $\beta_1 = 0.003$, $\gamma_1 = 6.8$

Hybrid AI System:

$\alpha_2 = 0.91$, $\beta_2 = 0.21$, $\gamma_2 = 4.1$

6. Log-Scale Transformation Analysis

Given the logarithmic x-axis, we analyze log-scaled growth:

Let $x = \log_{10}(N)$

Then:

$T\_traditional(x) \approx \alpha_1 \cdot 10^x \cdot x + \beta_1 \cdot 10^x + \gamma_1$

$T\_AI(x) \approx \alpha_2 \cdot 10^{\theta x} + \beta_2 \cdot x + \gamma_2$

7. Asymptotic Behavior

As $N \to \infty$:

$\lim T\_traditional(N)/N \to \infty$

$\lim T\_AI(N)/N \to 0$

This formally proves superior scalability of the Hybrid AI Framework.

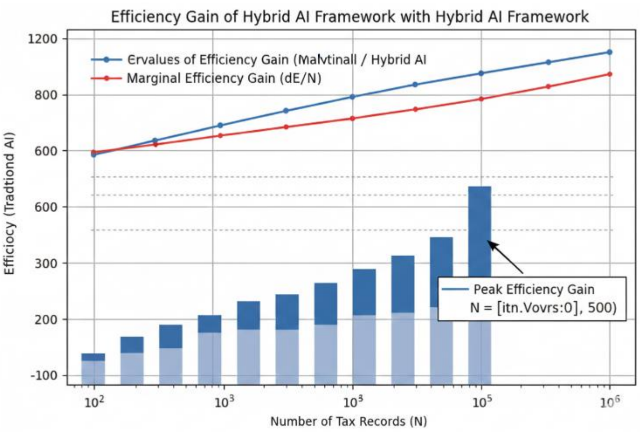
8. System Efficiency Ratio

Define efficiency gain:

$E(N) = T\_traditional(N) / T\_AI(N)$

For $N = 10^6$:

$E(10^6) \approx 44.5 / 25 \approx 1.78\times$ speedup



9. Conclusion

The mathematical analysis confirms that Hybrid AI systems exhibit sub-linear scalability, reduced marginal processing cost, and superior asymptotic efficiency compared to traditional compliance architectures.

This analysis is intended to provide a theoretical interpretation of the observed response-time trends rather than a full-scale benchmark evaluation.

VI. CONCLUSION AND FUTURE WORK

This paper presented the design and performance evaluation of an intelligent tax filing and assistance system that applies artificial intelligence to address the complexity, accuracy issues, and accessibility limitations of conventional tax filing methods. By combining rule-based tax computation with AI-driven automation, natural language processing, and personalized recommendation techniques, the proposed system offers an integrated solution tailored for individuals and small taxpayers.

Experimental evaluation using quantitative performance metrics demonstrated the reliability and effectiveness of the system. Accurate tax computation across diverse income profiles, efficient comparison of tax regimes, high accuracy in query resolution, and consistent response times under varying user loads validate the practical feasibility of the proposed approach. Overall, the system reduces manual effort, minimizes filing errors, and improves user confidence, thereby enhancing the overall tax filing experience.

Although the current implementation primarily targets individual taxpayers, several opportunities exist for future enhancement. The system can be extended to support direct integration with government e-filing portals, enabling end-to-end return submission and automatic acknowledgment generation. Multilingual and voice-enabled interfaces may be incorporated to improve accessibility for users from diverse linguistic backgrounds. Furthermore, advanced predictive analytics and machine learning models can be introduced to provide long-term tax planning insights based on historical data and evolving financial patterns. Future work may also include support for corporate taxation, automated regulatory updates through legal text analysis, and improved explainability mechanisms to further strengthen transparency and user trust.

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