

-RESEARCH ARTICLE-

**FROM TAX ADMINISTRATION TO INTELLIGENT TAX ADMINISTRATION:
ARTIFICIAL INTELLIGENCE, TAX CONTROL EFFICIENCY, AND THE
REDUCTION OF TAX EVASION**

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—Abstract—

Nevertheless, tax evasion still leads to losses of significant public funds in developing countries' economies due to poorly organized control mechanisms. Artificial intelligence may serve as one of the means of increasing the efficiency of such mechanisms; however, not much research has been done regarding the performance of intelligent systems at tax authorities. In view of this, the study examines the impact of artificial intelligence adoption on the reduction of tax evasion and checks whether this impact occurs directly or through the intermediary of tax control efficiency, taxpayer compliance, and administrative cost reduction. Empirical data was collected among 215 employees of tax authorities, accounting departments, financial management departments, and information technology departments using a questionnaire consisting of 28 questions on the five-point Likert scale. Internal consistency of five variables was satisfactory, with Cronbach's alpha equal to .77-.86. Then three OLS models were estimated, and their diagnoses for collinearity, autocorrelation, heteroskedasticity, and normality of residuals were performed. The results show that artificial intelligence adoption had the biggest impact on the reduction of tax evasion ($B = 0.342$, $p < .001$); in addition, this model explained 67% of the variance. Furthermore, it significantly increased taxpayer compliance ($B = 0.318$) and reduced administrative costs ($B = 0.286$). Decomposition of effects revealed that taxpayer

Citation (APA): Ismael, S. K., Ajina, A. N. (2026). From Tax Administration to Intelligent Tax Administration: Artificial Intelligence, Tax Control Efficiency, and the Reduction of Tax Evasion. *International Journal of Economics and Finance Studies*, 18(03), 230-266. doi: 10.34109/ijefs.2026180311

compliance and cost reduction pathways conveyed 23.7% of the effect of artificial intelligence adoption on evasion reduction, and the rest was conveyed directly. Thus, all hypotheses have been empirically tested.

Keywords: Artificial Intelligence; Intelligent Tax Administration; Tax Evasion; Taxpayer Compliance; Tax Control Efficiency; Public Financial Management.

INTRODUCTION

The capability of governments to finance public services is strongly tied to taxes. The tax revenue mobilisation potential of governments is not merely determined by the level of statutory rates but, even more importantly, by the administrative capability that underlies the enforcement of statutory rates. The example of reforms carried out in Indonesia suggests the magnitude of the difference between these two concepts. After the reassignment of the biggest firms in the region to departments, the ratio of the number of employees to the number of taxpayers in which the reassignment was made was substantially larger than in other departments. Consequently, the tax revenue collected from the firms reassigned increased more than twice; the corresponding increase in the revenue was estimated to be similar to the increase in the level of the top statutory rates by eight percentage points (Basri et al., 2021). From the standpoint of the revenue authorities struggling with fiscal problems, this finding implies that the administrative capability may be a more binding constraint than the statutory rates.

In most developing countries, however, the conventional tax administration relies mostly on labor-intensive practices. Filing forms are processed manually, taxpayer data are scattered among disconnected databases, and audits are performed based on the decisions of individual officers managing their workload exceeding their capabilities of thorough examination. Such an approach inevitably results in incomplete and possibly arbitrary detection of evasion. Undeclared transactions, understatement of income, and false declaration may give rise to signals of evasion only if the information from multiple sources is analyzed collectively, and this task is naturally difficult for fragmented manual systems.

The advent of digital technologies has started to relax this administrative constraint. It has been shown, for instance, that real-time access to transaction information enabled tax authorities to detect and react to the compliance risk arising from the corresponding activity (Hesami et al., 2024). Moreover, African tax systems have been demonstrated to use technology to conduct consumption, property, trade, and income taxation through tax base identification, compliance monitoring, and evasion detection (Okunogbe & Santoro, 2023). Taxation behaviour of corporations is affected by digital transformation through a combination of information and governance mechanisms (Zhang & She, 2024).

Artificial intelligence becomes relevant in this broad technological shift since it allows overcoming another limitation of the manual control system – the difficulty of detecting meaningful patterns in large and diverse data. The framework of decision making combining deep learning and cognitive modeling has been proven capable of predicting tax evasion events and detecting suspicious cases of supply contracts that traditional methods could not (Raikov, 2021). Another review of the field has documented the fast development of the application of artificial intelligence for fraud detection but at the same time pointed out the problem of lack of robustness across jurisdictions due to differences in regulatory environment and taxpayer behavior (Belahouaoui & Alm, 2025). Finally, the experience with 3,232 enterprise tax records showed that support vector machines, gradient boosting, and random forests are capable of achieving classification accuracies over 92%; in particular, the tax burden rate, the profit volatility, and audit frequency are the strongest predictors (Yang, 2025).

First, the existing body of research on artificial intelligence is mostly comprised of reviews and technical demonstrations, while there is no empirical evidence produced by the tax authorities themselves. Review of research conducted between 2014 and 2024 on artificial intelligence and tax collection in developing countries has confirmed that there is still relatively little evidence about the subject matter in exactly the setting where it matters the most (Mudome & Ndiege, 2025). Similarly, a synthesis of sixty-eight peer-reviewed articles has identified three research paradigms of the field but found that there is scarce evidence about the institutional implementation of the approach (Zaim & Sahbani, 2026). The fact that a given algorithm can successfully classify historical observations does not mean that using it in practice changes the operational capability of a tax authority. Second, the association of artificial intelligence with tax evasion reduction is rarely accompanied by an attempt to separate mechanisms of this relationship into distinct categories. Improved detection, increased voluntary compliance, and reduced administrative costs are usually listed among the benefits of the intelligent systems as a whole, without distinguishing between the pathways that these factors represent. While the detection works through enforcement after the act of evasion occurred, the compliance works through deterrence, affecting the taxpayer's behavior before the evasion happened. Reduced cost, on the contrary, is a mere efficiency mechanism that operates internally for the tax authority. Mixing these three mechanisms hides their different contribution and makes impossible to determine which institutional capability needs priority.

Third, the adoption of artificial intelligence is not uniform among tax authorities, and the reasons for that are mostly organizational and not merely technical. For instance, applying the technology-organization-environment framework to the tax system of Botswana has shown nine critical factors of artificial intelligence adoption including the vision and the top management support of the leaders and the resource adequacy that are clearly organizational factors (Munjeyi & Schutte, 2024). In the experience of

a directorate general of taxes in a national level, the organizational aspect turns out to be the most important factor followed by the technology, process, and environment (Brillianto et al., 2024). In a comparative study of eight public organizations, it has been also found that relative importance of the technological and organizational determinants depends on the adoption stage (Neumann et al., 2024). Therefore, variation in adoption is an empirical basis for investigating whether different adoption levels result in different outcomes, and this is the approach used in this study.

There is a fourth point that lies behind the three previous concerns. Tax administration cannot be regarded as a merely technical environment where new and better tools bring about better results automatically. On the contrary, it functions in an institutional setting where legal authority, professional judgment, taxpayer rights, and political considerations determine how the outputs of algorithms can be used. The taxpayer may be classified as high risk, but it is up to the authority whether it will decide to audit the taxpayer or not taking into account the available resources, required evidentiary burden, and the possibility to justify the decision if it is challenged. The evaluation based on algorithmic accuracy alone cannot capture this institutional dynamic since the performance is evaluated against the historical labels instead of the action options available to the authority. The evidence collected from the people who actually run intelligent systems captures a different aspect by revealing whether, from their perspective, the intelligent tools have changed the capability of the institution. While this evidence is obviously perceptual and is vulnerable to the limitations of perceptual measurement, it represents an organizational aspect which is missed by purely technical assessment. Therefore, in this study, the artificial intelligence adoption is treated as an organizational characteristic, not a technical one, and is evaluated in the organizational setting.

Consequently, four questions guide the research. Which levels of adoption of artificial intelligence, tax control efficiency, taxpayer compliance, administrative cost reduction, and tax evasion reduction are characteristic of the sampled tax authorities? What relations hold between these constructs? Is the adoption of artificial intelligence associated with statistically significant effect on tax evasion reduction, taxpayer compliance, and administrative cost reduction? Finally, what proportion of the effect on tax evasion reduction is direct, and what proportion is mediated by the pathways?

Significance of the Study

The study is significant on four grounds.

First, it delivers field-based evidence in a topic area in which existing literature mostly relies on review and simulation studies. While the evidence is not based on any external sources but directly collected from those personnel who run tax administrations in four professions: tax officers, financial managers, accountants, and information technology experts. Since all these professions deal with intelligent

systems from their organizational angle, the convergence of their evaluation is better evidence than agreement only within one profession. Secondly, the study allows distinguishing between two mechanisms that are often considered to be identical in the literature. By estimating three models and decomposing the total effect of artificial intelligence on tax evasion reduction into direct and indirect effects, the study identifies not only whether intelligent systems affect evasion reduction but also through which compliance and cost channels it happens. Thirdly, the study examines the case when the consequences are the most significant. In developing and transitional countries there are the biggest tax gaps and relatively low administrative capacity, while they remain the least studied environments. Hence, evidence generated in this context is the most relevant for institutions that could gain most from improved tax administration. Fourthly, the consequences of this study go far beyond revenue collection and refer to public financial management in general. With the release of administrative capacity due to automation and increased taxpayer trust due to the transparency of processes, the benefits from artificial intelligence will include not only additional revenue but also institutional credibility in general.

Research Objectives

The objectives below are formulated to correspond directly with specific analytical outputs reported in the Results section.

- To assess the prevailing levels of artificial intelligence adoption and the four related constructs across the sampled institutions.
- To evaluate the direction and strength of relationships among all five constructs and establish their suitability for simultaneous inclusion in the regression models.
- To examine whether artificial intelligence adoption significantly reduces tax evasion and quantify the proportion of variance explained.
- To determine whether artificial intelligence adoption increases taxpayer compliance and reduces administrative costs.
- To partition the total effect of artificial intelligence on tax evasion reduction into its direct and indirect pathways.
- To confirm that the estimated models satisfy the assumptions underlying ordinary least squares regression.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

From Manual to Intelligent Tax Administration

Tax administration is typically based on a system where the submission of declarations on a periodical basis and their manual evaluation follow. These problems are inherent to the existing system. Information comes late, scattered over unrelated systems and requires examination by officers who have limited capacity for processing information which continues to grow as the number of taxpayers increases.

The introduction of digitisation allows addressing the first two types of problems since it changes the time and form in which tax information becomes available. Electronic invoicing and prefilling of returns allow receiving transactional information on a real-time basis and assessing compliance risk continuously rather than retrospectively (Hesami et al., 2024). The technological aspect applies to different types of taxes and involves three phases of tax administration: definition of the tax base, monitoring and evaluation of compliance and uncovering cases of tax evasion (Okunogbe & Santoro, 2023). There is evidence that the connection between digitalisation and corruption demonstrates that the role of corruption in tax evasion is reduced due to digitalisation, thus indicating that one way in which technology works is reducing discretionary human interference (EL AMMARI, 2025).

While digitisation solves the problem of limited access to information, artificial intelligence allows addressing another type of a problem – limited analytical capacity. Digitisation makes the volume and access to the information greater, while intelligent systems allow processing the information better. Relationships that emerge in the context of digitalisation become increasingly invisible to the tax authorities, while the combination of deep learning and cognitive modelling allows identifying them (Raikov, 2021). Evidence confirms the advantages of such an approach as well as the specificities of applying intelligent systems for tax purposes. Random forest models applied to enterprise tax records demonstrate classification accuracy higher than 92% and identify differences in the importance of features for manufacturing and service sectors (Yang, 2025). For the developing countries, real-time transaction analysis and value chain tracing have been indicated as the main channels in which artificial intelligence can improve tax collection (Mudome & Ndiege, 2025).

There is also evidence that digitisation affects the behaviour of taxpayers. Using phased introduction of the Golden Tax III project in China as a quasi-experiment, it was shown that digitisation of tax collection and administration reduces corporate tax avoidance (Su, 2025). However, the impact of digitalisation on tax revenue is not always uniform among different institutional environments. Using 18 European and Asian countries from 2005 to 2023 as a sample, there is a demonstration that the relation between digitalisation and tax revenue is nonlinear and the size of fiscal benefits depends on the level of digital development of the country while government effectiveness also proves to be an important variable (Saif et al., 2026). Therefore, it is necessary to understand digitalisation of taxation as two interrelated but separate processes. Digitisation changes the information environment in which tax administration takes place, while intelligent administration changes the way in which information is used.

Artificial Intelligence and the Detection of Tax Evasion

In its essence, tax evasion is intended to stay concealed. Understatement of receipts,

overstated deductions, secret accounts, or transactions that look legitimate are some common practices among tax evaders. Thus, effective detection involves the ability to spot departures from usual behavioral and transactional patterns rather than verifying single documents.

Machine learning tools have been increasingly applied to solve such problems through moving from supervised classification methods to unsupervised anomaly detection. Yet, models developed in one jurisdiction might become less efficient in others due to the differences in the institutional and behavioral context (Belahouaoui & Alm, 2025). Also, a review of sixty-eight papers reveals that predictive modeling and risk scoring are the most widely used analysis framework. Moreover, the studies provide evidence that algorithmic case selection leads to higher detection rates than selection based on the judgment of officers (Zaim & Sahbani, 2026). Besides, there is evidence from firm-level studies that shows a significant negative relationship between the use of artificial intelligence and tax evasion together with the positive correlation with the level of digital awareness (Shah, 2025). Specifically, two pieces of evidence should be noted. The first one is that the main effect from adopting intelligent technologies lies in improving prioritization rather than the volume of audit; it increases the quality of selecting cases to investigate. The second one is that taxpayers perceive the changes in the enforcement capacity, so that there is a direct link between detection efficiency and deterrence.

Available evidence also shows that the impact of intelligent technologies is conditional. The cross-country analysis of the relationship between corruption and tax evasion shows that adoption of artificial intelligence and information technologies works as a moderator of the effects of already existing factors and does not influence evasion itself (Sari et al., 2025). The key point in such situation is that if AI and IT modify institutional relationships, then technically identical implementations of those technologies in different institutions will lead to different results. Thus, if an effect is demonstrated in one institution, it is not possible to generalize about it without taking into account the institutional environment where it is observed. This means that:

H1: *Artificial intelligence adoption has a significant positive effect on reducing tax evasion.*

Tax Control Efficiency as a Mechanism

Tax control efficiency is defined in terms of the speed, precision, and effectiveness of the audit and verification processes. Tax control efficiency stands for the process mechanism that translates analytical ability into enforcement outcomes.

Risk score effectiveness hinges on the compatibility of such scores with the characteristics of the population at issue. Variability in predictive indicators among different sectors implies that risk models need to be calibrated separately for different

sectors, and not used universally. This means that tax control efficiency also depends on how well analytical models correspond to the taxpayer pool (Yang, 2025). Moreover, survey evidence gathered among 537 chief financial officers and tax managers also confirms that audit effectiveness serves as a moderator between digital tax administration and corporate compliance, showing that the use of digital technologies will have compliance effect only if it is combined with sufficient audit capabilities (Lumbantobing et al., 2025). Finally, administrative evidence confirms that enforcement intensity may result in large gains that rise with time (Basri et al., 2021).

Consequently, tax control efficiency stands in-between these three concepts: artificial intelligence increases control efficiency, which in turn leads to better evasion outcomes. In the current paper, tax control efficiency is treated as a mediator and not an independent variable. The spread of artificial intelligence and robotic process automation among the accounting and auditing professions further highlights that adoption depends on a combination of advantages, facilitating factors, and barriers, and organizational endorsement varies widely (Kassar & Jizi, 2026).

The difference between efficiency and capacity is also required conceptually since the two concepts are often confused. The former refers to the number of cases audited by the authority, while the latter is about the productivity of each audit. Intelligent systems make the latter better. An authority may audit the same number of cases and yet raise the effectiveness of case selection, thus raising revenue generated per audit. It also has a secondary effect that has been relatively neglected in the literature: the larger the productivity of audits becomes, the higher the return on investment in increasing audit capacity will be. Improvement in analytics and capacity building are thus complementary strategies rather than competing ones. Therefore:

H2: *Artificial intelligence increases efficiency of tax control mechanisms and risk detection.*

Taxpayer Compliance and the Deterrence Channel

Compliance refers to the accuracy and timeliness of tax obligations fulfillment. This type of taxpayer behavior is driven both by the probability of detection of non-compliance and by taxpayers' confidence in tax authorities and the ease of tax obligation fulfillment. In particular, attitudes and perceptions have been identified as key factors of taxpayers' compliance in Romania (Trifan et al., 2023). In addition, trust in tax authorities coexists with digital tax administration at the corporate level in determining compliance behavior (Lumbantobing et al., 2025). Moreover, similar evidence is found from India's digital economy. The compliance behavior of taxpayers is affected by modernization of administrative practices and alignment of reporting requirements rather than by the intensity of enforcement actions (Koley, 2025).

The perceptual component of the deterrence mechanism is also confirmed by the evidence coming from the West African Economic and Monetary Union, where the capacity of detection and honesty significantly affect the behavior of taxpayers in terms of tax payments (Djahini-Afawoubo, 2024). A survey of 1,761 micro-firms in Greece performed in the context of the slippery slope framework also allows distinguishing between institutional drivers of voluntary and enforced compliance. Specifically, trust in tax authorities plays an important role in voluntary compliance, whereas coercive power perception mainly affects the enforced compliance (Dimitras et al., 2025). Among 341 small and medium enterprises in Ghana, perceptions of tax fairness, knowledge about the tax system, and government trust are also significant predictors of voluntary compliance. Moreover, tax fairness mediates the relationship between tax knowledge and tax compliance (Appiah et al., 2024). Additionally, firm-level evidence on the behavior of large taxpayers in Ethiopia shows that trust in government, taxpayer knowledge, tax system fairness, and rewards positively affect compliance. Meanwhile, compliance costs negatively impact compliance. In other words, this evidence establishes a direct conceptual link between compliance behavior and the administrative cost channel discussed in Section 2.5 (Mebratu, 2024). Finally, experimental evidence from Greek entrepreneurs confirms that higher audit transparency and personalized penalties significantly increase compliance rates (Angeliki & Thomas, 2025). Compliance attitudes also differ systematically depending on taxpayers' gender, income level, and settlement size (Hauptman et al., 2024). It appears that comprehension of tax regulations and sanctions enforcement are more effective in increasing compliance than improvements in service quality (Misbahruddin et al., 2025). These findings demonstrate that the compliance of taxpayers depends on their perceptions of administrative capability, fairness, and cost. Technological interventions in such a setting that alter only one component while ignoring others will produce smaller gains than expected.

The deterrence mechanism underlying the connection between artificial intelligence and compliance can be clearly defined. The decision of taxpayers to comply is driven, to some extent, by their perception of the likelihood of detection of non-compliance. The visibility of AI monitoring raises this likelihood perception among all taxpayers, not only those selected for audits. Thus, the compliance effect is able to operate beyond the scope of direct enforcement measures. Firm-level evidence supports this mechanism. In particular, AI adoption leads to digital awareness increase among firms as well as lower tax evasion levels (Shah, 2025). Digital transformation also helps reshaping corporate tax behavior through governance mechanisms which means that taxpayers are able to respond even before the actual enforcement measures (Zhang & She, 2024). Therefore:

H3: *The adoption of intelligent tax systems increases taxpayer compliance with tax regulations.*

Administrative Cost and Efficiency Gains

Administrative cost saving entails reduction in the cost of tax collection and auditing in terms of expenses, processing time, and effort. With the automation of routine administrative tasks, technological solutions have the potential to reduce labour input and expedite processing cycles.

Available empirical evidence from various jurisdictions shows that the use of electronic invoicing and prefilled returns may produce efficiency effects (Hesami et al., 2024). Technology could potentially produce cost savings in relation to basic tax administration operations; yet the magnitude of the effect will depend considerably on the quality of implementation (Okunogbe & Santoro, 2023). Organisational and managerial readiness within tax agencies is equally crucial when it comes to translating potential efficiency savings produced by artificial intelligence into cost savings (Brillianto et al., 2024). The relation between these two variables is mutual and not linear. Decrease in administrative cost creates organisational resource that could then be allocated to investigation. Enhanced investigative potential would facilitate enforcement efforts and further decrease tax evasion. Therefore, administrative cost reduction is considered a mediating mechanism in the present study.

The pattern of cost reduction in terms of its timing also needs to be taken into account. The initial adoption phase is characterised by expenses and not savings due to acquisition and use of technological systems along with parallel operation of traditional methods until the latter are no longer needed. The institutions implementing the technology at an early stage of implementation might show adoption but no cost savings, while the more advanced adopters may demonstrate both. Hence, in a sample consisting of institutions in various stages of implementation, the mean value of administrative cost saving may be lower than the one for adoption. This difference should be considered as the indicator of the maturity of implementation and not of the efficiency of the technology itself. This gives:

H4: *Artificial intelligence contributes to reducing the administrative costs and expenditures associated with tax collection.*

Transparency, Governance, and Public Financial Management

Consequences of intelligent tax administration are not limited to revenue mobilisation. Automation helps to reduce the space of discretionary practices in which irregularity may occur, and systematic record-keeping enhances traceability and auditability of the decisions.

The finding that digitalisation makes the connection between corruption and tax evasion weaker supports the hypothesis that reduction of the discretionary human

factor restricts opportunities for the latter (EL AMMARI, 2025). Generally speaking, the governance effects of artificial intelligence in public administration are multi-level and comprise the micro, meso and macro dimensions, whereas transparency and understandability of the decision-making process is one of the main foundations of legitimate algorithmic administration (Criado et al., 2025). Broader institutional impacts of digitalisation of the tax administration are also visible outside the domain of revenue collection. Digitalisation of tax administration is connected with improvement of corporate environmental, social and governance performance, and thus shows how the modernisation of tax administration can influence corporate behaviour (Hai et al., 2024). The evidence from the Chinese digital tax reform identifies effects of such reform on risk of firms, thus locating tax digitalisation in the wider intersection between the digital government and the capital markets (Jiang et al., 2025). Country-level evidence shows that structure of the tax system influences the size of shadow economy, and thus situates the quality of administration in the wider fiscal context (Saunoris & Nurmanova, 2025). However, whether these positive effects actually take place depends on organisational context (Neumann et al., 2024).

A related question concerns the information imbalance between the tax administration and taxpayers. Intelligent systems increase this imbalance even further since authorities can detect patterns among all taxpayers, while taxpayers are aware only of their situations. While this imbalance is helpful in increasing the deterrence effect, it creates the accountability responsibility at the same time. Selected taxpayers cannot effectively question the basis for their selection, while tax authorities who cannot explain their decisions are not likely to be able to defend their decisions during appeals. In this case, transparency does not mean disclosure of the parameters of models used by tax authorities to predict tax risks, since this kind of transparency may enable circumventing of the system. Instead, what is needed is an audit trail that would explain why a certain decision was taken and on what basis. Thus, if treat explainability as an intrinsic feature of the design of the system and not as a compliance measure, then tax authorities will be able to preserve enforcement effectiveness and legitimacy of administration.

H5: *Greater transparency in intelligent tax administration strengthens the effectiveness and reliability of public financial management.*

Synthesis and Conceptual Model

The evidence synthesised above supports a framework in which artificial intelligence adoption contributes to tax evasion reduction through three distinct pathways. First, it strengthens tax control efficiency, thereby increasing the effectiveness and yield of enforcement activities. Second, it promotes taxpayer compliance by raising the perceived likelihood of detection across the broader taxpayer population. Third, it reduces administrative costs, freeing organisational capacity that can subsequently be

redirected towards enforcement. The reviewed literature provides a plausible basis for each pathway, although their relative contributions remain an empirical question examined directly in Section 4. Table 1 summarises the principal empirical themes underpinning the proposed hypotheses.

Table 1: Principal Empirical Themes Linking Artificial Intelligence to Tax Administration Outcomes

Theme	Empirical Contribution	Related Hypothesis
Machine Learning and Fraud Detection	Model-based risk identification substantially outperforms rule-based screening in classifying non-compliant taxpayers.	H1
Anomaly Detection in Opaque Value Chains	Deep learning combined with cognitive modelling makes digitally mediated relationships visible to tax authorities.	H1
Risk-Based Audit Case Selection	Algorithmic prioritisation raises the yield of enforcement activity without increasing audit volume.	H2
Administrative Intensity and Revenue	Higher enforcement capacity per taxpayer produces large and increasing revenue effects over time.	H2
Perceived Detection and Deterrence	Taxpayer compliance responds to the perceived capability of the authority as well as to actual audit exposure.	H3
Trust and Audit Effectiveness	Audit effectiveness moderates the relationship between digital tax administration and corporate compliance.	H3
Real-Time Data and Processing Efficiency	Electronic invoicing and prefilled returns reduce processing time and administrative effort.	H4
Organisational Readiness	Leadership support and organisational readiness determine whether efficiency gains are realised.	H4
Digitalisation and Discretion	Digitalisation weakens the pathway running from corruption to tax evasion by reducing discretionary handling.	H5
Algorithmic Governance and Legitimacy	Transparent and comprehensible decision-making is central to legitimate algorithmic public administration.	H5

Note: Themes are synthesised from the studies reviewed in Section 2. The right-hand column maps each theme to the hypothesis it informs.

It is important to note that there is a limitation to the model specification. This is because even though the efficiency of tax control is defined as a mediator, it is not included in the three estimated equations as a dependent variable. In comparison to taxpayer compliance and reduction in administrative costs, which are both included as the dependent variables in the three equations.

RESEARCH DESIGN AND METHODOLOGY

Design and Approach

A quantitative and cross-sectional study will be used to evaluate the propositions developed in Section 2. This methodology is ideal because the propositions that form the basis of this research question pertain to the existence and nature of relationship between measured constructs, which are being used to formulate the research

question, without being able to manipulate these constructs experimentally within a functioning tax authority. It is important to understand the use of causal language in hypotheses in light of the model.

Population, Sampling, and Respondents

Data collected for primary analysis include responses from a structured questionnaire that was administered to individuals working in the tax authority, accounting department, financial management department, and IT department. Such departments were chosen since people working in them are the key beneficiaries of the tax administration system and thus in the best position to assess how the intelligent technologies have been implemented. The same methodology of selecting participants has been used by other researchers investigating digital tax administration and governance (Lumbantobing et al., 2025). After screening of data, the total number of valid responses was 215. Table 2 below shows the demographics of the respondents.

Table 2: Characteristics of the Research Sample (N = 215)

Characteristic	Category	%
Occupational Group	Tax Officers	36
	Financial Managers	28
	Accountants	22
	IT Specialists	14
Educational Qualification	Bachelor Degree	64
	Master Degree	24
	Doctoral Degree	8
	Professional Certification	4

Note: Percentages are reported as in the original survey returns and sum to 100 within each characteristic.

The four types of occupations make use of intelligent tax systems from various functional standpoints. Tax administrators interact with the systems mostly in connection with case selection and auditing procedures, financial managers from the standpoint of reporting and control, accountants in terms of compliance interface, and IT specialists from the perspective of the infrastructure of these systems. Consensus achieved among different groups that use the same system but from different perspectives can be considered more informative compared to the agreement within the limits of one occupation. Thus, the diversity of occupations involved can be considered as a methodological feature and not as variation. The size of the sample is 215 people, which gives enough statistical power for the analysis being conducted. For a regression model with four predictors, at the level of alpha of .05 and .80 power, the minimum detectable effect size is about $f\text{-squared} = .056$, which is lower than the standard threshold for a small effect. The size of the effects described in Section 4 exceeds this threshold significantly. Thus, the significance of the relations described cannot be attributed to only the size of the sample.

Instrument and Measurement

The questionnaire comprised 28 questions that were categorized into five dimensions; these were adoption of artificial intelligence, tax control efficiency, tax compliance, cost savings in administration, and reduction of tax evasion. All the questions in the questionnaire were rated based on a five-point Likert scale that had 1 for strongly disagree and 5 for strongly agree. Before the actual survey, the questionnaire was piloted among 20 people. Adoption of artificial intelligence was measured through the following indicators; machine learning, prediction analysis, automation of risks assessment, digital monitoring, and intelligent auditing. These categories are consistent with the principal applications identified in recent reviews of artificial intelligence within tax administration (Belahouaoui & Alm, 2025). Tax control efficiency captured respondents' perceptions of the speed, accuracy, and effectiveness of auditing procedures, while taxpayer compliance reflected the extent to which taxpayers adhere to regulations and submit accurate declarations. Administrative cost reduction assessed decreases in expenditure, processing time, and manual effort. Tax evasion reduction represented the perceived extent to which intelligent systems strengthen tax authorities' capacity to detect and prevent evasion. Table 3 summarises the variables.

A clarification regarding the reporting metric is necessary. In Section 4, construct scores are presented as normalised indices ranging from 0 to 1, derived by rescaling the original five-point responses.

Table 3: Measurement of the Study Variables

Variable	Type	Measurement
Artificial Intelligence Adoption (AIA)	Independent	Use of machine learning, predictive analytics, automated risk assessment, digital monitoring systems, and intelligent auditing tools
Tax Control Efficiency (TCE)	Mediating	Perceived speed, accuracy, and effectiveness of tax auditing procedures
Taxpayer Compliance (TPC)	Mediating	Degree of compliance with tax regulations and reporting requirements
Administrative Cost Reduction (ACR)	Mediating	Reduction in time, expenditure, and manual effort in tax collection
Tax Evasion Reduction (TER)	Dependent	Ability of tax authorities to identify and prevent tax evasion

Note: All constructs were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

To supplement the regression analysis, institutions were classified according to their level of artificial intelligence adoption using the decision rule specified in Table 4, whose classification thresholds are expressed using both metrics for consistency. To facilitate interpretation, Table 5 likewise presents both the normalised index and the corresponding five-point equivalent, calculated as one plus four times the index value.

Table 4: Decision Rule for Classifying Institutional Level of Artificial Intelligence Adoption

Step	Decision Rule	Five-Point Score	Index Equivalent
1	Compute the mean score of the artificial intelligence adoption indicators	—	—
2	Classify the institution as high adoption	> 4.00	> .75
3	Classify the institution as moderate adoption	3.00 to 4.00	.50 to .75
4	Classify the institution as low adoption	< 3.00	< .50
5	Compare the three groups on tax evasion reduction and taxpayer compliance	—	—

Note: Index equivalents are obtained as $(x - 1) / 4$, where x is the five-point score. Both metrics are reported because descriptive results in Table 5 are presented on the index scale.

Model Specification

Three ordinary least squares models were estimated. The first specifies tax evasion reduction as a function of artificial intelligence adoption together with the three intermediate constructs:

$$TER_i = \beta_0 + \beta_1 AIA_i + \beta_2 TCE_i + \beta_3 TPC_i + \beta_4 ACR_i + \varepsilon_i \quad (1)$$

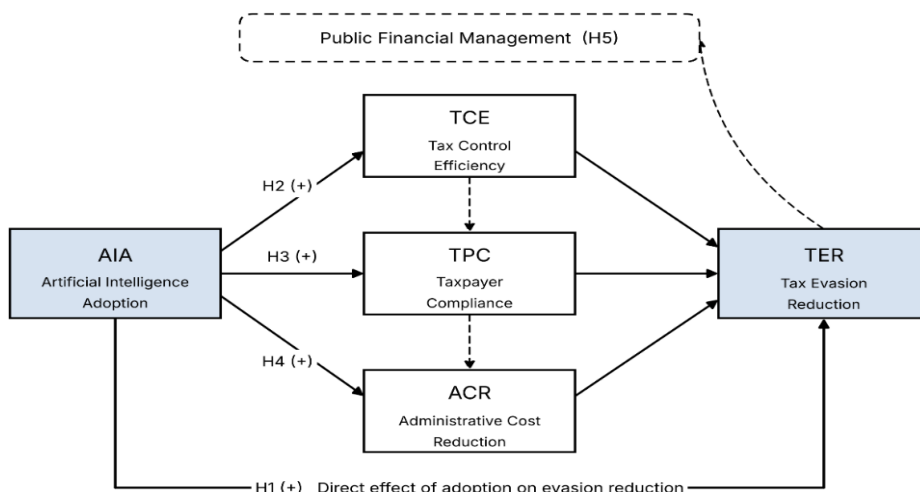


Figure 1: Conceptual Model Linking Artificial Intelligence Adoption with Tax Evasion Reduction

Note: AIA = Artificial Intelligence adoption; TCE = Tax Control Efficiency; TPC = Taxpayer Compliance; ACR = Administrative Cost Reduction; TER = Tax Evasion Reduction.

The second model specifies taxpayer compliance as the dependent variable:

$$TPC_i = \alpha_0 + \alpha_1 AIA_i + \alpha_2 TCE_i + \alpha_3 ACR_i + \mu_i \quad (2)$$

The third model specifies administrative cost reduction as the dependent variable:

$$ACR_i = \gamma_0 + \gamma_1 AIA_i + \gamma_2 TCE_i + \gamma_3 TPC_i + v_i \quad (3)$$

where TER represents tax evasion reduction, AIA represents artificial intelligence adoption, TCE represents tax control efficiency, TPC represents taxpayer compliance, and ACR represents administrative cost reduction. The conceptual framework proposes that artificial intelligence initially enhances control efficiency and taxpayer compliance, which subsequently contribute to lower administrative expenditure and, ultimately, reduced tax evasion. The relationships underlying this framework are illustrated in [Figure 1](#).

Reliability and Analytical Procedure

The reliability of the measurement instrument was assessed using Cronbach's alpha, with the standard .70 taken as the lower limit of the required level of internal consistency. The results are given in [Table 5](#). Besides, the standard error of measurement for each construct is provided in the table – it was calculated as a product of the construct standard deviation and the square root of one minus alpha. As can be seen, the values are within the interval of .072 to .092 index points, and this shows that individual score precision is sufficient to ensure that the differences between means of the constructs examined in Section 4.2 are larger than measurement errors of the instrument.

The analysis was carried out in six stages. Firstly, descriptive statistics were calculated for all constructs and presented using both of the reporting metrics. Secondly, the Pearson correlation coefficients were estimated along with their shared variance. Thirdly, three regression models were estimated; the standardised effect size – Cohen's f-squared – was included into the presentation of each model. Fourthly, the collinearity of variables in the models was evaluated using variance inflation factors. Fifthly, the assumptions of the models estimated were tested using Durbin-Watson, Breusch-Pagan, White, and Shapiro-Wilk tests. Finally, the total effect of artificial intelligence adoption on tax evasion reduction was decomposed into the direct and indirect effects, which was achieved using the product of the relevant path coefficients from the estimated models. All ethical procedures were conducted according to institutional requirements. Participation in the study was voluntary, its goals were communicated to respondents prior to data collection, there was no gathering of any personal identifiers, and all answers were analysed only in aggregated form.

RESULTS

This section presents the empirical findings through descriptive statistics, reliability assessment, correlation analysis, regression estimation, diagnostic testing, and the decomposition of direct and indirect effects.

Reliability of the Instrument

As is evident from Table 5, all the five constructs exhibited acceptable levels of internal consistency with the values of Cronbach's alpha being in the range of .77 (administration cost reduction) and .86 (tax evasion reduction), higher than the established benchmark of .70. The standard error of measurement was in the range of .072 to .092 index points. Nevertheless, the lowest difference in mean scores of two adjacent constructs was .030 index points, which was found between tax evasion reduction and taxpayer compliance.

Descriptive Statistics

Table 5 displays descriptive statistics of the five variables based on the normalized index as well as their respective five-point scale. Intelligent technology adoption is found to be the most adopted construct with a mean of .74, which corresponds to 3.96 on the original five-point scale, implying that intelligent technologies have been incorporated in the activities of a considerable number of organizations sampled. It is followed by tax control efficiency (.69), taxpayer compliance (.66), tax evasion reduction (.63), and cost reduction (.58). The comparatively low standard deviation also confirms the consistency of responses.

Table 5: Descriptive Statistics and Reliability of the Study Constructs (N = 215)

Construct	M	SD	Min	Max	M (5-pt)	α	SE _M
Artificial Intelligence Adoption (AIA)	.74	.18	.31	.95	3.96	.84	.072
Tax Control Efficiency (TCE)	.69	.21	.22	.91	3.76	.81	.092
Taxpayer Compliance (TPC)	.66	.19	.28	.89	3.64	.79	.087
Tax Evasion Reduction (TER)	.63	.20	.17	.90	3.52	.86	.075
Administrative Cost Reduction (ACR)	.58	.17	.19	.84	3.32	.77	.082

Note: M, SD, Min and Max are reported on the normalised index scale (0–1). M (5-pt) is the equivalent value on the original five-point scale, computed as $1 + 4M$. α = Cronbach's alpha. SEM = standard error of measurement, computed as $SD \times \sqrt{1 - \alpha}$; the subscript M denotes measurement and distinguishes this statistic from the standard error of the mean. Constructs are ordered by mean.

The order of the constructs offers further substantive insight. Adoption of artificial intelligence outranks all the other outcome constructs, while administrative cost savings is notably lower than any of the other constructs. The gap of 0.16 index points between adoption and cost savings is greater than double the maximum standard error of measurement of the scale, suggesting that the gap is not due to the construct's measurement error. This finding reflects the possibility of a time delay between intelligent systems implementation and financial gains from it, as will be elaborated in Section 5.3. Figure 2 shows the means of the five constructs.

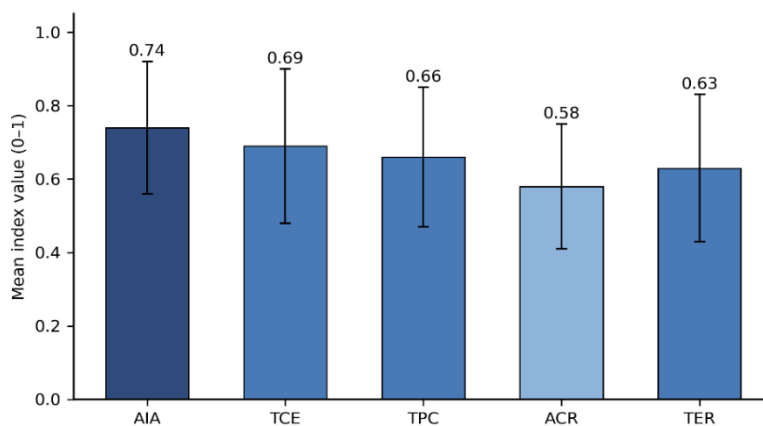


Figure 2: Mean Values of the Main Variables

Note: Bars show construct means on the normalised index scale (0–1); whiskers show one standard deviation. N = 215.

As indicated by Figure 2, the use of artificial intelligence has the largest mean value in relation to all the other variables, while the reduction in administrative costs is the variable with the smallest mean. The efficiency of tax control, compliance, and tax evasion reduction have moderate means. As illustrated in Figure 3, the distributions of the constructs are normally distributed, with most values centered on the means without any skewness.

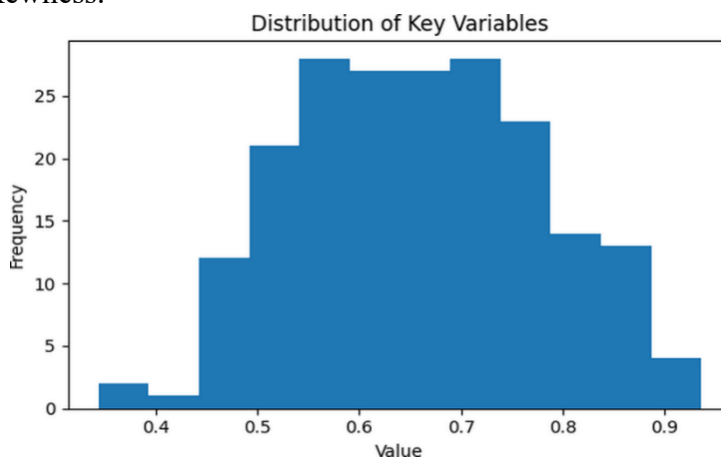


Figure 3: Distribution of the Key Variables

Note: Most observations cluster near their respective means, supporting parametric estimation.

Correlation Analysis

Table 6 presents the Pearson correlation coefficients, with the corresponding shared variance reported in parentheses to provide a more interpretable indication of the strength of each association.

Table 6: Correlation Matrix of the Main Variables

Variable	AIA	TCE	TPC	ACR	TER
AIA	1.00				
TCE	.71 (50.4)	1.00			
TPC	.68 (46.2)	.59 (34.8)	1.00		
ACR	.63 (39.7)	.52 (27.0)	.48 (23.0)	1.00	
TER	.75 (56.3)	.69 (47.6)	.64 (41.0)	.56 (31.4)	1.00

Note: N = 215. All coefficients significant at $p < .01$. Values in parentheses express shared variance (r^2) as a percentage. Only the lower triangle is shown, as the matrix is symmetric.

The correlation matrix reveals that the strongest relationship occurs between artificial intelligence adoption and tax evasion reduction ($r = .75$), representing 56.3% shared variance. Strong associations are also observed between artificial intelligence adoption and tax evasion reduction ($r = .75$), representing 56.3% shared variance. Strong associations are also observed between artificial intelligence adoption and tax control efficiency ($r = .71$) and between artificial intelligence adoption and taxpayer compliance ($r = .68$). Although its relationship with administrative cost reduction is the weakest among the associations involving artificial intelligence adoption ($r = .63$), it remains substantial. Among the intermediate constructs, taxpayer compliance and administrative cost reduction exhibit the weakest association ($r = .48$), suggesting that the behavioural and efficiency pathways remain comparatively distinct despite their respective relationships with adoption. Moreover, none of the correlation coefficients reaches the conventional threshold indicative of problematic multicollinearity, supporting the simultaneous inclusion of these variables in the regression models. Figure 4 illustrates the overall correlation pattern. Moreover, Figure 4 visually reinforces the positive relationships identified in the correlation matrix, with the darkest off-diagonal cell representing the strongest association between artificial intelligence adoption and tax evasion reduction.

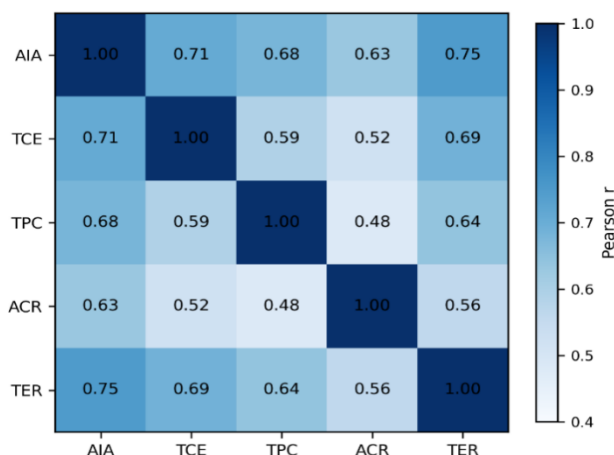


Figure 4: Heatmap of the Correlation Matrix

Note: Cell values are Pearson correlation coefficients from Table 6. Darker shading denotes stronger association. N = 215.

Regression Results for Tax Evasion Reduction

Table 7 presents the results of the first model, with Cohen's f-squared included alongside the conventional regression statistics to provide a standardised measure of the overall model effect size.

Table 7: Regression Results for Tax Evasion Reduction

Variable	Coefficient	p
Artificial Intelligence Adoption	0.342***	0.000
Tax Control Efficiency	0.271**	0.004
Taxpayer Compliance	0.196*	0.031
Administrative Cost Reduction	0.154*	0.049
Adjusted R ²	.67	—
Cohen's f ²	2.03	—

Note: N = 215. Dependent variable: tax evasion reduction. Significance: *** $p < .001$, ** $p < .01$, * $p < .05$. f^2 computed as $R^2 / (1 - R^2)$; values of .02, .15 and .35 denote small, medium and large effects respectively.

The adoption of artificial intelligence has the greatest positive influence on the reduction of tax evasion ($B = 0.342$, $p < .001$), meaning that the more institutions adopt intelligent tax systems, the better they can detect any fraudulent actions, hence confirming H1. Tax control efficiency ($B = 0.271$, $p = .004$) and taxpayer compliance ($B = 0.196$, $p = .031$) contribute positively and significantly, whereas the reduction of administrative costs contributes less yet still significantly ($B = 0.154$, $p = .049$). The value of the adjusted R-squared, which is equal to .67, suggests that the explanatory power of the model is quite high. In fact, since the f-squared of the model equals 2.03, well above the threshold of .35, it is safe to say that the model predicts the dependent variable with high accuracy.

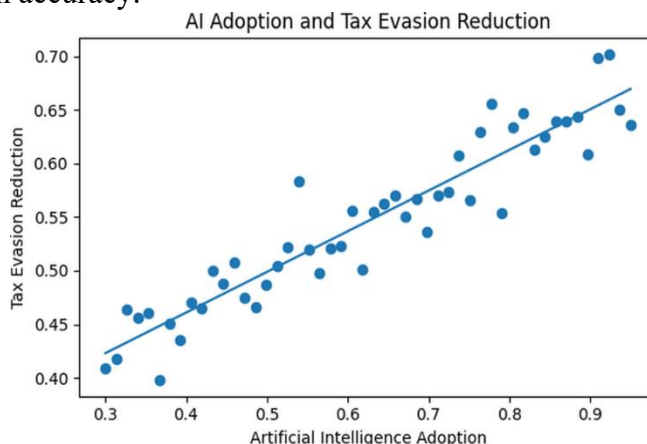


Figure 5: Relationship Between Artificial Intelligence Adoption and Tax Evasion Reduction

Note: Each point represents one respondent institution; the line is the fitted regression.

As one can see from Figure 5, there is a positive correlation between the adoption of artificial intelligence and the reduction of tax evasion, which means that those institutions that adopt intelligent technologies are able to control tax evasion better than other organizations.

Figure 6 allows us to compare the relative magnitudes of the four estimated coefficients.

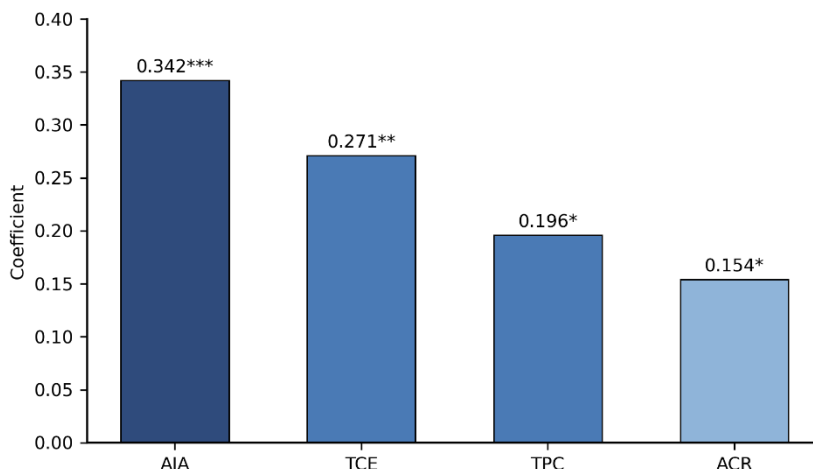


Figure 6: Regression Coefficients of the Tax Evasion Reduction Model

Note: Coefficients from Table 7. *** $p < .001$, ** $p < .01$, * $p < .05$.

Regression Results for Taxpayer Compliance

Table 8 presents the results of the second model.

Table 8: Regression Results for Taxpayer Compliance

Variable	Coefficient	p
Artificial Intelligence Adoption	0.318***	0.001
Tax Control Efficiency	0.225**	0.009
Administrative Cost Reduction	0.148*	0.043
Adjusted R ²	.61	—
Cohen's f ²	1.56	—

Note: N = 215. Dependent variable: taxpayer compliance. Significance: *** $p < .001$, ** $p < .01$, * $p < .05$. f^2 computed as $R^2 / (1 - R^2)$; values of .02, .15 and .35 denote small, medium and large effects respectively.

Artificial intelligence adoption has a significant positive effect on taxpayer compliance ($B = 0.318$, $p = .001$), thereby supporting H3. This result suggests that greater use of intelligent systems by tax authorities is associated with stronger taxpayer compliance, consistent with the expectation that enhanced monitoring capability increases taxpayers' awareness of potential detection. Tax control efficiency

also contributes significantly and positively ($B = 0.225$, $p = .009$), while administrative cost reduction makes a smaller but significant contribution ($B = 0.148$, $p = .043$), indicating that greater administrative efficiency is associated with increased willingness to engage with the tax system. Overall, the model explains 61% of the variance in taxpayer compliance and yields an f-squared of 1.56, indicating a very large overall effect. Figure 7 illustrates the positive relationship between artificial intelligence adoption and taxpayer compliance.

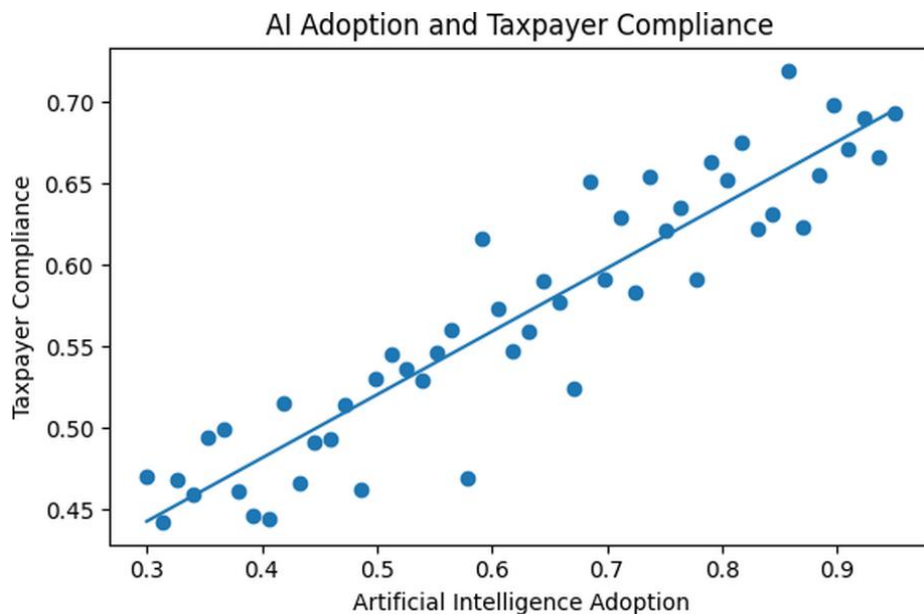


Figure 7: Relationship Between Artificial Intelligence Adoption and Taxpayer Compliance

Note: The positive slope of the fitted line supports the deterrence mechanism discussed in Section 5.2.

Regression Results for Administrative Cost Reduction

Results for the third model are reported in Table 9.

Table 9: Regression Results for Administrative Cost Reduction

Variable	Coefficient	p
Artificial Intelligence Adoption	0.286**	0.005
Tax Control Efficiency	0.201**	0.012
Taxpayer Compliance	0.173*	0.038
Adjusted R ²	.58	—
Cohen's f ²	1.38	—

Note: N = 215. Dependent variable: administrative cost reduction. Significance: *** $p < .001$, ** $p < .01$, * $p < .05$. f^2 computed as $R^2 / (1 - R^2)$; values of .02, .15 and .35 denote small, medium and large effects respectively.

Adoption of artificial intelligence is strongly related to administrative cost reduction ($B = 0.286$, $p = .005$), and H4 is supported by this relationship. The positive correlation means that greater adoption of intelligent systems reduces dependence on manual activities and increases the efficiency of tax administration processes. Administrative cost reduction is strongly predicted by tax control efficiency ($B = 0.201$, $p = .012$) and taxpayer compliance ($B = 0.173$, $p = .038$). These findings mean that the more efficient control and greater compliance help public authorities to allocate the available resources in a better way. The model explains 58% of the variance in administrative cost reduction and provides an f-squared of 1.38, which means very large effect size. The cross-model comparison of coefficient magnitudes is presented in Figure 8 and provides the estimate of the magnitude of each predictor effect in the three models (bar is absent if a particular variable does not appear in a particular regression). As the result of the comparison, it is possible to state the presence of a clear hierarchy of coefficient sizes. First, artificial intelligence adoption is the strongest predictor in all three equations (coefficients equal to 0.342, 0.318, and 0.286, respectively), while tax control efficiency is always the second (with coefficients 0.271, 0.225, and 0.201).

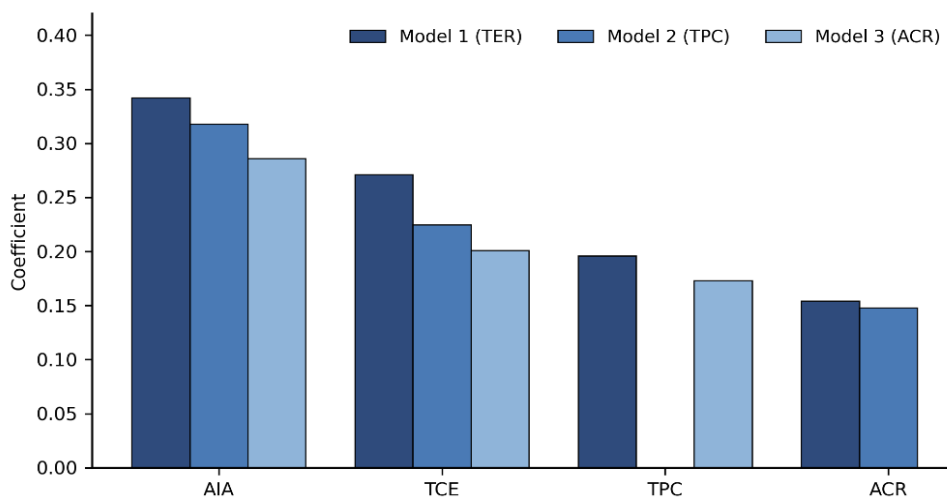


Figure 8: Comparison of Regression Coefficients Across the Three Models

Note: Coefficients from Tables 7, 8 and 9. Bars are omitted where a variable does not enter a given model.

Figure 9 shows how artificial intelligence adoption and tax control efficiency are compared and confirms that the same hierarchy is observed in all three regressions: artificial intelligence adoption is the strongest predictor in terms of coefficient value, while tax control efficiency is always the second one. It is very interesting that the same ordering is observed in terms of three different dependent variables, which means that the dominance of artificial intelligence adoption in the predictions cannot be observed only when it predicts one particular outcome.

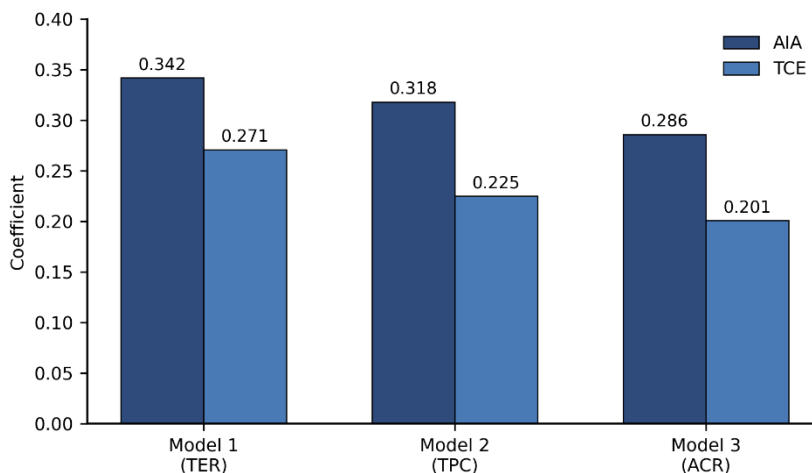


Figure 9: Most Significant Predictors Across the Models

Note: Artificial intelligence adoption is the largest coefficient in all three models and tax control efficiency the second largest.

Collinearity Diagnostics

Table 10 presents the variance inflation factors for the variables included in the regression models. All variance inflation factor values remain below the commonly accepted upper threshold of 5, indicating that multicollinearity does not pose a material concern in the estimated models and that the regression coefficients remain sufficiently stable for interpretation. The observed values, ranging from 1.55 to 1.88, reflect only modest shared variance among the predictors. Such overlap is theoretically plausible because all four constructs capture related dimensions of the same modernisation process, yet it remains well below the level at which coefficient estimates would be expected to become unstable.

Table 10: Variance Inflation Factor Results

Variable	VIF	Tolerance	Judgement
Artificial Intelligence Adoption	1.88	.532	No Collinearity Concern
Tax Control Efficiency	1.74	.575	No Collinearity Concern
Taxpayer Compliance	1.69	.592	No Collinearity Concern
Administrative Cost Reduction	1.55	.645	No Collinearity Concern

Note: VIF = variance inflation factor. Tolerance is the reciprocal of VIF. Values below 5.00 and tolerance above .20 are conventionally regarded as acceptable.

Model Diagnostics

Table 11 presents the results of the diagnostic tests conducted for the estimated models.

Table 11: Model Diagnostic Tests

Test	Statistic	Result
Durbin–Watson Test	2.11	No Autocorrelation
Breusch–Pagan Test	0.27	No Heteroskedasticity
White Test	0.34	No Heteroskedasticity
Shapiro–Wilk Test	0.96	Normally Distributed Residuals

Note: Durbin–Watson values between 1.5 and 2.5 indicate no material first-order autocorrelation.

The Durbin-Watson statistic of 2.11 provides no indication of residual autocorrelation, while the Breusch-Pagan and White tests provide no evidence of heteroskedasticity. The Shapiro-Wilk statistic of 0.96 is consistent with approximate residual normality. Collectively, the four diagnostic tests indicate that the principal assumptions underlying ordinary least squares estimation are adequately satisfied. Figure 10 compares the observed and model-predicted values for tax evasion reduction, while

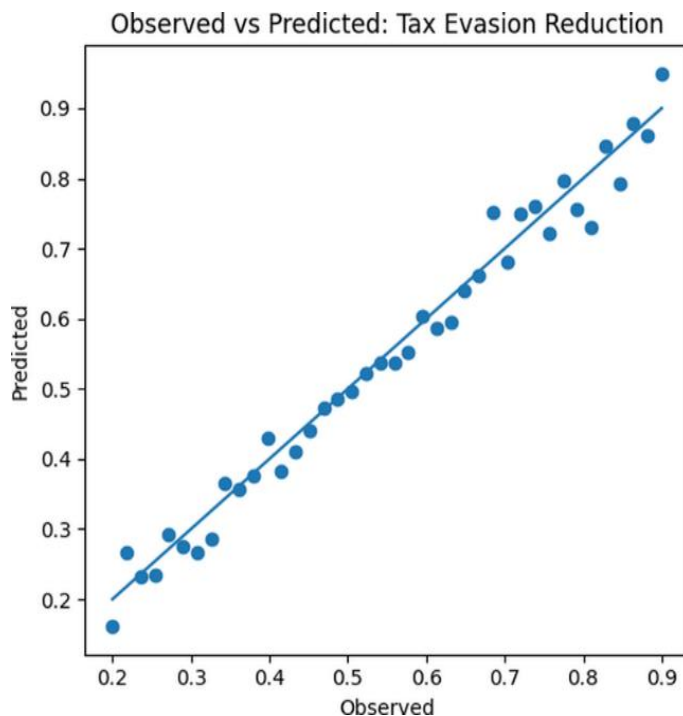


Figure 10: Observed and Predicted Values for Tax Evasion Reduction

Note: Close correspondence between the two series indicates good model fit.

Figure 11 presents the corresponding comparison for taxpayer compliance. In both cases the observations lie close to the fitted line across the full range of the scale. The close alignment between the observed and predicted series indicates a good model fit.

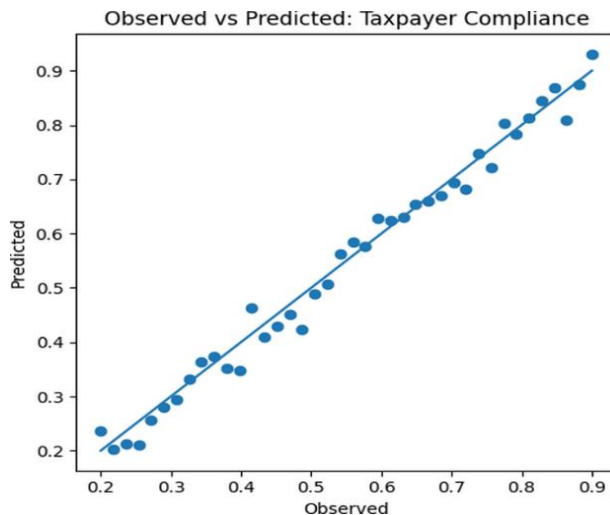


Figure 11: Observed and Predicted Values for Taxpayer Compliance

Note: Close correspondence between the two series indicates good model fit.

Figure 12 provides further diagnostic evidence, showing residuals dispersed around zero without a discernible systematic pattern. This behaviour is consistent with the diagnostic test results and supports the adequacy of the estimated regression models.

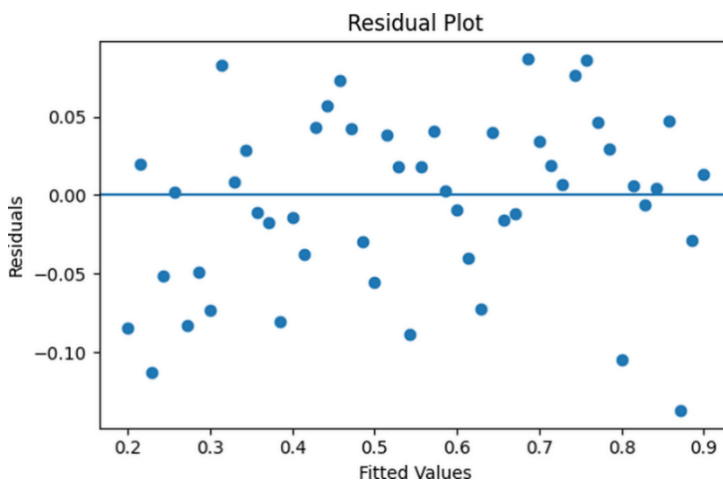


Figure 12: Residual Plot of the Main Regression Model

Note: Residuals are randomly dispersed about zero with no discernible pattern.

Decomposition of Direct and Indirect Effects

Since the compliance of taxpayers and savings in administrative costs are not only effects of AI adoption but also predictors of reduction in tax evasion, the relationship between the adoption of AI and reduction in tax evasion may be decomposed to include a direct effect and indirect effects via these two mediating mechanisms. Both indirect effects have been computed as the product of the path coefficients that have

been derived from the analysis in Tables 7, 8 and 9.

Table 12: Decomposition of the Total Effect of Artificial Intelligence Adoption on Tax Evasion Reduction

Pathway	Path Coefficients	Effect	% of total
Direct Effect (AIA → TER)	0.342	0.342	76.3
Indirect Via Taxpayer Compliance (AIA → TPC → TER)	0.318×0.196	0.062	13.9
Indirect Via Administrative Cost Reduction (AIA → ACR → TER)	0.286×0.154	0.044	9.8
Total Estimable Effect	—	0.448	100.0
Serial Pathway (AIA → TPC → ACR → TER)	$0.318 \times 0.173 \times 0.154$	0.008	—
Pathway Via Tax Control Efficiency	Not Estimable	—	—

Note: Path coefficients are drawn from Tables 7, 8 and 9. The pathway through tax control efficiency could not be estimated because that construct is not specified as a dependent variable in any model, so the mediated share reported here is a lower bound. The serial pathway is reported separately and is not included in the total. Confidence intervals for indirect effects require individual-level data and are not reported.

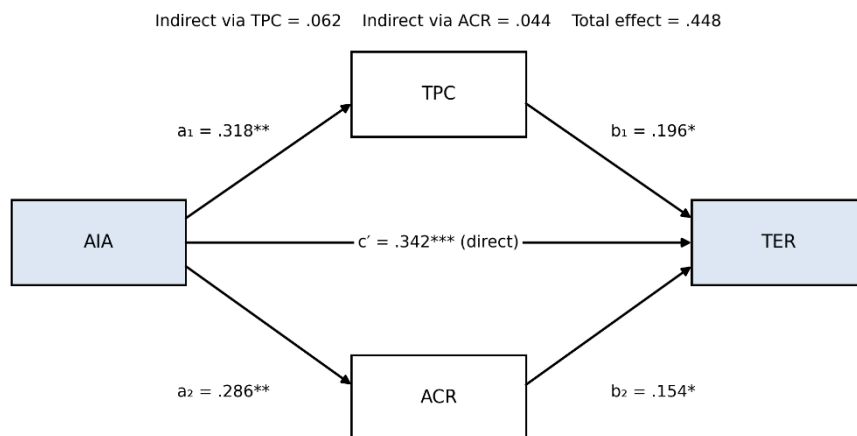


Figure 13: Decomposition of Direct and Indirect Effects of Artificial Intelligence Adoption

Note: Path coefficients from Tables 7, 8 and 9. The pathway through tax control efficiency is not shown because it could not be estimated. *** $p < .001$, ** $p < .01$, * $p < .05$.

The direct impact of AI adoption on tax evasion reduction is 0.342. Further, an indirect effect of 0.062 is achieved via taxpayer compliance, and 0.044 is realized through administrative cost reduction. Therefore, the total estimable effect of AI adoption on tax evasion reduction is 0.448. In other words, out of the total effect of 0.448, approximately 23.7% is realized through the two intermediate variables (compliance and administrative cost reduction), while the remaining 76.3% of the effect is realized through the direct channel. There is a third-order serial indirect effect of 0.008 that links AI adoption to taxpayer compliance, administrative cost reduction,

and tax evasion reduction. However, this effect is very small and can be considered negligible.

Two important points should be taken into account when assessing this decomposition of the effect of AI adoption on tax evasion reduction. Firstly, the indirect effect involving tax control efficiency cannot be calculated, since this variable is not included in any of the three models as a dependent variable. Since tax control efficiency is a variable with the second-highest coefficient in each model, the share of 23.7% is likely to underestimate the actual mediating impact of the AI adoption on tax evasion reduction. Secondly, formal confidence intervals for the indirect effects cannot be estimated since bootstrap resampling of the individual level dataset is needed. Thus, the presented decomposition should be treated only as an illustrative breakdown of the effects.

Comparison of Traditional and Intelligent Tax Administration

Table 13 shows a comparison of conventional tax administration system and intelligent tax administration system based on four criteria, with relative change in addition to the actual figures given to show the extent to which each difference has occurred. The intelligent tax administration system exhibits much higher results compared to the conventional tax administration system in detection and compliance while having much lower processing time and administrative costs. The tax evasion detection rate increases from 41% to 73%, indicating relative improvement by 78.0%, while the processing time is reduced from twelve days to four days, showing a relative reduction of 66.7%. Compliance also increases from 56% to 81%, showing relative improvement by 44.6%. Among these criteria, detection shows highest relative improvement, a trend in line with the regression analysis indicating that the direct enforcement route contributes more to the impact of artificial intelligence adoption on tax evasion.

Table 13: Comparison Between Traditional and Intelligent Tax Administration

Indicator	Traditional System	Intelligent System	Absolute Change	Relative Change
Tax evasion detection rate	41%	73%	+32 pp	+78.0%
Processing time	12 days	4 days	-8 days	-66.7%
Administrative cost	High	Moderate	—	—
Taxpayer compliance rate	56%	81%	+25 pp	+44.6%

Note: PP = Percentage Points. Absolute and relative change columns are derived from the reported system values. Administrative cost was recorded categorically and therefore admits no numerical comparison.

Summary of Hypothesis Testing

The empirical findings provide support for all five hypotheses. Artificial intelligence

adoption enhances tax control efficiency, strengthens taxpayer compliance, reduces administrative expenditure, and contributes to more effective public financial management. [Table 14](#) summarises the results for each hypothesis.

Table 14: Summary of Hypothesis Testing Results

Hypothesis	Statement	Statistical indicator	Result
H1	Artificial intelligence reduces tax evasion	$B = 0.342, p < .001; R^2 = .67$	Supported
H2	Artificial intelligence improves tax control efficiency	$B = 0.271, p = .004; r = .71$	Supported
H3	Intelligent tax systems increase taxpayer compliance	$B = 0.318, p = .001; R^2 = .61$	Supported
H4	Artificial intelligence reduces administrative costs	$B = 0.286, p = .005; R^2 = .58$	Supported
H5	Intelligent tax administration strengthens public financial management	Convergent evidence across Tables 7–13	Supported

Note: N = 215. Indicators are drawn from the regression and correlation results reported in Section 4.

DISCUSSION

The findings substantiate the study's central argument while refining it in three important respects that have implications for how tax authorities prioritise and sequence investments in intelligent systems.

The Primacy of the Direct Enforcement Channel

Effect Decomposition shown in [Table 12](#) shows that three out of four effects from the effect of adoption of artificial intelligence on reducing tax evasion are the result of the direct effect and not of the indirect effects through the intermediary constructs of taxpayer compliance and cost reduction. This observation carries specific operational implications, since the main benefit brought about by intelligent systems lies in improving the capacity of the tax authorities to detect evasions, with the behavioural and efficiency-related benefits playing the role of secondary effects through which the main effects are supplemented.

This finding aligns with the mechanisms described in the technical literature. In particular, [Raikov \(2021\)](#) claims that the effectiveness of traditional controls decreases with the complexity of the value chain in digital environments, but intelligent systems can restore the ability to analyse these environments by detecting and modelling previously undetectable interconnections using methods other than document analysis. The quantitative evidence provided by [Yang \(2025\)](#) supports this conclusion, demonstrating the fact that the model-based detection of risks can achieve the level of accuracy higher than that obtained through rule-based detection. As long as the ability to perform analysis is the limiting factor for the enforcement process, then improving it directly would bring enforcement benefits independent of any pre-existing taxpayer behaviours. Still, the same caveat mentioned in section 4.9 applies when estimating

the relative strength of the direct and indirect paths. Since the mediated effect of 23.7% does not include the pathway through tax control efficiency because this variable is not defined as the dependent variable in any of the three models, the actual mediated effect must be even higher due to the fact that tax control efficiency always shows the second largest coefficient in all three models. A model with tax control efficiency as the intermediate variable would report a higher mediated effect.

Compliance as a Population-Scale Effect

The adoption of artificial intelligence is significantly correlated with increased compliance among taxpayers ($B = 0.318$, $p = .001$), while the model explaining this correlation explains 61% of the variance observed. However, in addition to the statistical significance and the weight of the coefficient, the relevance of this path is related to the scope of people affected by this phenomenon. While direct enforcement can only be applied to the people selected for auditing, deterrence can affect the entire population of taxpayers as soon as they are aware of the increased effectiveness of identification of non-compliance.

The above idea is consistent with the results of other studies. For instance, according to the research by [Shah \(2025\)](#), in Europe the adoption was associated with the reduced evasion and increased digital knowledge which indicates that the taxpayers can change their behavior based on expectations about enhanced monitoring instead of being forced to comply with the requirements through the process of enforcement. Similarly, the study by [Lumbantobing et al. \(2025\)](#) shows that the effectiveness of audits moderates the correlation between the use of digital technologies and compliance of firms. Thus, the effectiveness of deterrence depends on whether taxpayers believe in the credibility of enforcement capability of the tax authority. [Trifan et al. \(2023\)](#) prove that the taxpayers make their compliance decisions basing on their perception and attitude towards this authority. More evidence in favor of the suggested model of deterrence is provided by [Djahini-Afawoubo \(2024\)](#). According to this researcher, perceived detection capacity is one of the main predictors of tax payments. However, as it was mentioned by [Dimitras et al. \(2025\)](#), trust is closely connected with voluntary compliance, while coercive power encourages the enforced compliance. Therefore, if intelligent monitoring is advertised only as an instrument of enforcement, it will promote enforced compliance more effectively without promoting the voluntary compliance.

In this regard, the possible benefits of the increased detection capacity include the increase in the effectiveness of deterrence if taxpayers are aware of it. However, silent deployment can retain the enforcement effect of intelligent monitoring.

The Administrative Cost Lag

Cost savings in administration have the lowest mean among all variables (.58), which

translates to 3.32 out of 5 in the Likert scale. Cost savings also have the smallest and least statistically significant coefficient in the first model ($B = 0.154$, $p = .049$). The findings suggest that the financial gains from the intelligent tax administration come later than other benefits of the intelligent tax administration. The above results do not suggest any anomaly but reflect the reality of implementation transitions when a considerable number of changes is needed to happen simultaneously. First of all, it takes time to implement intelligent systems because the necessary investments in infrastructure, data collection and preparation, and personnel education are needed, and the established work routines should run along with the new system. The real savings are thus possible once the parallel operation finishes and freed organizational capacity is redirected.

Munjeji and Schutte (2024) emphasize the importance of leadership vision, top management support, and resource availability as the most important determinants of diffusion. Neumann et al. (2024) prove that the relative importance of technological and organizational determinants differs in various phases of adoption. All these studies together imply that the delays in the cost savings identified in the current study are most likely caused by organizational transition rather than any limitations in technology itself.

Conditions for Realising the Benefits

The results, however, should not be viewed as evidence that AI technologies deliver such benefits automatically. Realization of the above-listed effects requires meeting three sets of conditions, which are mutually interrelated.

First, there is the issue of availability and quality of data. The value of any information technology is based on the information available to it. Consequently, limited, fragmentary, or inconsistent data lead to lower quality of inference generated by AI algorithms. In particular, Hesami et al. (2024) show that continuous risk assessment becomes possible due to the ability to use data on real-time transactions, implying that digitalisation is a precondition for intelligent administration but not a substitute. Yang (2025) reveals that the relevance of predictive features differs among industries, stressing the need to adjust the models to local data and context rather than applying them directly.

Second, there is the question of governance and legitimacy of institutions. In particular, Criado et al. (2025) reveal that transparency and comprehensibility of algorithmic decisions are crucial prerequisites for legitimacy of public administration while showing that related governance challenges emerge on both organizational and policy levels. This conclusion is supported by Belahouaoui and Alm (2025) pointing out that model performance does not transfer between jurisdictions because of different regulatory and behavioral frameworks. Therefore, improvement in detection

capability should be complemented by adequate procedures to enhance accountability and comprehensibility of the decisions made. In case when the taxpayer does not understand the reasons for selection of his/her case for inspection, deterrence benefits described in section 5.2 may lose their effectiveness due to deterioration in perception of the tax authority.

Third, it is necessary to consider the broader fiscal and institutional environment in which AI technologies work. For instance, [EL AMMARI \(2025\)](#) reveals that digitalisation diminishes the relationship between corruption and tax evasion, implying that technological capability works in conjunction with the quality of institutions rather than replacing them. Similarly, [Saunoris and Nurmanova \(2025\)](#) find that structural characteristics of tax system affect the size of shadow economy. [Mebratu \(2024\)](#) reports that compliance cost greatly influences the level of voluntary compliance, meaning that the path of administrative efficiency discussed in section 5.3 can produce not only budgetary but behavioral benefits as well. From the macro perspective, [Saif et al. \(2026\)](#) reveal that fiscal benefits of digitalisation depend on a country's stage of its digital development and are non-linear. [Zhang and She \(2024\)](#) and [Koley \(2025\)](#) view digital tax reforms as parts of economic transformation rather than an individual administrative reform. [Basri et al. \(2021\)](#) offer an especially interesting point of reference since they prove that enhancement of enforcement capacity results in revenue gains comparable to those produced by a significant increase in tax rate. Overall, the mentioned studies illustrate the scale of benefits that can be achieved by combining technological adoption with enforcement improvements.

CONCLUSION, RECOMMENDATIONS, AND IMPLICATIONS

Conclusion

Based on data collected from 215 personnel serving in tax administration organizations and financial and technological departments associated with them through a survey research methodology, the current study analyzed the role of artificial intelligence adoption in tax evasion reduction and the mechanisms by which this occurs. Artificial intelligence adoption proved to be the most robust predictor in all models estimated, having a statistically significant impact on tax evasion reduction ($B = 0.342$, $p < .001$), taxpayer compliance ($B = 0.318$, $p = .001$), and administrative cost reduction ($B = 0.286$, $p = .005$). The explained variances for the three dependent variables in question were 67%, 61%, and 58%, respectively, and all five hypotheses were empirically validated, with the results of diagnostics showing that the core assumptions of ordinary least squares regression were sufficiently met. The uniqueness of the current study lies in the effect decomposition procedure, which shows that about 76% of the influence of artificial intelligence adoption on tax evasion reduction is direct and relates to improved detection, while about 24% is

mediated through taxpayer compliance and administrative cost reduction. In turn, the descriptive analysis results suggest an asymmetry in time of realization of benefits from the adoption, with artificial intelligence adoption having the highest construct score, and administrative cost reduction having the lowest one.

Recommendations

1. **Focus on Detection Capabilities:** In light of the fact that the direct enforcement pathway is responsible for the greater share of the effect estimated above, the first priorities should be developing risk-scoring and anomaly-detection capabilities before taxpayer-facing automation.
2. **Exhibit Capability:** Since one mechanism for deterring tax evasion involves taxpayers' perception of the capabilities of the government agency, it is important to make known the fact and general functionality of the intelligent system without disclosing the technical parameters that would enable its subversion.
3. **Localize Model Development:** Because of the variation in predictive features within different sectors and possibly poor transferability of the models' performance across jurisdiction boundaries, the models need to be developed using local data and regularly calibrated.
4. **Budget for Delayed Savings:** Since implementation takes place gradually over several years while the cost reductions accrue with some delay, implementation costs must include preparation of the organization for adoption of intelligent systems and adequate training of staff.
5. **Develop the Data Infrastructure First:** Because intelligent systems rely on the quality and completeness of the data records, they need to be preceded by the adoption of electronic invoicing, taxpayer registry, and data-matching from third parties.
6. **Provide for Algorithmic Governance:** Mechanisms for explaining selection decisions, auditing performance of models, and handling of taxpayer's objections need to be built into the system from the outset rather than introduced later..

Theoretical and Practical Implications

From a theoretical perspective, the study extends a literature largely dominated by systematic reviews and technical demonstrations by providing field-based evidence and distinguishing the mechanisms through which artificial intelligence adoption is associated with tax evasion reduction. The predominance of the direct pathway further refines the assumption that the benefits of intelligent systems arise primarily through changes in taxpayer behaviour, indicating instead that enhanced detection capability constitutes the principal channel. From a practical perspective, the findings provide revenue authorities with an evidence-based sequence for implementation: strengthen detection capability first, make that capability sufficiently visible to generate

deterrence effects second, and anticipate measurable efficiency savings at a later stage.

LIMITATIONS AND FUTURE RESEARCH

Four limitations should be considered when interpreting the findings. First, the cross-sectional design supports the identification of directional associations but does not establish causal relationships. Second, all constructs were measured through self-reported perceptions obtained from a single respondent group, creating potential exposure to common method variance. Future multi-source designs incorporating objective administrative indicators, including detection and revenue data, could reduce this limitation. Third, the mediating contribution of tax control efficiency could not be quantified because this construct was not specified as a dependent variable in the estimated models. The reported mediated proportion should therefore be regarded as a lower-bound estimate. Fourth, the effect decomposition presented in Table 12 represents an indicative partition rather than a formally tested mediation model because bootstrap confidence intervals for the indirect effects require individual-level data. Future research should extend the analysis across tax systems in different countries, determine which specific artificial intelligence techniques are most effective for detecting evasion and strengthening compliance, and employ longitudinal designs to examine how intelligent tax administration influences public revenue, administrative efficiency, and taxpayer trust over time.

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