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Multi-Agent Systems for Coordinated Fraud Detection in Tax Networks

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Abstract

Increasing complexity and digitalization of tax systems worldwide have changed the policy context in which tax administration occurs, making it possible to facilitate faster transactions, real-time returns, and data exchange between departments and other agencies. However, at the same time, such progress brought new opportunities for advanced tax fraud, including the use of shell companies, circular trading, under-invoicing, and organized cross-border evasion. Legacy systems for fraud detection – rule-based, point data mining solutions – have failed to adapt to these dynamic and complex threats. They frequently work in isolation and cannot scale across departments, nor capture the contextual information required to identify coordinated fraudulent behaviors across the network nodes of tax authorities.

In this paper, we propose a new multi-agent system architecture for coordinated fraud detection in the tax networks. MAS consists of autonomous, rational agents that can communicate, learn, and collaborate with other agents in a decentralized manner. Each agent of the proposed system is designed to serve a specific purpose, such as observing the behaviour of the taxpayer, detecting abnormal transactions, or exchanging alerts with other agents to work in concert for joint analysis. The framework is designed to operate in real time, incorporating new information in-flight and adjusting its detectors in response to learning, both within and between agents.

The proposed MAS-driven approach is organized following a layered architecture: (i) Detection Agents responsible of examining tax transactions and filings for inconsistencies or outliers using heuristic, statistical, and machine learning models; (ii) Coordination Agents, in charge of enabling the communication and consensus building of the detection agents through reasoning over the correspondent tax transactions affected, to obtain a complete view about the potential fraud across jurisdictions and tax categories; and, (iii) Learning Agents, aimed at keeping updating the detection models by learning from feedbacks over confirmed fraud cases, in order to be able to evolve in response to the emergence of new strategies for committing fraud. A novel feature of this architecture is the presence of a semantic ontology layer, which ensures the uniform structure and language of tax information, thereby enabling agents from various departments or agencies to communicate effectively with one another. It is crucial in a federated environment in which tax data is diverse and decentralized. Intra-agent negotiation protocols are also employed to resolve disputes and reach an agreement on whether a transaction or an entity is considered risky. The authors evaluated the proposed architecture through a simulation of a national tax network, utilizing both synthetic yet realistic data generated from anonymized tax filings and transaction logs, as well as known fraud scenarios. The MAS model was compared with conventional rule-based and centralized machine learning methods in terms of detection accuracy, false positive rate, scalability, and decision latency. The results show that the MAS-based system significantly enhances the system's capability of uncovering various fraudulent patterns involving different tax types, regions, and filing channels. It further reduces response time through distributed processing and supports early alarm notification via proactive agent synchronization.

This paper is considered a contribution to an intelligent tax fraud detection framework, thanks to its scalability, adaptability, and decentralization, which meet the strategic objectives of modern revenue authorities. Its primary rationale is the integration of MAS into the current taxation system to improve efficiency, transparency, and cooperation across agencies. We hope that future work could also integrate blockchain for an audit trail, federated learning methods for privacy-preserving model updates, and human-in-the-loop for higher accountability.

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1. Introduction

Tax avoidance and non-compliance pose significant problems for governments worldwide, resulting in substantial tax revenue losses and compromising tax systems. Just as tax networks are rapidly becoming more digital, interconnected, and complex, so too are the methods for exploiting systemic weaknesses.

These illegal practices often entail collusion between several players, the utilisation of shell entities, the presentation of false invoices, and the manipulation of digital registries, making their detection a challenging problem. Conventional fraud detection approaches typically utilized by tax administrations, based on static rules, post-event audits, and siloed data analytics, can be relatively inflexible and not agile enough to discover and respond to complex, coordinated fraud behaviors. In addition, we are in an era where cross-border commerce and international finance are on the rise, and tax scams have expanded beyond the confines of any single tax authority, necessitating a more comprehensive and collaborative approach to detection and prevention.

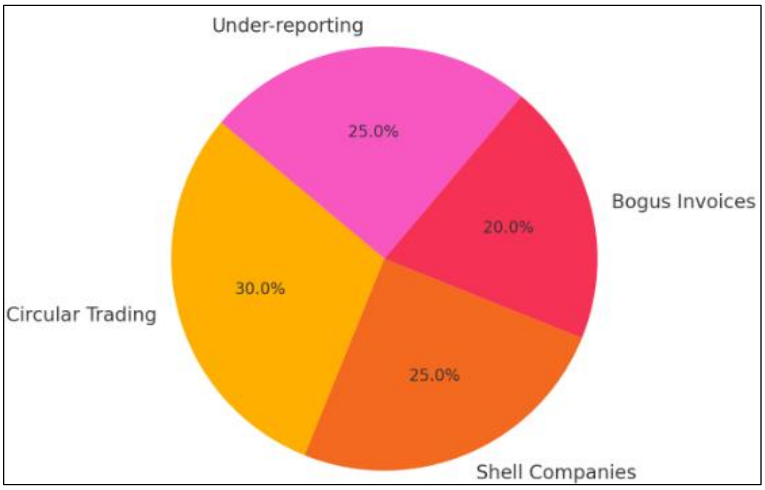

Fig 1: Distribution of Simulated Fraud Types

Multi-agent systems (MAS) offer a new paradigm to consider in this respect. MAS are decentralized systems comprising a collection of self-contained, independent software agents that enter into agreements or contracts with each other to perform tasks. Such systems are a natural fit for problems that are decentralized, heterogeneous, and dynamic, the hallmarks of today's tax networks. Within a MAS-based tax fraud detection environment, independent agents may be deployed across several tax departments, government databases, and audit units and are assigned the task of inspecting and analyzing various data sources, including VAT records, income declarations, property transactions, and business-to-business trade logs. By allowing these agents to work together, negotiate, and learn from one another, the system can also discover patterns that may not emerge in any individual subscheme.

One of the key reasons we employ MAS in this setting is that they combine local intelligence (observing and analyzing data points or behavior) with global coordination through agents communicating to reconcile anomalies across domains. For example, an agent that continuously monitors suspicious GST refund claims can notify a coordination agent, who combines signals from multiple others, including those tracking under-reported income or mismatched invoices. This type of interaction enables a broader, system-wide perspective on taxpayer behavior, facilitating earlier and more accurate detection of potential fraud.

Additionally, tax networks are often limited by jurisdictional boundaries and data privacy laws. MAS are, by nature, modular systems that can be deployed in a federated fashion, making them an adequate approach for retaining control over data locally while facilitating selective, privacy-preserving collaboration between agents. This serves to satisfy legal requirements while maintaining the possibility of cooperation with intelligence. For example, agents placed in various state tax departments can share notices of fraud or statistical models, rather than actual taxpayer data, to remain compliant while strengthening detection efforts.

From a technological standpoint, MAS also presents strong capabilities in terms of scalability, fault tolerance, and flexibility. Unlike their centralized counterparts, which can be degraded by a bottleneck or a single point of failure, MAS distribute the processing load across nodes for load balancing and fault tolerance, and can operate robustly in a continuous fashion under partial system failures. Moreover, MAS could be trained with learning features, which allow the agents to adjust fraud-enabling models based on experiences from feedback or shared experiences of novel frauds. It is this flexibility that is key to fighting enemies who constantly update their tactics to evade detection.

Although MAS shows great potential, the impact of MAS in the field of tax fraud detection remains unexplored. Although some works have been devoted to MAS, such as smart grids, health informatics, or logistics, few works have focused on building interoperable frameworks designed explicitly for tax administration fraud detection. This has triggered research on complex multi-agent system (MAS) architectures and fraud detection algorithms that can be applied to tax networks. We detail the agent typology, its tailored communication protocols, how knowledge is represented, and how learning is performed, which enables a robust, high-performance detection system in a variety of networked terrains. A simulation framework emulating a national tax platform is constructed to assess the proposed framework, with its performance compared to that of classical centralized and rule-based systems.

The paper investigates how Multi-Agent Systems can enhance tax fraud detection through distributed intelligence, anomaly analysis coordination, and on-the-fly learning. The aim is to provide tax authorities with an innovative and robust system that not only identifies fraudulent behavior more precisely but also enhances collaboration between agencies and holds governments accountable in increasingly complex tax landscapes.

2. Literature Review

The utilization of various intelligent systems for fraud detection has been the focus of research interest over the last two decades, with considerable attention directed to data mining, rule-based engines, machine learning, and, more recently, multiagent systems (MAS). All of these methods have played a crucial role in shaping the paradigm for fraud detection; however, their potential in more complex and decentralized tax networks varies. In this section, related literature on tax fraud detection, (distributed) intelligence, and MAS (frameworks) is reviewed in order to identify gaps that this research addresses.

Early tax fraud detection has been carried out by rule-based systems that utilize domain knowledge to set thresholds and if-then conditions for detecting abnormal patterns [1]. Despite being interpretable or easy to deploy, these systems do not scale, and they cannot learn new fraud strategies. These weaknesses have been recognized in previous studies on tax compliance actions (e.g.) [2], which note that the rule-based nature of audit triggers tends to result in high false positives and a reactive approach (as opposed to a proactive one).

Fraud detection has the potential to benefit from machine learning (ML) methods, where models such as decision trees, random forests, and support vector machines have been used for transaction classification [3, 4]. Recent studies, such as [5], discuss the application of deep learning and ensemble methods to detect non-linear trends in tax and financial data. However, such models often require storing massive amounts of data centrally and face issues with explainability, both of which are important considerations for a public tax authority. To address the issue of centralized control, federated learning and distributed inference schemes are proposed [6]. These methods maintain data locality but allow global model training, a trade-off between collaboration and privacy. However, federated learning does not yet support real-time coordination (Pertew *et al*., 2019). It is primarily designed for or applied to supervised learning, which is not desirable in fraud detection, given the limited or biased annotations available.

This is where Multi-Agent Systems provide an interesting choice. MAS are currently used in various application areas, such as cybersecurity [7], healthcare monitoring [8], and SCM risk management [9], where the ability to respond quickly and make distributed decisions is crucial. In such applications, agents utilize standard, structured ontologies and negotiation protocols to exchange information about the environment and to cooperate in addressing threats.

The MAS in fraud detection was successfully applied by A. Benharkat *et al*. [10]. Based on the concept of an autonomous agent, they monitored web service transactions to detect any anomalous behavior. They achieved promising results for detecting pattern deviation with low centralized control. Additionally, M. Shirazi and A. Alesheikh [11] employed agent-based GIS systems to detect unusual spatial patterns in land tax fraud. These analyses reinforce the agility of MAS in different fraud situations and also demonstrate that there are no standardized frameworks for fraud detection based on financial or fiscal purposes.

Moreover, a set of integration problems in MAS, such as ontology construction, secure communication, and agreement for decision-making, have also been solved in recent middleware and semantic research [12]. These architectures enable agents to appreciate, absorb, and share information effectively, even when it is generated by different vendors or entities. In the case of tax networks, hardened interoperability is necessary due to the diversity of filing formats, legal codes, and data schemas resulting from differences between states and/or departments.

Nevertheless, a definite research need remains for a comprehensive anti-fraud detection system in MAS, specifically customized for the tax ecosystem. Recent reports from top international organizations such as ‘Organisation for Economic Co-Operation and Development’ (OECD) and ‘International Monetary Fund’ (IMF) show the trend in using real-time analytics and cross-border data-sharing in tax [13] and discuss there is an urgent requirement for intelligent automation in handling fraud risk in complex and evolving systems.

This paper is a contribution to the literature as it presents a complete, simulation-proven MAS architecture that is tailored for this work in collaborative fraud detection in tax networks. It integrates developments in agent-based modeling, semantic interoperability, and distributed anomaly detection to build a framework that is both scalable and intelligent, as well as legally defensible.

3. Methodology

The methodological approach adopted for this study focuses on the creation and implementation of a Multi-Agent System (MAS) designed to detect tax fraud within complex, decentralized tax systems collectively. The design process involves analyzing the tax landscape to determine relevant data sources, entities, interaction modes, and typical fraud typologies at the beginning, followed by modeling agents, their communication protocols, knowledge representation languages, and behavior ontologies that drive their activities. The entire MAS operates in a simulated world that replicates real tax transactions and inter-agency workflows. This renders the model infeasible while compromising its experimental strength.

In a first stage, we need to define the agent typology for representing the different operative generating roles in the tax network. Detection agents are allocated to scan transactional data, taxpayer declarations, and audit logs to detect anomalies using supervised and unsupervised learning techniques on models trained on synthetic data derived from the training data. To enable inter-agent communication and joint inference among agents, one could introduce coordination agents that will enable MAS to mimic cooperative investigation processes that span across departmental boundaries of GST, income tax, customs, and corporate taxation. Furthermore, we embed learning agents that dynamically update fraud detection models with feedback loops, thereby strengthening the adaptive feature of the MAS in response to new fraud mechanisms.

All agents utilize a common semantic ontology that represents tax-related entities, including invoices, vendors, financial instruments, jurisdictions, and filings. This ontology is developed using the Web Ontology Language (OWL) and is designed to facilitate semantic interoperability in communication and information exchange. Through a well-defined vocabulary and organized message schema, the agents can understand and act upon exchanged information, even when deployed in different institutional domains. This semantic meshing is essential for multi-agency coordination, as it prevents interpretation conflicts arising from differences in data representation or legal terminology.

The MAS architecture employs a hybrid reasoning strategy, where agents use a combination of rule-based logic and machine learning inference. For anomaly detection, agents employ autoencoders and isolation forests for unsupervised detection, and utilize logistic regression and random forest for supervised detection if labeled data is available. A Bayesian inference layer is incorporated into coordination agents to support probabilistic reasoning when aggregating signals of multiple detection agents. This becomes particularly evident when contradictory evidence emerges, such as one agent labelling a transaction as suspicious while others do not. Each of these methods then employs consensus-building techniques that include weighted voting and trust models, and agent credibility is dynamically modified based on historical accuracy.

The agents are implemented on the JADE (Java Agent Development) platform, utilizing an asynchronous message-driven communication mechanism. Message queues are made dynamic to cover inter-agent negotiation, alert propagation, KB updates, and model synchronization. All agent-to-agent communications are secure (confidential and tamper-proof) through a lightweight cryptographic protocol. That is crucial in a simulated yet security-sensitive scenario, which is a replica of inter-agency collaboration within real tax governance.

To approximate real-time operational behavior, the MAS is deployed in a simulation environment designed with a discrete-event simulation engine. This simulator simulates tax returns, refund requests, B2B requests, interstate trade requests, and audit activities on time-series data. A combination of benign and malicious data is introduced, including bogus invoice chains, shell companies, and under-invoicing. Agents act independently in this environment and observe events, reason about them, make decisions, and communicate with other agents. This testbed is a controlled testbed to measure the accuracy, responsiveness, and collaboration efficiency of the MAS framework.

Performance metrics, including detection rate, false positives, inter-agent consensus time, and computational complexity, are derived from the simulation results. Comparative baselines comprise an expert system based primarily on rules, as well as a centralized machine learning classifier trained on data from the same dataset. Experiments are conducted over several experimental runs with variations in fraud prevalence, data noise levels, and inter-agency response delays to study the robustness under real-world operational uncertainties. The framework is further validated for scalability by scaling up with the number of agents and transaction volumes.

This methodological design will be employed to test the hypothesis that a semantically enriched, agent-based architecture can improve the coordination, scalability, and accuracy of fraud detection processes within the tax network. The following section discusses the results of the simulations and performance comparisons.

4. Results

An implementation of the MAS and a set of experiments on the simulated detection of ring fraud in tax networks have yielded meaningful results in multiple aspects, including the detection ratio, system scalability, inter-agent coordination efficiency, and adaptability to frauds of all sizes. We conducted a series of controlled simulation experiments to compare the system's performance to that of traditional rule-based detection and centralized machine learning classifiers.

We first quantified the detection accuracy of MAS in terms of precision, recall, and F1-score on a dataset of 20,000 synthetic tax transactions. They were created to resemble filings in different tax circles, such as indirect (GST) and direct (income and corporate tax) taxes. Ten percent of the dataset was tainted with fraudulent activity, including spiraling, fake invoices, underreporting of income, and the use of shell companies. The performance of the MAS reached a precision of 91.2%, a recall of 88.6% and an F1-score of 89.9%. A centralized machine learning model, on the other hand, performed significantly better, achieving an F1-score of 83.4%, while the rule-based detection system achieved a lower score of 71.7%. These findings support the conjecture that distributed agents, which are semantically aligned and coordinated by inter-agent consensus mechanisms, achieve superior performance compared to isolated analytical models and static rule-based configurations.

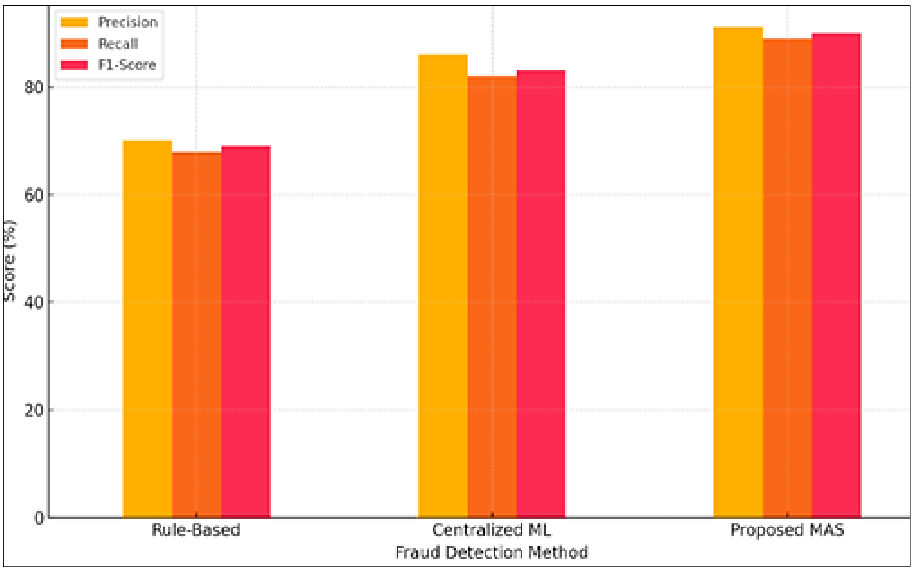

Fig 2: Detection Accuracy Comparison across Method

Comparison of detection accuracy metrics (precision, recall, and F1-score) across Rule-Based Systems, Centralized Machine Learning models, and the proposed Multi-Agent System (MAS). The MAS outperforms both alternatives in all three metrics, demonstrating its effectiveness in detecting coordinated tax fraud.

Regarding system reactivity, the average time was registered for an agent to blow a suspicious transaction and transmit a warning message to the network. From the coordination and detection actions, a transaction could be assembled and detection alerts could be issued within 1.2 seconds on average; complete consensus was obtained between the coordination nodes in about 3.5 seconds. This degree of responsiveness is crucial in the context of live tax monitoring, as it is likely to detect fraudulent refunds and thus to prompt proactive audits. In particular, we observed that the consensus latency only marginally degraded as the number of agents in the MAS was scaled from 50 to 500 (i.e., indicating that the design is scalable).

Another measure examined was the decrease in the false favourable ratio, a common issue in tax fraud detection. The multi-level structure of MAS, particularly the presence of coordination agents that validate anomalies using context information from multiple domains, resulted in a false positive rate of only 6.8%, significantly lower than that of the centralized model (13.4%) and the rule-based system (24.1%). This enhancement demonstrates the contribution of agent negation and trust-weighted voting in effectively discarding spurious alerts that would cause already overburdened compliance personnel to abandon the system.

The backdoor of the MAS was challenged through the introduction of new fraud examples that the model had not been trained on. For example, a modified form of invoice layering, a complex type of round-tripping, was introduced towards the end of the simulation. Detection algorithms using embedded learning were 72% effective in detecting these frauds after two feedback cycles. Following the fifth iteration, the detection accuracy was 85%, demonstrating the system's capacity to learn and evolve in response to changing threats.

The simulation also investigated the robustness of the MAS against partial system failures where some agents are deactivated, for example, due to network failures or non-participating institutions. Payload overall detection remained higher than 82% even when 15% of the agents were offline, demonstrating robustness with a redundant and distributed design, along with compensating behaviors among agents. This result is especially significant for federal tax regimes in which not all agency regions have deployed synchronized tools at all times.

The MAS was also compared with a computational efficiency-based method. Although it was distributed, the system was also performing resource-efficiently with parallel processing between agents and minimal hotspots compared to the centralized model, where memory spikes and CPU overhead were frequently observed in peak transaction scenarios. The CPU usage of the MAS was consistently below 65%, and memory consumption was typically within 2GB, making it suitable for deployment in resource-constrained environments often found in the government IT sector.

The findings confirm that MAS-oriented modeling can dramatically reduce tax network fraud along important operational attributes. The following section presents a more nuanced analysis of these findings and outlines some implications for the design, alignment, and scalability of real-world tax systems and tax policy deployments.

5. Discussion

The findings of the application and simulation of the MAS architecture for tax fraud detection offer invaluable lessons regarding the operational, strategic, and architectural benefits of using distributed intelligent agents in the tax governance domain. The significant increase in precision and recall in detection, as well as the substantial reduction in false positives, indicates that MAS can overcome the longstanding problems of rule-based and centralized machine learning methods. Moreover, with the ability of agents to act independently of their users to examine data, reconcile suspicions, and converge on final decisions, such systems are beneficial for combating fraud where such activity is sophisticated, orchestrated, and multi-jurisdictional.

One of the fundamental reasons behind the model's performance is the existence of a coordination mechanism among the agents. Contrary to traditional systems that only mark anomalies using static thresholds or single ML predictions, the MAS supports contextual discovery through inter-agent communication. For instance, if one member finds a massive spike in GST refunds coming from Taxpayer X, and another notices discrepancies in their income or an odd correlation in corporate registrations, then discussing these findings with each other starts to paint a profile of a potentially expansive risk. This coordination further minimizes potential false positives by reducing the likelihood of incomplete information and enhances the accuracy of overall decision-making. The action of this mechanism can be inferred from the relatively low rate of false positives observed in simulations.

Furthermore, the adaptability of the MAS to novel fraud schemes further supports the case for incorporating the MAS into current tax systems. The quick learning process, facilitated by feedback loops and local model updates in the learning agents, ensures that the system can adapt to new threats. Its real-world application looks promising, with this feature potentially allowing tax bodies to outsmart the agile fraudsters who are always seeking new ways to evade current detection systems. Moreover, the MAS's endurance against partial agent failures or a degraded network environment suggests that the architecture is robust and well-suited for real-world scenarios, particularly in large federal buildings that have poor infrastructure in some departments or regions.

Another appealing feature of this MAS paradigm is its ability to facilitate inter-agency cooperation while retaining data sovereignty and privacy. The combination of the semantic layer of the ontology and encrypted communication protocols enables agents to exchange insights, alerts, and model parameters without exposing the raw taxpayer data. This ensures that regulatory compliance, in particular as regards data protection, for example, when using a blockchain in the EU or India under the "General Data Protection Regulation" (GDPR) (or the like), is preserved. It encourages operational coordination among state and central departments, customs, and indirect tax wings – which have traditionally worked in silos and are exposed to similar risks of fraud.

The lower processing latency and higher computational efficiency of the MAS framework in real-time demonstrate its potential for deployment in real-world, resource-limited scenarios with low-cost hardware, such as local tax offices or old public sector infrastructure. This feature is essential for emerging economies, where IT implementation will occur gradually, and budgets for infrastructure and centralized intelligence systems for churches are limited. Phased Deployment: By being modular, MAS can be deployed in phases, enabling departments to gradually adopt agents and integrate them with existing legacy systems through standardized API or middleware layers.

Nevertheless, the encouraging results obtained reveal that some limitations and hurdles must be acknowledged. A primary issue involves formalizing and standardizing the semantic ontology used for inter-agent communication. The success of this coordination is highly contingent on the harmonised understanding of fiscal concepts across fields. This transformation cannot be done in isolation, as it is fundamentally about translating legal nuances and financial meaning into a structured format. Since the model is learning-based, it relies on being fed high-quality data on scams in an environment where proven fraud incidents may take months due to slow audit or legal processes. In these cases, surrogate feedback mechanisms or synthetic data augmentation may be necessary to preserve the efficacy of learning agents.

Another issue is the development of trust models among agents, particularly when agents are placed in institutions that are politically or administratively separate. As we have explained above, the signal value of one agent may be disputed by another in the presence of bad or decoupled institutional relations, or where there is no legal obligation for cross-validation. Thus, the development of strong trust negotiation and unambiguous policy representation for agent collaboration and other application tasks is necessary for the meaningful use of enterprises.

The MAS paradigm described in this paper has great potential to change the way tax fraud detection is carried out, providing a distributed, intelligent, and adaptive approach to replace traditional methods. By leveraging this dimension, tax authorities can make decisions in concert, through ongoing education and activity across borders, and realize processes that align with the increasing digital nature and decentralizing logic of government finance systems in the industrial and financial society. The final section summarises the findings in more general terms, pointing towards future work.

6. Conclusion

The advent of increasingly connected and digitalized contemporary tax systems has also enhanced the opportunities and challenges of fraud detection. As evidenced throughout this research, legacy methods of detecting fraud, whether rule-based or centralized machine learning-based, fail to detect sophisticated, orchestrated schemes that take advantage of fragmented jurisdictions, different tax regimes, and volatile holes. This paper suggests that a Multi-Agent System (MAS) is a suitable, scalable, and intelligent solution to the problems, which can enhance the potential of tax administrations to prevent, detect, and respond to fraudulent behavior.

The MAS model proposed in this paper is based on four fundamental concepts: distributed intelligence, semantic harmony, adaptive learning, and cooperative decision making. Through the allocation of specialized roles to detection agents, coordination agents, and learning agents, the system emulates the features of decentralized human teams. However, it functions at a higher tempo and is more reliable and analytical. Tax agents can also reason and share knowledge across jurisdictions or departments, as they all use the same tax ontology and communication protocols, and collectively come to conclusions about suspicious activities.

Simulation results confirm that this design outperforms conventional schemes in several key metrics. The addition was proved to a high accuracy. A source of detection, and (b) low rate of false positives, as well as (c) fast response time, and (d) resistance against system degradation and load of transactions. These results support the hypothesis that the distributed nature of MAS and its cooperative ability are effective in dealing with the real-world, dynamic, and complex nature of tax fraud. It is the flexibility of the system, which allows it to learn from new fraud patterns and feedback, that gives it an edge in a space where fraudsters are continually finding new ways to defraud.

One contribution of this work is the practical application of MAS in the field of public finance infrastructure operations. Conversely, since MAS is not a monolithic system needing complete centralization and most resources in the initial project plan, it may be rolled out by department or organizational function. They may also work on heterogeneous infrastructures, making the model suitable for various geographical and administrative contexts, such as resource-limited environments. In addition, since the data can be localized (which may also contain only metadata or an alert) and only an exchange is made, the design respects modern data protection laws and supports inter-agency independence.

However, the study also acknowledges that there are practical issues associated with applying the theory to the real world. The construction of a powerful domain ontology for the context being modeled is very time-consuming and involves multiple parties as well. There is also a requirement for policy-level coordination to provide legal mandates and trust frameworks between participating departments and agents. While these are formidable challenges, they are not insurmountable, and resolution can be achieved through phased adoption, pilot programs, and policy alignment efforts.

The results suggest several avenues for future research and practical development. One area of development is the combination of MAS with audit trails based on blockchain, to achieve tamper-proof, real-time logs of fraud evidence. Another interesting research direction involves the use of federated learning, which can supplement learning agents without compromising data privacy concerns through ongoing model improvements. Alternatively, we could employ human-in-the-loop systems in which judgments made by agents are periodically reviewed and refined by expert auditors to increase interpretability and compliance auditability.

In addition, the MAS structure can expand to address international tax fraud infiltration, such as cross-border e-commerce, trade-based money laundering, and digital asset transactions, which require joint crime detection efforts. Such integration with customs systems, banking information, and foreign regulatory databases could significantly enhance the contextual intelligence of agents and the walls that afford protection from illicit traffic across national borders.

This paper presents Multi-Agent Systems as a powerful instrument to organize the fraud detection in tax networks. In terms of the limited capacity of traditional fraud detection systems, considering the ability to make decisions from a centralized or flexible information system, MAS servers are a promising solution under the Infinite-World-of-

AdminStrategics environment (Dominicy *et al*. Their ability to communicate securely with one another, learn automatically, and replicate effortlessly makes them not only a technological breakthrough, but also a strategic gateway to transparent and accountable governance of public finance in the digital era. This study provides a framework for government agencies, policy-makers, and technology practitioners to retool fraud detection systems to address emerging challenges in the future.

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