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Validation of an Artificial Intelligence–Based Tax Policy-Making Model for Reducing Tax Evasion

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Abstract

This study aimed to validate an artificial intelligence–based tax policy-making model for reducing tax evasion and to examine the contribution of its behavioral, technological, institutional, environmental, and operational dimensions. This quantitative, applied, descriptive-survey study was conducted among taxpayers in Urmia, Iran. Using Cochran's formula for an unlimited population, 384 respondents were selected for the main survey, while 15 academic and executive experts participated in the structural assessment of the model. Data were collected through a researcher-developed questionnaire covering data-driven technologies, institutional and governance requirements, taxpayer behavior, environmental challenges, and intelligent systems for tax-evasion detection and prevention. A pilot test of 30 questionnaires confirmed acceptable internal consistency, with Cronbach's alpha coefficients ranging from 0.75 to 0.88. Data were analyzed using SPSS and AMOS through confirmatory factor analysis, structural equation modeling, and goodness-of-fit assessment. Confirmatory factor analysis showed that all retained factor loadings exceeded 0.70 and that the five measurement models demonstrated acceptable fit. In the final structural model, all five dimensions had statistically significant relationships with the overall AI-based tax policy-making model at $p < 0.001$. Taxpayer behavior showed the strongest standardized effect ($\beta = 0.89$), followed by intelligent systems ($\beta = 0.84$), institutional requirements ($\beta = 0.75$), environmental challenges ($\beta = 0.74$), and data-driven technologies ($\beta = 0.71$). The critical ratios for all structural paths exceeded 1.96, confirming the significance of the proposed relationships. The findings support the validity of a multidimensional AI-based tax policy-making framework in which behavioral, institutional, technological, environmental, and intelligent operational components jointly contribute to reducing tax evasion.

Keywords: Artificial Intelligence; Tax Policy-Making; Tax Evasion; Tax Compliance; Data-Driven Technologies; Structural Equation Modeling

1. Introduction

Tax evasion remains one of the most persistent challenges confronting contemporary fiscal systems because it weakens domestic revenue mobilization, reduces the resources available for public services, undermines horizontal and vertical equity, and can erode citizens' confidence in the legitimacy of taxation. The problem has become more complex as economic activity has increasingly shifted toward digital platforms, cross-border transactions, informal arrangements, and technologically mediated business models that are difficult to capture through conventional administrative techniques. Studies of tax evasion and the informal economy show that noncompliance cannot be understood merely as an isolated act of concealment but should be regarded as a phenomenon embedded in institutional quality, economic incentives, regulatory arrangements, administrative

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capacity, and the broader relationship between taxpayers and the state (Bitzenis et al., 2026; Wyciszkiewicz & Schneider, 2026). The expansion of the digital economy has further complicated the ability of tax administrations to identify taxable events, trace income streams, and ensure that new forms of value creation are incorporated into the tax base, thereby intensifying the need for more sophisticated approaches to tax policy and revenue mobilization (Zubairu et al., 2026). At the same time, research on tax capacity and collection effectiveness indicates that variations in administrative performance are not solely attributable to statutory tax rates or formal regulations; they also reflect differences in institutional capacity, tax effort, enforcement quality, and the ability of administrations to translate available fiscal potential into actual revenue (Allahverdi & Çelikay, 2025; Mabugu & Rakabe, 2026). Consequently, reducing tax evasion increasingly requires a multidimensional policy approach that combines technological capability, institutional governance, taxpayer behavior, environmental conditions, and intelligent monitoring rather than relying exclusively on traditional audit and enforcement mechanisms.

Tax administration is therefore undergoing a transition from a predominantly document-based and reactive model toward a data-intensive, technology-supported, and increasingly predictive system of fiscal governance. Digitalization has already transformed the mechanisms through which taxpayers register, file returns, make payments, communicate with tax authorities, and receive administrative services. The growing use of electronic filing has demonstrated that technological interfaces can affect both the efficiency of tax administration and the compliance behavior of taxpayers, although the effects depend on accessibility, usability, trust, and implementation quality (Dzingirai et al., 2026). More broadly, digital government tools have been associated with improved transparency, administrative traceability, and opportunities to strengthen public-sector integrity by reducing discretionary interactions and enabling more systematic monitoring of transactions and decisions (Santiso, 2022). Digital fiscal tools may likewise strengthen the effectiveness of decentralized and local revenue systems by expanding information availability, improving administrative coordination, and facilitating the monitoring of fiscal activities across different levels of government (Monkam & Mangwanya, 2024). Nevertheless, digitalization by itself does not guarantee effective compliance. The performance of tax administration continues to depend on the quality of administrative practices, organizational procedures, taxpayer services, enforcement mechanisms, and institutional capacity (Olumoh, 2024). An integrated conceptualization of tax administration must therefore encompass legal, managerial, technological, and institutional elements rather than treating technological innovation as an independent substitute for administrative reform (Nurbekova et al., 2024).

Within this transformation, artificial intelligence has emerged as one of the most consequential technologies for modern tax administration. Artificial intelligence allows tax authorities to process large and heterogeneous datasets, detect complex patterns, classify taxpayers according to risk, identify anomalies, prioritize audits, support decision-making, and potentially predict noncompliant behavior before revenue losses become irreversible. Recent scholarship has increasingly examined artificial intelligence not only as a technical instrument but also as an institutional mechanism capable of reshaping tax compliance, tax enforcement, and strategies for mitigating tax evasion (Zaim & Sahbani, 2026). Comparative assessments of AI applications across tax administrations indicate that artificial intelligence is becoming embedded in the operational architecture of revenue agencies, although adoption differs across institutional settings and depends on data infrastructure, regulatory readiness, governance capacity, and organizational maturity (Angelov, 2026). From a broader public-administration perspective, artificial intelligence is also being promoted as a tool for improving governance and public-service delivery, particularly in contexts where limited administrative capacity and rapidly growing service demands require more efficient allocation of public resources (Mhlanga, 2026). These developments suggest that AI in tax administration should not be reduced to automated fraud detection; rather, it should be incorporated into a broader policy-making framework connecting data, institutions, taxpayers, oversight structures, and administrative outcomes.

The analytical capabilities of machine learning constitute a particularly important component of this transformation. Machine-learning models can process historical tax data and identify patterns associated with tax liabilities, payment behavior, underreporting, suspicious transactions, and other forms of fiscal risk. Research reviewing the application of machine learning to tax prediction highlights its potential for improving the accuracy and responsiveness of tax-related forecasting and risk identification (Akinrinola et al., 2024). Empirical applications have also demonstrated the relevance of techniques such as

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random forests for tax-risk identification in specific sectors, showing how algorithmic models can support the classification of high-risk cases and assist revenue authorities in directing limited audit resources more effectively (Xu & Kong, 2024). Similarly, machine-learning approaches have been proposed for maximizing tax collection through improved prediction and prioritization of tax cases (Ourdani et al., 2024). The use of machine learning in tax compliance has also been associated with opportunities to reduce fraud and improve revenue collection by moving administrative systems from retrospective detection toward proactive risk management (Olabanji, Olaniyi, & Olagbaju, 2024). These capabilities are especially important in environments characterized by large taxpayer populations, complex transaction networks, resource constraints, and rapidly evolving forms of economic activity, where conventional manual approaches may be unable to analyze the volume and complexity of available data in a timely manner.

Artificial intelligence may become even more effective when integrated with complementary technologies such as blockchain and advanced digital audit systems. AI and blockchain have been discussed as mutually reinforcing technologies capable of increasing transparency, strengthening traceability, automating compliance monitoring, and supporting revenue generation in public finance (Olabanji, Olaniyi, & Olaoye, 2024). Comparative assessments of AI-driven and blockchain-based models in tax administration suggest that both technologies can contribute to the evolution of compliance systems by improving data integrity, monitoring capabilities, and administrative efficiency (Adelekan et al., 2024). Blockchain may also contribute to tax transparency and risk control in complex multinational settings by generating tamper-resistant records and improving the traceability of transactions across organizational and jurisdictional boundaries (Liang, 2025). At the same time, the growing reliance on technologically integrated tax systems creates new requirements for information-technology auditing, cybersecurity, data governance, and risk control. The implementation of IT audit systems within tax administrations therefore represents an important dimension of digital fiscal integrity because technological expansion must be accompanied by mechanisms capable of assessing system reliability, data security, operational risk, and accountability (Umbet et al., 2025). Accordingly, an AI-oriented tax policy model must consider not only analytical power but also the infrastructure and governance mechanisms required to ensure that intelligent systems operate reliably and responsibly.

The effectiveness of artificial intelligence in tax policy also depends on organizational implementation. The existence of advanced technology does not automatically lead to effective adoption or administrative transformation. Research on technology implementation in tax administration highlights the potential gap between formal technological adoption and the actual integration of new systems into organizational routines, decision processes, professional practices, and compliance operations (Darono & Panggabean, 2026). Successful implementation therefore requires organizational readiness, appropriate skills, managerial support, institutional coordination, and mechanisms through which technological outputs are translated into administrative action. Comparable findings from broader AI policy domains suggest that AI-driven frameworks should be designed as integrated governance systems rather than narrow technical solutions, because regulatory compliance alone is insufficient when technological systems influence strategic decision-making, organizational risk, and public outcomes (Korkut et al., 2026). This concern is particularly important in taxation because algorithmic recommendations can affect audit selection, assessments, penalties, enforcement priorities, and taxpayer treatment. The institutional environment must consequently determine how AI outputs are verified, interpreted, challenged, documented, and incorporated into legitimate administrative decisions.

The governance dimension also raises important questions of fairness, transparency, explainability, and accountability. Algorithmic decision-making may improve consistency and efficiency, but it can also reproduce biases embedded in historical data or generate classifications that are difficult for taxpayers and administrators to interpret. Emerging discussions of algorithmic tax justice emphasize that the use of automated systems in taxation must be evaluated not only in terms of efficiency but also in relation to due process, fairness, legal safeguards, and the equitable treatment of taxpayers (Estares et al., 2026). The increasing use of interpretable artificial intelligence in tax management responds directly to this concern by attempting to make predictive models more understandable and administratively defensible, thereby allowing decision-makers to identify the variables driving model outputs rather than relying on opaque classifications (Han et al., 2025). These considerations reinforce the need for responsible AI governance, particularly where tax systems combine automated risk scoring with enforcement decisions. Corporate governance research also indicates that AI-enabled governance may interact with organizational

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characteristics in shaping tax-avoidance behavior, demonstrating that technology operates within broader governance structures rather than independently of them (Mansour et al., 2026). Thus, the institutional design of AI-based tax policy must include mechanisms for accountability, oversight, transparency, ethical use, and managerial responsibility.

Taxpayer behavior represents another indispensable component of any effective tax policy framework. Compliance is not determined solely by the probability of detection and the severity of punishment; taxpayers also respond to perceptions of fairness, trust, tax morale, social norms, administrative experience, and their ability to comply. Evidence concerning tax morality and tax culture indicates that internalized values and social attitudes can significantly shape willingness to meet tax obligations (Ihenyen et al., 2023). Trust in electronic government is similarly relevant because taxpayers' acceptance of digital tax systems may depend on whether they perceive government institutions and digital platforms as reliable, competent, secure, and legitimate (Alkhatib & Alshrouf, 2024). Behavioral differences may also arise from taxpayers' socioeconomic positions and their practical ability to meet obligations, meaning that apparent noncompliance cannot always be interpreted exclusively as unwillingness to pay. Research examining gender and tax compliance, for example, highlights the importance of distinguishing unwillingness from inability and considering constraints that may influence payment behavior (López-Luzuriaga & Scartascini, 2023). Evidence from taxpayers receiving government benefits likewise indicates that compliance intentions are shaped by behavioral and contextual factors beyond enforcement alone (Saptono & Khozen, 2023). These findings suggest that AI-based tax policy should incorporate behavioral information carefully and should distinguish between deliberate evasion, compliance difficulty, administrative misunderstanding, and other sources of noncompliance.

This behavioral dimension is increasingly intertwined with technological transformation among firms, particularly small and medium-sized enterprises. The adoption of digital systems by businesses is shaped by regulatory barriers, policy conditions, capabilities, costs, and perceived opportunities, all of which may affect the extent to which economic activity becomes visible to tax administrations (Josiah, 2025). FinTech innovations may create new opportunities to narrow tax gaps by increasing transaction traceability, facilitating digital payments, and reducing dependence on cash-based business practices, although the ultimate effects remain connected to entrepreneurial behavior, digital readiness, and regulatory design (Skandalis & Skandali, 2025). The rapid evolution of digital commerce and financial technologies therefore creates both opportunities and risks for tax administrations. On one hand, digitized transaction trails can expand the information available for risk analysis; on the other hand, fragmented platforms, cross-border operations, novel financial products, and informal digital commerce may create new channels through which taxable activities remain outside conventional monitoring systems. This makes technological adaptation a continuous rather than one-time administrative requirement.

Environmental and structural conditions are equally important because AI-based tax systems operate within broader economic and institutional environments. Tax evasion is often closely connected to informality, weak institutional trust, regulatory complexity, fiscal pressures, and economic uncertainty (Bitzenis et al., 2026; Wyciszkiewicz & Schneider, 2026). Revenue mobilization is likewise influenced by fiscal governance and the capacity of institutions to coordinate policy, enforce rules, and sustain administrative reforms (Mabugu & Rakabe, 2026). In rapidly transforming economies, tax administrations must simultaneously address established forms of noncompliance and new challenges created by digital business models, emerging markets, and cross-border transactions. The taxation of digital-economy entities illustrates the extent to which revenue outcomes are increasingly conditioned by new economic structures and by the ability of governments to adapt their policies and administrative systems to them (Zubairu et al., 2026). Innovative enforcement strategies are therefore needed to ensure sustainable economic development without imposing unnecessary compliance burdens or undermining legitimate economic activity (Michael et al., 2024). The effectiveness of enforcement must also be complemented by reliable financial information and audit mechanisms, as evidence regarding financial-statement auditing and revenue collection suggests that improvements in information assurance can contribute to stronger tax administration (Mudakemwa et al., 2022).

Taken together, the emerging literature demonstrates a significant shift from isolated compliance interventions toward integrated intelligent tax administration. However, much of the existing research examines individual technologies, specific machine-learning applications, blockchain systems, digital filing, taxpayer behavior, governance arrangements, or individual dimensions of administrative performance separately. The growing technological sophistication of tax administration therefore

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creates a need for models capable of integrating these dimensions into a coherent tax policy architecture. Artificial intelligence should be embedded within a framework in which data infrastructure supports analytical capabilities, institutional governance defines legitimate use, organizational readiness enables implementation, taxpayer behavior informs differentiated interventions, and environmental conditions shape both risks and policy responses. The use of digital and AI-based tools without such integration may produce technically advanced systems that remain institutionally fragmented or behaviorally ineffective. Conversely, a coordinated framework can link intelligent risk detection to preventive intervention, supervisory operations, continuous system learning, and managerial decision support. This is consistent with the broader evolution of tax compliance toward digitally enabled models (Adelekan et al., 2024), the increasing role of machine learning in fraud reduction and revenue collection (Olabanji, Olaniyi, & Olagbaju, 2024), the incorporation of AI into governance and public administration (Mhlanga, 2026), and the recognition that technological adoption must be accompanied by institutional and organizational adaptation (Darono & Panggabean, 2026).

An additional gap concerns the need to validate such integrated frameworks empirically rather than assuming that the presence of technology itself will produce better fiscal outcomes. The multidimensional nature of tax evasion requires a model that can simultaneously account for foundational environmental pressures, institutional and governance prerequisites, data-driven technological capacities, taxpayer behavioral responses, and intelligent operational systems for detecting and preventing evasion. Such a model should also recognize that these dimensions occupy different functional positions: environmental conditions establish the broader context, institutional arrangements provide the governance and organizational foundations, data-driven technologies supply analytical capacity, taxpayer behavior represents the human response to tax policy and administration, and intelligent systems translate these capabilities into concrete detection, prevention, monitoring, learning, and managerial-support functions. The value of such an integrated structure is that it provides a basis for moving tax policy away from fragmented technological experimentation toward coordinated, evidence-based, and institutionally accountable implementation. This orientation is supported by research emphasizing intelligent tax-compliance mechanisms (Zaim & Sahbani, 2026), comparative AI adoption in tax administrations (Angelov, 2026), algorithmic fairness in taxation (Estares et al., 2026), interpretable AI for tax management (Han et al., 2025), digital fiscal risk governance (Umbet et al., 2025), and the integration of AI and blockchain for improved compliance and public revenue (Olabanji, Olaniyi, & Olaoye, 2024). It also acknowledges that the effectiveness of fiscal technologies is ultimately conditioned by tax-administration practices (Olumoh, 2024), formal and informal economic structures (Bitzenis et al., 2026), taxpayer trust and attitudes (Alkhatib & Alshrouf, 2024), tax culture and morality (Ihenyen et al., 2023), and the capacity of governments to mobilize revenue under changing economic conditions (Allahverdi & Çelikay, 2025).

Accordingly, the aim of this study was to validate an artificial intelligence–based tax policy-making model for reducing tax evasion.

2. Methods and Materials

This study employed a quantitative, applied, descriptive-survey research design with a correlational approach and was conducted to validate an artificial intelligence–based tax policy-making model aimed at reducing tax evasion. The quantitative design was selected because the principal purpose of the study was to empirically examine the measurement structure of the proposed model, assess the relationships among its latent constructs, determine the contribution of the identified dimensions to the overall framework, and evaluate the goodness of fit of the model using data obtained from the target population. The statistical population consisted of taxpayers in Urmia, Iran. Because the size of the taxpayer population was considered sufficiently large and practically unlimited for sampling purposes, Cochran's formula for an infinite population was applied to determine the required sample size. Based on a 95% confidence level, a 5% margin of error, and the conventional assumptions of maximum population variability, a minimum sample of 384 respondents was calculated and included in the study. Participants were recruited from eligible and accessible taxpayers, while efforts were made to achieve adequate representation of individuals with direct experience of the tax system and its administrative procedures. Eligibility for participation required sufficient familiarity with tax processes and the ability to provide informed responses concerning the technological, institutional, behavioral, environmental, and administrative dimensions incorporated into the proposed model. Participation

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was entirely voluntary, informed consent was obtained prior to questionnaire completion, and respondents were assured that the information collected would remain confidential and would be reported only in aggregate form. In addition to the main survey sample, a panel of 15 academic and executive experts with professional knowledge of taxation, accounting, financial management, public administration, or artificial intelligence applications in financial and tax systems was used for the structural assessment and prioritization of the model components. Expert eligibility was based on relevant academic or professional expertise, sufficient work experience in tax, accounting, financial, or administrative fields, and familiarity with the application of intelligent and data-driven technologies in tax administration. This expert assessment was used exclusively as a quantitative component of the study to examine the structural positioning and interrelationships of the model dimensions. The overall research framework was therefore designed to provide empirical validation of the proposed tax policy-making model through quantitative measurement, factor validation, structural relationship testing, and assessment of model fit.

Data were collected using structured questionnaires developed to operationalize the constructs of the artificial intelligence–based tax policy-making model. The principal research instrument was a researcher-developed questionnaire comprising items corresponding to the major dimensions of the proposed framework, namely data-driven technologies, institutional and governance requirements, taxpayer behavior, environmental dimensions, and intelligent systems for the detection and prevention of tax evasion. The items were formulated as closed-ended statements and were scored using a Likert-type response scale, enabling the perceptions and evaluations of respondents regarding each component of the model to be quantified for subsequent statistical analysis. Higher scores represented a greater perceived presence, importance, or effectiveness of the corresponding component in the development and implementation of AI-supported tax policy. A separate structured expert questionnaire was also administered to the 15 specialists for the quantitative assessment of relationships among the principal components and their hierarchical positioning within the model. Before administration of the final questionnaire, its face and content validity were examined by academic specialists and professionals in taxation, accounting, financial management, and related areas. The reviewers evaluated the clarity, relevance, comprehensibility, coverage, and conceptual appropriateness of the items, and modifications were made where necessary to improve wording and ensure adequate representation of the constructs. The instrument was subsequently pilot-tested on 30 respondents drawn from the target population to assess its internal consistency prior to the main survey. Reliability was evaluated using Cronbach's alpha coefficient in SPSS. The obtained coefficients were 0.78 for data-driven technologies, 0.75 for institutional and governance requirements, 0.81 for taxpayer behavior, 0.88 for environmental dimensions, and 0.75 for intelligent systems for detecting and preventing tax evasion. All coefficients exceeded the commonly accepted threshold of 0.70, indicating satisfactory internal consistency for the dimensions of the instrument. Construct validity was subsequently evaluated through confirmatory factor analysis using the complete study sample. Standardized factor loadings were examined to determine whether the observed questionnaire items adequately represented their intended latent constructs. The measurement model was also assessed in terms of overall fit, and items with inadequate psychometric performance were examined before the final structural model was interpreted. The complete questionnaire was administered under standardized conditions, and respondents were informed that there were no correct or incorrect answers and that responses should reflect their actual perceptions and experiences concerning taxation, artificial intelligence, institutional conditions, taxpayer behavior, and the mechanisms used to detect and prevent tax evasion.

Quantitative data analysis was conducted using SPSS and AMOS software. Data analysis began with screening of the completed questionnaires for missing values, incomplete response patterns, coding errors, and other data-quality problems. Descriptive statistics were subsequently calculated to summarize both participant characteristics and the main research variables. Frequencies and percentages were used for categorical characteristics, whereas means, standard deviations, variances, minimum and maximum scores, and other relevant measures of central tendency and dispersion were calculated for continuous or composite variables. The internal consistency of the questionnaire dimensions was assessed using Cronbach's alpha, with coefficients of 0.70 or greater considered indicative of acceptable reliability. The empirical structure of the measurement instrument was then assessed by confirmatory factor analysis. In this analysis, each observed item was specified as an indicator of its theoretically corresponding latent variable, and standardized factor loadings were examined to determine the strength with which each observed variable represented the underlying construct. A higher-order confirmatory factor model was also examined where appropriate to determine whether the principal dimensions could be represented as components of the broader artificial intelligence–based tax policy-making framework. Following validation of the measurement model, structural equation modeling was performed to assess the relationships among the latent constructs and to determine whether

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the empirical covariance structure supported the proposed model for the reduction of tax evasion. Standardized path coefficients, critical ratios or corresponding test statistics, standard errors, and significance levels were used to assess the magnitude, direction, and statistical significance of the structural relationships. Statistical significance was evaluated at the conventional alpha level of 0.05. The explanatory capability of the structural model was additionally considered through the proportion of variance explained in endogenous constructs, particularly those reflecting intelligent tax-evasion detection and prevention and the effectiveness of AI-supported tax policy-making.

The adequacy of both the measurement and structural models was evaluated using multiple goodness-of-fit indices rather than relying on a single statistic. The chi-square statistic and the chi-square-to-degrees-of-freedom ratio were examined together with the Root Mean Square Error of Approximation (RMSEA), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Comparative Fit Index (CFI), and other fit indices generated by AMOS. The chi-square-to-degrees-of-freedom ratio was used as an indicator of relative model fit, while lower RMSEA values were interpreted as evidence of reduced approximation error. Incremental and absolute fit indices were jointly considered to determine the overall correspondence between the hypothesized model and the observed data. Modification indices were considered only when statistically justified and theoretically defensible, so that improvements in model fit would not compromise the conceptual integrity of the proposed framework. In addition to confirmatory factor analysis and structural equation modeling, the expert-based quantitative data were analyzed through interpretive structural modeling to identify the hierarchical levels of the major model components and clarify the pattern of influence among them. The experts' judgments concerning pairwise relationships between the model dimensions were transformed into a structural self-interaction matrix and subsequently into a binary reachability matrix. Transitivity relationships were incorporated into the final reachability matrix, after which the reachability and antecedent sets of each component were determined. The intersection of these sets was used to allocate the dimensions to hierarchical levels and to establish the structural configuration of the model. Taken together, descriptive analysis, reliability analysis, confirmatory factor analysis, structural equation modeling, goodness-of-fit assessment, and quantitative structural analysis provided the empirical basis for evaluating the validity, reliability, structural coherence, and explanatory adequacy of the artificial intelligence–based tax policy-making model for reducing tax evasion.

3. Findings and Results

The structural analysis of the proposed model resulted in five hierarchical levels comprising 25 variables. The first level represented the operational outputs and actions directly associated with the prevention and detection of tax evasion, while the second level reflected taxpayer behavioral responses and compliance. The third level comprised data-driven technologies and information analytics, the fourth level encompassed institutional, governance, and organizational readiness requirements, and the fifth level represented the fundamental environmental drivers and challenges affecting the tax policy-making system. The hierarchical positioning of these variables indicates that environmental conditions and institutional arrangements constitute the foundational layers of the model, while technological capacities and taxpayer behavioral responses form the intermediate mechanisms through which intelligent tax-evasion prevention and detection outcomes are ultimately generated. The detailed leveling of the variables is presented in Table 1.

Table 1. Hierarchical Levels of the Variables in the Proposed Model

Model Level	Variable Code	Variable
Level 1: Outputs and operational actions for prevention and detection	21	Intelligent detection of tax violation patterns
	22	Intelligent preventive monitoring and intervention
	23	Intelligent support for supervisory and audit operations
	24	Continuous learning and improvement of intelligent systems
	25	Evaluation and managerial support of intelligent systems
Level 2: Taxpayer behavioral responses and compliance	11	Taxpayer cognitive beliefs and perceptions regarding the tax system
	12	Internal and value-based motivations for tax compliance
	13	Taxpayer behavioral evaluation of the benefits and consequences of compliance or violation
	14	Taxpayer interaction capability and behavioral adaptation
	15	Social and experiential influences on the formation of tax behavior

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Level 3: Data-driven technologies and information analytics	1	Integration and management of tax data infrastructures
	2	Assurance of tax data quality and richness
	3	Intelligent analysis of financial data and detection of information patterns
	4	Tracking and monitoring of financial information flows
	5	Data-driven analytical support for tax decision-making
Level 4: Institutional, governance, and organizational readiness requirements	6	Institutional framework and strategic regulation of tax-related artificial intelligence
	7	Accountable governance and organizational oversight mechanisms
	8	Institutional synergy and stakeholder participation
	9	Organizational readiness for intelligent transformation
	10	Responsible governance and organizational trustworthiness
Level 5: Fundamental environmental drivers and challenges	16	Macroeconomic environmental instability
	17	Expansion of economic activities outside formal supervision
	18	Challenges in the legal and policy environment
	19	Structural transformations of the economy and emerging markets
	20	Cross-border pressures and economic competition

Before estimating the structural equation model, the construct validity of the research instrument was assessed. Confirmatory factor analysis was therefore conducted separately for the variables at each hierarchical level using AMOS. CFA was employed as a theory-driven approach for determining whether the observed indicators were sufficiently associated with their corresponding latent constructs and whether the empirical measurement structure was consistent with the theoretically specified framework. Model fit was evaluated through a combination of absolute, comparative, incremental, and parsimonious goodness-of-fit indices. Modification indices were also considered where necessary to improve the adequacy of the measurement models, and indicators with insufficient factor loadings were excluded. Across all five levels, the retained indicators exhibited factor loadings greater than 0.70, indicating satisfactory convergence between the observed indicators and their corresponding latent variables.

For the first-level variables, all retained factor loadings exceeded 0.70, demonstrating an adequate relationship between the questionnaire items and the latent constructs associated with intelligent tax-evasion prevention and detection outcomes. The CMIN/DF value was 1.52, which falls within the acceptable range of 1 to 5. The RMSEA was 0.025, indicating a very low approximation error. The GFI, AGFI, NFI, CFI, and related comparative fit indices were generally within acceptable ranges. Collectively, these findings indicate that the measurement structure of the first-level variables was adequately supported and that construct validity was established.

Table 2. Goodness-of-Fit Indices for the First-Level Variables

Fit Type	Index	Abbreviation	Acceptable Criterion	Observed Value
Absolute fit	Degrees of freedom	DF	–	385
Absolute fit	Significance level	P	< 0.05	0.000
Absolute fit	Chi-square/degrees of freedom	CMIN/DF	1–5	1.52
Absolute fit	Chi-square statistic	Chi-Square	–	2.369
Absolute fit	Goodness-of-Fit Index	GFI	> 0.90	0.921
Absolute fit	Adjusted Goodness-of-Fit Index	AGFI	> 0.90	0.917
Comparative fit	Non-Normed Fit Index	NNFI (TLI)	> 0.90	0.911
Comparative fit	Normed Fit Index	NFI	Close to 1	0.926
Comparative fit	Comparative Fit Index	CFI	> 0.90	0.914
Comparative fit	Relative Fit Index	RFI	> 0.50	0.78
Comparative fit	Incremental Fit Index	IFI	0–1	0.957
Parsimonious fit	Parsimonious Normed Fit Index	PNFI	> 0.50	0.89
Parsimonious fit	Parsimonious Goodness-of-Fit Index	PGFI	> 0.50	0.64
Parsimonious fit	Root Mean Square Error of Approximation	RMSEA	< 0.10	0.025
Parsimonious fit	Normed chi-square	CMIN	1–3	2.14

For the second-level variables, confirmatory factor analysis similarly showed that all retained standardized factor loadings were greater than 0.70. The CMIN/DF value was 1.23, supporting an adequate fit between the empirical covariance matrix and the proposed measurement structure. The RMSEA was 0.012, which indicates a particularly strong level of approximation fit.

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Moreover, GFI, AGFI, NNFI, NFI, and CFI all exceeded 0.90. The remaining indices were also within the stated acceptance ranges, indicating that the measurement model for taxpayer behavioral responses and compliance demonstrated satisfactory construct validity.

Table 3. Goodness-of-Fit Indices for the Second-Level Variables

Fit Type	Index	Abbreviation	Acceptable Criterion	Observed Value
Absolute fit	Degrees of freedom	DF	–	385
Absolute fit	Significance level	P	< 0.05	0.000
Absolute fit	Chi-square/degrees of freedom	CMIN/DF	1–5	1.23
Absolute fit	Chi-square statistic	Chi-Square	–	3.254
Absolute fit	Goodness-of-Fit Index	GFI	> 0.90	0.956
Absolute fit	Adjusted Goodness-of-Fit Index	AGFI	> 0.90	0.920
Comparative fit	Non-Normed Fit Index	NNFI (TLI)	> 0.90	0.936
Comparative fit	Normed Fit Index	NFI	Close to 1	0.914
Comparative fit	Comparative Fit Index	CFI	> 0.90	0.952
Comparative fit	Relative Fit Index	RFI	> 0.50	0.84
Comparative fit	Incremental Fit Index	IFI	0–1	0.984
Parsimonious fit	Parsimonious Normed Fit Index	PNFI	> 0.50	0.79
Parsimonious fit	Parsimonious Goodness-of-Fit Index	PGFI	> 0.50	0.66
Parsimonious fit	Root Mean Square Error of Approximation	RMSEA	< 0.10	0.012
Parsimonious fit	Normed chi-square	CMIN	1–3	1.40

The CFA results for the third-level variables also supported the validity of the measurement model. All factor loadings were greater than 0.70, demonstrating that the observed indicators adequately represented the data-driven technology and information-analysis constructs. The CMIN/DF value was 2.39, which remained below the maximum acceptable value of 5. The RMSEA was 0.055, suggesting acceptable approximation fit. GFI, AGFI, NNFI, NFI, and CFI were all above 0.90, further indicating consistency between the empirical data and the theoretically proposed factor structure. Although some supplementary indices were comparatively lower, the overall pattern of evidence supported the adequacy of the third-level measurement model.

Table 4. Goodness-of-Fit Indices for the Third-Level Variables

Fit Type	Index	Abbreviation	Acceptable Criterion	Observed Value
Absolute fit	Degrees of freedom	DF	–	385
Absolute fit	Significance level	P	< 0.05	0.000
Absolute fit	Chi-square/degrees of freedom	CMIN/DF	1–5	2.39
Absolute fit	Chi-square coverage level	Chi-Square	> 5%	0.26
Absolute fit	Goodness-of-Fit Index	GFI	> 0.90	0.915
Absolute fit	Adjusted Goodness-of-Fit Index	AGFI	> 0.90	0.940
Comparative fit	Non-Normed Fit Index	NNFI	> 0.90	0.911
Comparative fit	Normed Fit Index	NFI	Close to 1	0.99
Comparative fit	Comparative Fit Index	CFI	> 0.90	0.945
Comparative fit	Relative Fit Index	RFI	> 0.50	0.69
Comparative fit	Incremental Fit Index	IFI	0–1	0.71
Parsimonious fit	Parsimonious Normed Fit Index	PNFI	> 0.50	0.99
Parsimonious fit	Parsimonious Goodness-of-Fit Index	PGFI	> 0.50	0.924
Parsimonious fit	Root Mean Square Error of Approximation	RMSEA	< 0.10	0.055
Parsimonious fit	Normed chi-square	CMIN	1–3	2.90

The fourth-level CFA examined the institutional, governance, and organizational-readiness constructs. All standardized factor loadings were greater than 0.70, confirming that the measurement items were appropriately associated with their designated latent factors. The CMIN/DF value was 1.56, indicating acceptable model fit. The RMSEA was 0.011, substantially below the 0.10 threshold. GFI, AGFI, NNFI, NFI, and CFI were above 0.90, while the remaining fit indices were largely within their designated acceptance ranges. These findings confirmed the construct validity of the fourth-level variables and indicated that the empirical data were appropriately aligned with the specified institutional and governance structure.

Table 5. Goodness-of-Fit Indices for the Fourth-Level Variables

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Fit Type	Index	Abbreviation	Acceptable Criterion	Observed Value
Absolute fit	Degrees of freedom	DF	–	385
Absolute fit	Significance level	P	< 0.05	0.000
Absolute fit	Chi-square/degrees of freedom	CMIN/DF	1–5	1.56
Absolute fit	Chi-square coverage level	Chi-Square	> 5%	0.025
Absolute fit	Goodness-of-Fit Index	GFI	> 0.90	0.925
Absolute fit	Adjusted Goodness-of-Fit Index	AGFI	> 0.90	0.947
Comparative fit	Non-Normed Fit Index	NNFI	> 0.90	0.911
Comparative fit	Normed Fit Index	NFI	Close to 1	0.945
Comparative fit	Comparative Fit Index	CFI	> 0.90	0.925
Comparative fit	Relative Fit Index	RFI	> 0.50	0.89
Comparative fit	Incremental Fit Index	IFI	0–1	0.66
Parsimonious fit	Parsimonious Normed Fit Index	PNFI	> 0.50	0.98
Parsimonious fit	Parsimonious Goodness-of-Fit Index	PGFI	> 0.50	0.930
Parsimonious fit	Root Mean Square Error of Approximation	RMSEA	< 0.10	0.011
Parsimonious fit	Normed chi-square	CMIN	1–3	2.30

For the fifth-level variables, representing the underlying environmental drivers and challenges, all retained factor loadings likewise exceeded 0.70. The CMIN/DF ratio was 1.69, which was within the acceptable range. The fit table yielded an RMSEA value of 0.066, remaining below the maximum threshold of 0.10 and therefore supporting acceptable approximation fit. In addition, GFI, AGFI, NNFI, NFI, and CFI exceeded 0.90, while the other reported indices also generally indicated adequate fit. Accordingly, the measurement structure of the fifth-level environmental constructs was accepted and their construct validity was supported.

Table 6. Goodness-of-Fit Indices for the Fifth-Level Variables

Fit Type	Index	Abbreviation	Acceptable Criterion	Observed Value
Absolute fit	Degrees of freedom	DF	–	385
Absolute fit	Significance level	P	< 0.05	0.000
Absolute fit	Chi-square/degrees of freedom	CMIN/DF	1–5	1.69
Absolute fit	Chi-square coverage level	Chi-Square	> 5%	0.22
Absolute fit	Goodness-of-Fit Index	GFI	> 0.90	0.958
Absolute fit	Adjusted Goodness-of-Fit Index	AGFI	> 0.90	0.924
Comparative fit	Non-Normed Fit Index	NNFI	> 0.90	0.921
Comparative fit	Normed Fit Index	NFI	Close to 1	0.933
Comparative fit	Comparative Fit Index	CFI	> 0.90	0.910
Comparative fit	Relative Fit Index	RFI	> 0.50	0.69
Comparative fit	Incremental Fit Index	IFI	0–1	0.78
Parsimonious fit	Parsimonious Normed Fit Index	PNFI	> 0.50	0.912
Parsimonious fit	Parsimonious Goodness-of-Fit Index	PGFI	> 0.50	0.944
Parsimonious fit	Root Mean Square Error of Approximation	RMSEA	< 0.10	0.066
Parsimonious fit	Normed chi-square	CMIN	1–3	2.50

Following confirmation of the measurement models, the overall structural model was estimated using AMOS. The significance of each structural relationship was assessed on the basis of the critical ratio. A critical ratio greater than 1.96 or less than −1.96 was considered statistically significant at the 95% confidence level, whereas values between these limits were interpreted as not significantly different from zero. The results showed that all five hierarchical levels had significant standardized relationships with the overall artificial intelligence–based tax policy-making model for reducing tax evasion. As presented in Table 7, the standardized coefficient for the first level was 0.84, with a standard error of 0.029 and a critical ratio of 5.018. The standardized coefficient for the second level was 0.89, accompanied by a standard error of 0.085 and a critical ratio of 11.145. The third level had a standardized coefficient of 0.71, a standard error of 0.041, and a critical ratio of 17.210. The fourth level showed a standardized coefficient of 0.75, with a standard error of 0.042 and a critical ratio of 9.148, while the fifth level produced a standardized coefficient of 0.74, a standard error of 0.045, and a critical ratio of 10.344. All relationships were statistically significant at $p < 0.001$.

Table 7. Structural Model Results for the Artificial Intelligence–Based Tax Policy-Making Model for Reducing Tax Evasion

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Relationship	Standardized Estimate	Standard Error	Critical Ratio	Significance
Level 1 ← AI-based tax policy-making model for reducing tax evasion	0.84	0.029	5.018	< 0.001
Level 2 ← AI-based tax policy-making model for reducing tax evasion	0.89	0.085	11.145	< 0.001
Level 3 ← AI-based tax policy-making model for reducing tax evasion	0.71	0.041	17.210	< 0.001
Level 4 ← AI-based tax policy-making model for reducing tax evasion	0.75	0.042	9.148	< 0.001
Level 5 ← AI-based tax policy-making model for reducing tax evasion	0.74	0.045	10.344	< 0.001

The structural results therefore confirmed all five relationships at the 95% confidence level. Among the five dimensions, the second level, representing taxpayer behavioral responses and compliance, had the strongest standardized association with the overall model (β = 0.89), followed by the first level of operational prevention and detection outputs (β = 0.84). Institutional, governance, and organizational readiness constituted the next strongest component (β = 0.75), followed closely by the fundamental environmental drivers and challenges (β = 0.74). Data-driven technologies and information analytics also demonstrated a substantial and statistically significant contribution to the overall model (β = 0.71). Thus, the empirical results supported the multidimensional structure of the model and demonstrated that each hierarchical level contributed significantly to the overall framework of artificial intelligence–based tax policy-making for reducing tax evasion. The final model therefore reflects an integrated structure in which environmental conditions, institutional and governance requirements, technological capabilities, taxpayer behavioral responses, and intelligent operational mechanisms collectively contribute to the effectiveness of tax policy-making and the prevention and detection of tax evasion.

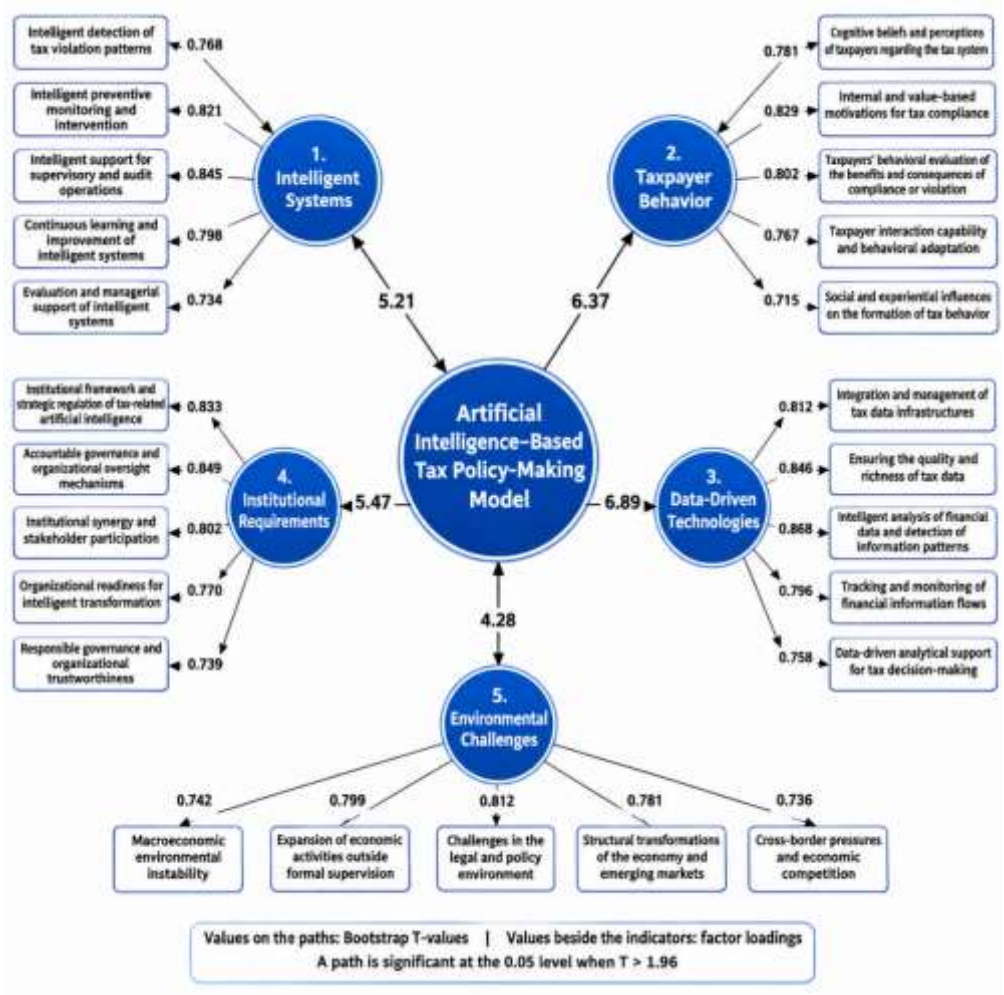


Figure 1. Path Analysis of the Artificial Intelligence–Based Tax Policy-Making Model for Reducing Tax Evasion

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4. Discussion and Conclusion

The findings of the present study provide empirical support for the proposed artificial intelligence–based tax policy-making model for reducing tax evasion and demonstrate that the model is multidimensional, hierarchically structured, and statistically valid. The structural analysis organized the model into five levels: intelligent systems as the operational output layer, taxpayer behavior as the behavioral response layer, data-driven technologies as the analytical infrastructure layer, institutional requirements as the governance and organizational readiness layer, and environmental challenges as the foundational contextual layer. Confirmatory factor analysis further showed that the indicators associated with all five levels had factor loadings greater than 0.70, while the goodness-of-fit indices for each measurement model were generally within acceptable ranges. In the final structural model, all five levels were significantly associated with the overall model at $p < 0.001$. The strongest standardized association was observed for taxpayer behavior ($\beta = 0.89$), followed by intelligent systems ($\beta = 0.84$), institutional requirements ($\beta = 0.75$), environmental challenges ($\beta = 0.74$), and data-driven technologies ($\beta = 0.71$). These results indicate that effective AI-supported tax policy cannot be reduced to a purely technological mechanism. Rather, its effectiveness depends on the interaction of behavioral, technological, institutional, organizational, and environmental elements, which together shape the capacity of tax administrations to detect, prevent, and respond to tax evasion.

The particularly strong role of taxpayer behavior is an important finding because it indicates that technological modernization alone cannot guarantee higher levels of tax compliance. Taxpayers' cognitive beliefs, perceptions of the tax system, internal motivations, assessments of the costs and benefits of compliance, behavioral adaptability, and social influences collectively constituted the strongest dimension of the overall model. This result is consistent with studies emphasizing that tax compliance is strongly influenced by tax morality, tax culture, trust, perceived legitimacy, and taxpayers' subjective evaluation of the tax system (Alkhatib & Alshrouf, 2024; Ihenyen et al., 2023). The finding also aligns with evidence showing that compliance should not be conceptualized solely as the result of deterrence because taxpayers may be willing but unable to comply due to economic, procedural, or contextual constraints (López-Luzuriaga & Scartascini, 2023). Similarly, the study by Saptono and Khozen indicates that tax-compliance intentions are shaped by behavioral and contextual considerations that extend beyond the direct threat of enforcement (Saptono & Khozen, 2023). The present results therefore support a behavioral interpretation of AI-based tax policy in which intelligent systems should not merely classify taxpayers as compliant or noncompliant but should help distinguish intentional evasion from administrative difficulty, misunderstanding, resource constraints, or weak trust. Such differentiation could enable tax administrations to adopt more targeted interventions, combining enforcement for high-risk intentional evasion with assistance, communication, simplification, or nudging for taxpayers whose noncompliance arises from other causes.

The strong contribution of intelligent systems to the model further confirms that the operational value of artificial intelligence lies in its ability to transform large volumes of fiscal information into actionable detection and prevention mechanisms. The first level of the model included intelligent detection of tax violation patterns, preventive monitoring and intervention, support for audit and supervisory operations, continuous learning and improvement, and managerial support. Its standardized coefficient of 0.84 indicates that these operational capabilities constitute a central mechanism through which AI can contribute to reducing tax evasion. This finding is consistent with previous research showing that machine-learning techniques can identify tax risks, detect anomalies, predict high-risk cases, and support more efficient allocation of audit resources (Akinrinola et al., 2024; Xu & Kong, 2024). The result also supports research proposing the use of machine-learning algorithms to maximize tax collection and improve the identification of cases requiring administrative intervention (Ourdani et al., 2024). Likewise, evidence on the transformation of tax compliance through machine learning suggests that data-driven classification and fraud-detection mechanisms can enhance revenue collection while reducing reliance on purely manual audit processes (Olabanji, Olaniyi, & Olagbaju, 2024). These studies collectively reinforce the present finding that intelligent systems should be understood as operational decision-support infrastructures capable of shifting tax administration from retrospective enforcement toward predictive and preventive control.

The importance of institutional requirements, with a standardized coefficient of 0.75, demonstrates that the implementation of AI in tax administration depends on more than technical infrastructure. Institutional frameworks, strategic regulation, accountable governance, oversight mechanisms, interorganizational cooperation, stakeholder participation, organizational

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readiness, and responsible governance were all necessary elements within the validated model. This result closely aligns with the argument that technology adoption in tax administration often encounters a gap between formal implementation and effective organizational use (Darono & Panggabean, 2026). The existence of sophisticated systems does not ensure that their outputs will be incorporated into professional routines, audit decisions, or policy processes unless appropriate institutional arrangements and managerial capacities are in place. Comparative evidence from tax administrations also shows that AI adoption differs substantially according to institutional maturity, governance capacity, data architecture, and administrative readiness (Angelov, 2026). More generally, the use of artificial intelligence in public governance requires appropriate organizational structures and institutional safeguards if technological innovation is to result in improved public-service outcomes rather than fragmented implementation (Mhlanga, 2026). The present findings therefore indicate that institutional and governance arrangements should be considered enabling conditions for AI-supported tax policy rather than secondary administrative concerns.

The validated role of institutional requirements also has implications for fairness, legitimacy, and algorithmic accountability. As tax authorities increasingly rely on automated risk assessment, classification, and predictive modeling, the potential consequences for taxpayers become more significant. The current findings suggest that responsible governance and organizational trustworthiness must be embedded within the AI tax policy framework. This is consistent with research on algorithmic tax justice, which emphasizes that efficiency should not displace considerations of due process, transparency, fairness, and the ability to challenge automated decisions (Estares et al., 2026). The result is also supported by studies on interpretable artificial intelligence in tax management, which show that explainable models can improve the sustainability and accountability of tax decision-making by making the determinants of algorithmic predictions more transparent (Han et al., 2025). In addition, the implementation of information-technology audit systems has been emphasized as a necessary component of digital fiscal integrity because AI-supported tax administration introduces new risks relating to data security, model reliability, system misuse, and organizational accountability (Umbet et al., 2025). Thus, the institutional dimension identified in the present study can be interpreted as the governance infrastructure that ensures AI is used not only efficiently but also legitimately and responsibly.

The significant contribution of data-driven technologies, although comparatively lower than the other dimensions at $\beta = 0.71$, confirms that high-quality data infrastructure remains a fundamental requirement for intelligent tax administration. The model emphasized integration and management of tax data infrastructure, assurance of data quality and richness, intelligent analysis of financial information, tracking of financial information flows, and analytical support for tax decision-making. These elements are closely consistent with previous studies demonstrating that AI applications are only as effective as the data environments within which they operate. Machine-learning models used for tax prediction and risk classification depend on sufficiently comprehensive, accurate, timely, and interoperable datasets (Akinrinola et al., 2024; Xu & Kong, 2024). Studies integrating artificial intelligence with blockchain also highlight the importance of reliable, traceable, and tamper-resistant financial data for improving tax compliance and revenue generation (Adelekan et al., 2024; Olabanji, Olaniyi, & Olaoye, 2024). Similarly, blockchain-supported tax transparency has been proposed as a mechanism for enhancing risk control in multinational enterprises by increasing the traceability of transactions and reducing information asymmetry (Liang, 2025). The comparatively lower coefficient of the data-driven technology dimension should therefore not be interpreted as reduced importance; rather, it suggests that technology may function as an enabling infrastructure whose effectiveness depends on behavioral acceptance, institutional readiness, and operational integration.

The environmental challenges dimension also showed a substantial standardized effect of 0.74, demonstrating that AI-supported tax policy is shaped by macroeconomic instability, economic activities outside formal supervision, legal and policy challenges, structural economic transformations, emerging markets, and cross-border competitive pressures. This finding corresponds with the literature showing that tax evasion and informality are deeply connected to broader socioeconomic and institutional conditions rather than being isolated administrative phenomena (Bitzenis et al., 2026; Wyciszkiewicz & Schneider, 2026). The result also aligns with evidence that domestic revenue mobilization is influenced by fiscal governance, administrative capacity, and the wider institutional environment in which tax authorities operate (Mabugu & Rakabe, 2026).

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The growing importance of the digital economy further intensifies this challenge because new forms of online and cross-border economic activity can weaken traditional mechanisms for identifying taxable transactions and determining jurisdictional tax obligations (Zubairu et al., 2026). In this sense, the environmental layer of the model represents the external conditions that generate pressure for technological and institutional adaptation. AI systems must therefore be sufficiently flexible to respond to changing economic structures, emerging digital business models, and increasingly complex flows of financial information.

The hierarchical arrangement of the model provides additional insight into the mechanism through which AI-based tax policy may operate. Environmental challenges formed the foundational level, followed by institutional requirements, data-driven technologies, taxpayer behavior, and finally intelligent operational systems. This configuration suggests that intelligent tax-evasion detection is not an isolated technological endpoint but the product of several preceding conditions. Environmental pressures create the need for adaptation; institutional governance provides the regulatory and organizational framework; data-driven technologies generate analytical capacity; taxpayer behavior determines the practical compliance response; and intelligent systems translate these elements into operational detection, prevention, monitoring, and managerial support. This interpretation is compatible with research showing that digital fiscal modernization requires both technological and institutional integration (Darono & Panggabean, 2026; Nurbekova et al., 2024). It also corresponds with studies emphasizing that government digitalization can improve transparency, administrative integrity, and the monitoring of economic activity when technological reforms are integrated with governance structures (Santiso, 2022). In decentralized fiscal environments, digital tools similarly enhance performance when they are embedded in broader administrative and institutional systems rather than deployed as stand-alone technologies (Monkam & Mangwanya, 2024).

The findings further suggest that AI-supported tax policy can strengthen enforcement while simultaneously improving preventive capabilities. Traditional enforcement often focuses on audits after noncompliance has occurred, whereas intelligent systems allow tax administrations to identify suspicious patterns earlier, continuously update risk profiles, and target supervisory resources more efficiently. This interpretation aligns with innovative approaches to tax enforcement that emphasize the importance of combining digital monitoring, data analytics, and administrative modernization to promote sustainable revenue generation (Michael et al., 2024). The importance of reliable accounting and financial information also remains evident, as the quality of audited financial statements can strengthen the informational foundation available to revenue authorities and contribute to improved tax collection (Mudakemwa et al., 2022). Furthermore, technology-assisted monitoring may help reduce opportunities for informal or concealed transactions when combined with digital payment systems and FinTech-based traceability (Skandalis & Skandali, 2025). However, the present findings imply that these tools should operate within a balanced framework in which detection capacity is accompanied by institutional legitimacy and taxpayer-oriented compliance strategies.

The results also reinforce the relevance of technological convergence in contemporary tax administration. Artificial intelligence, blockchain, digital payment platforms, and integrated information systems can jointly improve visibility over transactions, reduce information asymmetry, and support more dynamic forms of risk management. Previous research has emphasized the potential of AI and blockchain to improve compliance, fraud detection, and revenue generation (Adelekan et al., 2024; Olabanji, Olaniyi, & Olaoye, 2024). At the same time, technological adoption among firms is influenced by regulatory and policy barriers, especially among SMEs, meaning that the digitalization of taxable activity may remain uneven (Josiah, 2025). This creates an important policy implication: tax administrations must not assume that all taxpayers have equal technological capability or exposure. The use of AI should therefore be accompanied by differentiated policies that account for disparities in digital readiness, firm size, transaction patterns, and access to formal financial infrastructure.

Overall, the findings support the central proposition that effective AI-based tax policy should be designed as an integrated governance ecosystem rather than a single technological solution. The high standardized coefficients of all five dimensions demonstrate that reducing tax evasion requires coordinated progress across behavioral, institutional, technological, environmental, and operational domains. This conclusion is strongly aligned with the emerging literature on AI-enabled tax compliance and evasion mitigation, which emphasizes that artificial intelligence reshapes not only detection mechanisms but also institutional responsibilities, compliance strategies, and administrative decision-making (Zaim & Sahbani, 2026). The results also correspond with comparative evidence showing that AI can strengthen tax administration when deployment is

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supported by appropriate regulatory frameworks and organizational capacities (Angelov, 2026). Accordingly, the validated model contributes by integrating dimensions that have often been examined separately and by providing an empirical framework through which tax administrations can conceptualize AI as part of a broader policy-making architecture.

The present study has several limitations that should be considered when interpreting the findings. The quantitative data were obtained from taxpayers in Urmia, which may limit the direct generalizability of the findings to other geographical areas with different institutional, economic, technological, and cultural conditions. The cross-sectional design also captures perceptions at a single point in time and therefore cannot determine how the relationships among model dimensions may evolve as artificial intelligence technologies, tax regulations, and taxpayer behaviors change. Because the study relied on questionnaire-based self-reported data, the results may also be affected by response bias, social desirability, or differences in respondents' knowledge of intelligent tax systems. Moreover, although the model included a broad set of technological, institutional, behavioral, and environmental dimensions, other potentially relevant variables such as cybersecurity capability, digital literacy, perceived algorithmic fairness, taxpayer privacy concerns, organizational learning capacity, or regulatory enforcement intensity were not examined separately.

Future research could validate the proposed model in different provinces, countries, and tax-administration environments to determine whether its hierarchical structure remains stable across varying institutional and economic settings. Longitudinal studies would be particularly valuable for examining how the effects of data-driven technologies, taxpayer behavior, institutional readiness, and intelligent systems change over time as AI adoption becomes more mature. Future studies could also compare different groups of taxpayers, including individuals, SMEs, large corporations, digital-platform businesses, and multinational enterprises, to identify whether the relative importance of the model dimensions differs across taxpayer categories. Additional research could incorporate variables such as explainability, data privacy, cybersecurity, perceived fairness, digital trust, administrative burden, and taxpayer digital capability. Comparative evaluations of alternative AI techniques could further determine which combinations of predictive analytics, anomaly detection, machine learning, natural language processing, or network analysis provide the greatest practical value for specific forms of tax evasion.

From a practical perspective, tax authorities should approach artificial intelligence implementation as an integrated reform program rather than as the acquisition of isolated technological tools. Priority should be given to developing interoperable and high-quality tax databases, strengthening data governance standards, and creating mechanisms for continuous updating and verification of fiscal information. At the institutional level, clear responsibilities should be established for algorithmic oversight, system auditing, model validation, ethical review, and managerial accountability. Tax administrations should also invest in training employees to interpret AI-generated outputs and use them as decision-support tools rather than as unquestionable automated judgments. Because taxpayer behavior emerged as the strongest dimension of the model, intelligent enforcement should be complemented by measures that improve trust, simplify compliance, provide targeted assistance, and distinguish intentional evasion from unintentional noncompliance. Risk-based auditing, preventive alerts, intelligent case prioritization, and continuous monitoring can then be implemented within a transparent framework in which taxpayers understand the basis of administrative actions and have appropriate mechanisms for review and appeal. In this way, AI can be used not merely to increase detection but to build a more adaptive, efficient, fair, and sustainable tax administration.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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