Artificial Intelligence and Tax Compliance in the Gig Economy: Implications for Compliance, Privacy, and Fairness

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DOI: https://doi.org/10.51244/IJRSI.2026.1309000300

Received: 09 October 2026; Accepted: 14 October 2026; Published: 27 October 2026

ABSTRACT

Underreported income driven by the rapid growth of the gig economy poses significant challenges to tax authorities, particularly in developing countries. This study explores how AI-based tax Detection Mechanisms (AITDMs) can enhance tax compliance among gig workers. Drawing on the Slippery Slope Framework, it also examines privacy concerns and perceived fairness as moderating factors. A survey of 130 Nigerian gig workers was analysed using Partial Least Squares Structural Equation Modelling. Automated anomaly detection and predictive audit targeting significantly increased tax compliance, whereas data integration and real-time reporting tools did not. Neither privacy concerns nor perceived fairness significantly moderated the AI–compliance relationship. The findings suggest that perceived detection risk, rather than fairness or privacy considerations, primarily drives compliance. The study contributes empirical evidence from a developing-country context and underscores the value of AITDMs for gig-economy tax administration.

Keywords: Artificial intelligence, Gig economy, Tax evasion, tax compliance

INTRODUCTION

The gig economy has transformed global labour markets, with an estimated 540 million workers projected to contribute over USD 3 trillion to global GDP by 2025 (Hussein, 2023; McCarthy, 2025). However, it has also created significant tax administration challenges (Black, 2020). The OECD (2022) identifies the gig economy as a major contributor to the digital-age tax gap, largely because tax systems were not designed for decentralised, platform-mediated work (Adelakun, 2023). Poor awareness, non-automatic withholding, and low perceived audit risk have compounded evasion (Garin et al., 2025), with underreporting of self-employment income contributing an estimated 4–15% of the tax gap in OECD countries (Watson, 2019; Erastov & Balytska, 2025).

Traditional enforcement mechanisms struggle with the complexity of gig-economy fraud. AI-assisted tax detection methods (AITDMs)—encompassing automated anomaly detection, platform cross-data integration, predictive audit targeting, and real-time reporting—offer predictive, scalable alternatives (Pamisetty et al., 2022). While developed countries such as Australia and the Netherlands have adopted AI anomaly detection (OECD, 2022), developing nations face structural barriers including informality, cash-based transactions, low financial inclusion, and limited digital literacy (Anakpo et al., 2023; Khaltar, 2024). Regulatory measures alone are therefore insufficient, and countries such as Nigeria must explore AITDMs directly.

Existing research focuses largely on the technical capabilities of AITDMs, with limited attention to their ethical and behavioural consequences in the gig economy. The roles of privacy and fairness remain underexplored (Belahouaoui & Attak, 2024; Islam et al., 2025), and most studies are situated in developed economies (Alm, 2021; Ramgulam & Bourton, 2021). This study addresses that gap by analysing how privacy concerns and

perceived fairness moderate the relationship between AI-driven detection and tax compliance among Nigerian gig workers.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Conceptual Clarification

Tax compliance refers to the accurate reporting of income, correct computation of tax, timely filing, and payment of liabilities. In digital contexts it is not merely legal obedience but also reflects trust in systems and user knowledge (Ogunsola et al., 2022). It is multidimensional, incorporating voluntary observance, enforcement pressure, and perceived legitimacy (Pamisetty et al., 2022; Neuman, 2023).

Perceived fairness concerns whether rules, procedures, and outcomes are administered without discrimination. Procedural justice is as relevant as distributive outcomes (Bellon et al., 2022), and algorithmic fairness—the absence of systematic bias—is particularly pertinent for heterogeneous populations such as gig workers (Han et al., 2025). Where AI systems are perceived as biased or opaque, enforcement may be resisted despite technical accuracy.

Privacy concerns refer to the subjective sense of vulnerability to unauthorised access, misuse, or surveillance of personal information (Dinev & Hart, 2006; Adhikari et al., 2020; Martin et al., 2022). Platform work generates substantial personal and financial data, and intrusive AI monitoring may erode trust and willingness to comply.

AI-driven systems are adaptive computational technologies—machine learning, predictive analytics, and automated decision-making—that identify patterns and support enforcement (Heinemann & Stiller, 2025). Their influence is not purely technical; they raise questions of control, accountability, and the legitimacy of automated decisions.

Transparency and data governance are closely related. The "black box" problem undermines legitimacy (Neuman, 2023), while robust governance and security frameworks are needed to balance analytical benefits against taxpayer rights (Ogunsola et al., 2022; Fakhroni et al., 2022).

THEORETICAL REVIEW

2.2.1 Technology Acceptance Model (TAM)

According to Davis (1989), TAM holds that perceived usefulness and perceived ease of use determine technology adoption. Although criticised for neglecting contextual and ethical factors (Adhikari et al., 2020; Han et al., 2025), TAM provides a useful lens for understanding gig workers' acceptance of AI-driven tax systems.

2.2.2 The Slippery Slope Framework

Kirchler et al. (2008) in the slippery slope framework posits that compliance results from the interaction between authorities' power (enforcement, audits, penalties) and trust (fairness, legitimacy, transparency). A balance produces sustainable compliance; over-reliance on enforcement breeds resistance (Kirchler, 2019). The framework has been validated across contexts (Kogler et al., 2015; Gangl et al., 2019; Batrancea et al., 2022; Mardhiah et al., 2023), though it overlooks cultural, political, and technological influences (Nasution, 2024).

2.3 Empirical Evidence

2.3.1 Automated Anomaly Detection

Automated anomaly detection applies unsupervised machine learning to identify deviations from expected taxpayer behaviour (Liang et al., 2025). Theoretically, its compliance effect is expected to operate through two distinct channels in the Slippery Slope Framework. First, it raises the perceived detection probability — the power dimension — by reducing the information asymmetry that historically allowed gig workers to underreport

with impunity. Second, when the system is perceived as objective and rule-consistent, it can reinforce trust by signalling that enforcement is even-handed rather than arbitrary (Tusubira et al., 2024).

Empirical evidence largely supports a positive compliance effect, but the literature diverges on mechanism and magnitude. Fan et al. (2024) and Rahman et al. (2024) find significant compliance gains in the US, attributing them to reduced information asymmetry. Van-Duc et al. (2024) report similar findings in South Asia, while Zumaya et al. (2021) and Islam et al. (2025) emphasise administrative cost reduction as the primary pathway — a capacity rather than a deterrence explanation. Ariyibi et al. (2024) show that AI systems outperform rule-based detection in identifying complex fraud patterns, but their study measures detection accuracy, not taxpayer behaviour. Savic et al. (2022) and Abad-Segura et al. (2025) report positive effects across European jurisdictions but note substantial heterogeneity that they do not explain.

This divergence matters for the present study. If the compliance effect operates mainly through perceived detection probability, we would expect strong effects in contexts where baseline audit risk is low — as in the Nigerian gig economy. If it operates mainly through administrative efficiency, the behavioural effect on individual gig workers may be weaker. Crucially, none of the existing studies measure the behavioural compliance of gig workers specifically; they infer compliance from administrative data or detection accuracy. This is the gap H1 addresses.

H1: Automated anomaly detection is positively associated with tax compliance among gig economy workers.

2.3.2 Data Integration Across Platforms

Data integration consolidates information from multiple platforms to reconstruct a taxpayer's full income picture (Gudavalli, 2022). Its theoretical pathway to compliance is distinctive: unlike anomaly detection, which operates through deterrence, integration works primarily by removing the structural opportunity for underreporting. Where income from Platform A cannot be cross-referenced with Platform B, underreporting is rational; where it can, the cognitive and practical cost of evasion rises. In Slippery Slope terms, integration increases power — but it may simultaneously erode trust if perceived as surveillance rather than administration.

The empirical record is more mixed than the anomaly-detection literature. Gudavalli (2022) reports that sophisticated integration improves income taxation systems, and Jin et al. (2023) find, through multi-agent simulation, that platform data quality strongly conditions compliance — poor integration reduces compliance by creating perceived unfairness between those who are and are not captured. Mbise and Baseka (2022) find positive effects on SME compliance in Tanzania. However, these studies share a common limitation: they treat integration as a neutral technical instrument and do not model taxpayer perception of integration. Jin et al.'s (2023) finding that poor data quality erodes compliance is the closest the literature comes to acknowledging a perceptual mechanism, but it is framed as a technical rather than behavioural problem. Not many studies have tested whether integration affects gig workers' willingness to report, as distinct from their ability to conceal.

H2: Data integration across digital platforms is positively associated with tax compliance among gig economy workers.

2.3.3 Predictive Audit Targeting

Predictive audit targeting uses supervised machine learning on historical audit data, behavioural signals, and risk indicators to prioritise high-risk taxpayers (Karakoyun, 2024). Its theoretical pathway is the most explicitly deterrence-based of the four mechanisms: by concentrating audits where evasion is most likely, it raises the conditional probability of detection for those most inclined to evade. Under the Slippery Slope Framework, this is a pure power mechanism — and its effect on compliance should therefore be strongest among taxpayers who are aware of being at elevated risk.

The empirical literature is broadly supportive but reveals an important qualification. Beer et al. (2020) show that better-targeted audits in the US produce substantial direct revenue and subsequent compliance dividends among

self-employed taxpayers. Baghdasaryan et al. (2022), Chan et al. (2022), and Staudinger et al. (2025) demonstrate that machine-learning fraud prediction improves audit accuracy by up to 0.22 across Armenia, Austria, and India. However, Christiansen (2024) finds a critical asymmetry: predictive targeting produces durable compliance gains among unintentionally non-compliant taxpayers, but intentional evaders do not significantly change behaviour. This suggests that deterrence works on the margin of error, not on the margin of intent — a finding the existing literature has not fully absorbed, and which has direct implications for gig workers, whose non-compliance may be either inadvertent (complexity) or strategic (opportunism). Kasper and Alm (2020) similarly find that ineffective audits can reduce post-audit compliance, underscoring that targeting quality matters more than targeting volume.

Critically, the predictive-targeting literature is almost entirely developed-country. Whether the deterrence mechanism operates similarly in contexts of low baseline enforcement capacity, weak institutional trust, and high informality — the Nigerian gig-economy context — is untested.

H3: Predictive audit targeting is positively associated with tax compliance among gig economy workers.

2.3.4 Real-Time Reporting Tools

Real-time reporting tools — automated platform reporting, e-invoicing, streaming data exchange — operate through a different mechanism again: they remove the temporal gap between earning and reporting, reducing both the opportunity and the cognitive burden of non-compliance (Ogunsola et al., 2022; Pamisetty et al., 2022). Under the Slippery Slope Framework, this can enhance both power (immediate detection) and trust (simplified, transparent administration) simultaneously — a dual pathway that distinguishes it from the pure deterrence of audit targeting.

The evidence is positive but contextually bounded. Bellon et al. (2022) find that VAT e-invoicing in Peru increased compliance, and Heinemann and Stiller (2025) show that mandatory e-invoicing in Italy significantly reduced cross-border fraud. Han et al. (2025) attribute compliance gains to reduced information asymmetry. Fakhroni et al. (2022) find positive effects on reporting compliance, while Adhikari et al. (2020) find significant but heterogeneous effects — a heterogeneity they do not explain. Odetunde et al. (2022) and Lateefat and Bankole (2023) emphasise voluntary compliance effects through automation.

The gap is threefold. First, all these studies examine formal-sector or cross-border contexts; none examines platform-mediated gig work, where reporting infrastructure is controlled by private platforms rather than tax authorities. Second, none examines developing-country contexts with weak digital infrastructure, where real-time reporting may be technically infeasible or perceived as burdensome. Third, the mechanism is undertheorized for low-trust environments: if gig workers distrust the platforms transmitting their data, automated reporting may trigger reactance rather than compliance. This is precisely the context H4 tests.

H4: Real-time reporting tools are positively associated with tax compliance among gig economy workers.

2.4 Moderating Variables

This study modelled privacy concerns and perceived fairness as moderators of the aggregate AITDM construct rather than of each individual mechanism. This is because AITDMs are typically deployed as integrated systems, and gig workers are likely to experience them as a unified enforcement apparatus rather than as separable tools. Acknowledging the limitation: mechanism-specific moderation may differ — for example, privacy concerns may be especially salient for data integration, and fairness concerns for predictive audit targeting. Testing this is left to future research. The moderation hypotheses therefore ask whether the overall AI–compliance relationship is conditioned by privacy and fairness perceptions.

2.4.1 Privacy Concerns as a Moderator

The literature offers two competing predictions for how privacy concerns moderate the AI–compliance relationship, and this tension is central to the study's contribution.

The reactance prediction (negative moderation) – Here, privacy concerns reflect perceived intrusion into informational self-determination (Dinev & Hart, 2006; Martin et al., 2022). Where AI systems are experienced as opaque surveillance, taxpayers may respond with psychological reactance — reducing cooperation to reassert control (Alm & Torgler, 2011). Neuman (2023) finds that privacy concerns negatively moderate the effectiveness of AI-based tax collection, and Akinrinola et al. (2024) identify privacy and algorithmic fairness as the central ethical risks of AI in tax administration. Under this prediction, privacy concerns should weaken the positive AI–compliance relationship, particularly in contexts where workers have limited control over how platforms share their data — the Nigerian gig-worker condition.

The deterrence prediction (positive or null moderation) – In this school of thought, a competing reading, grounded in the Slippery Slope Framework, suggests that privacy concerns may be overwhelmed by enforcement power. Martin et al. (2022) note that intrusive monitoring does not generally reduce compliance where detection capacity is high and penalties are salient. If gig workers perceive the probability and cost of detection as concrete and immediate, while data-misuse risks are abstract and deferred, privacy concerns may fail to moderate the relationship — or may even strengthen it, if surveillance signals that authorities are serious about enforcement.

These competing predictions are not resolved in the literature, and no study tests them on gig workers. This study provides a direct test. Notably, the Slippery Slope Framework itself predicts the second outcome in high-power contexts, while reactance theory predicts the first — so the empirical result is theoretically informative either way.

H5: Privacy concerns moderate the relationship between AI-driven detection mechanisms and tax compliance among gig economy workers.

2.4.2 Perceived Fairness as a Moderator

Perceived fairness is the view that tax rules and enforcement are applied equitably across taxpayer groups (Wenzel, 2004). Under the Slippery Slope Framework, fairness is the trust-building counterpart to enforcement power: where taxpayers perceive procedures as fair, they internalise compliance as legitimate rather than merely coerced, producing durable voluntary compliance (Kirchler et al., 2008; Gangl et al., 2019). Conversely, perceived unfairness — for example, if gig workers believe they face disproportionate scrutiny relative to formal employees — can erode tax morale and trigger resistance (Braithwaite, 2017).

Three distinctions matter for theorising the moderation. Procedural fairness concerns how decisions are made (consistency, transparency, voice); distributive fairness concerns how burdens are allocated across groups; and retributive fairness concerns whether sanctions are proportionate (Bellon et al., 2022). AI-driven detection implicates all three: algorithmic opacity raises procedural concerns (Han et al., 2025), asymmetric capture of gig income raises distributive concerns (Cheng et al., 2023), and automated penalties raise retributive concerns. The literature has not disaggregated these in the AI–tax context.

The theoretical prediction for moderation is positive: perceived fairness should strengthen the AI–compliance relationship, because fair enforcement builds the trust that converts deterrence into voluntary compliance. However, a competing prediction exists. Braithwaite (2017) and Gangl et al. (2019) suggest that in highly monitored settings, fairness perceptions may be crowded out by enforcement salience — compliance becomes coercive rather than normative, and fairness ceases to moderate. If gig workers perceive AI enforcement as an unavoidable fact rather than a normatively evaluable process, fairness perceptions may not moderate their behaviour at all.

This tension — between the Slippery Slope prediction (positive moderation) and the crowding-out prediction (null moderation) — is unresolved for AI-driven tax enforcement, and untested on gig workers.

H6: Perceived fairness moderates the relationship between AI-driven detection mechanisms and tax compliance among gig economy workers.

METHODOLOGY

3.1 Design and Sampling

A cross-sectional survey design was used. The target population comprised Nigerian gig workers earning through digital platforms (ride-hailing, delivery, freelancing, content creation). Nigeria was selected as an African frontrunner in digital tax innovation that nonetheless faces high informality.

Purposive sampling was adopted for this study, with the following eligibility criteria: (1) age ≥18; (2) active on at least one digital gig platform; (3) ≥6 months of gig earnings. Respondents were recruited via online gig-worker communities and administered the questionnaire electronically. Participation was voluntary and anonymous.

Sample size - 130 valid responses were obtained. This meets PLS-SEM requirements: at minimum ten times the largest number of arrows pointing at a construct (Hair et al., 2022), and the inverse square root method (Kock & Hadaya, 2018) confirms sufficient power (0.80) to detect path coefficients of ~0.25 at 5% significance. The modest sample size is acknowledged as a limitation.

3.2 Measurement and Validity

AITDMs were measured across four dimensions (automated anomaly detection, data integration, predictive audit targeting, real-time reporting). Tax compliance was measured via reporting accuracy, timeliness, and willingness to disclose. Privacy concerns used the Information Privacy Concern scale (Dinev & Hart, 2006); perceived fairness used the procedural justice subscale (Gangl et al., 2019).

Table 1: Validity Test

Constructs	Composite reliability	Average Variance Extracted
Tax Compliance	0.846	0.481
AI-Driven Tax Detection Mechanisms	0.933	0.562
Perceived Fairness of the Tax System	0.753	0.506
Privacy Concern	0.885	0.665

Source: Author's Compilation

All composite reliability values exceed 0.70. The AVE for Tax Compliance (0.481) falls marginally below the conventional 0.50 threshold, indicating that the construct explains 48.1% of indicator variance. Following Fornell and Larcker (1981), AVE values between 0.40 and 0.50 may be acceptable where composite reliability is high, as here. Nonetheless, this limitation is acknowledged, and refinement of the tax compliance measure is recommended for future research.

3.3 Model Specification

The study used a moderated structural model based on the Slippery Slope Framework (Kirchler et al., 2008). The hypothesised model is specified as follows:

$$TCR_i = F(AITDMs_i) \quad \text{.....EQN 1}$$

$$TCR_i = \beta_0 + \beta_1 AAD_i + \beta_2 DIAP_i + \beta_3 PATi + \beta_4 RTRT_i + \epsilon_i \quad \text{.....EQN 2}$$

Moderation (Aggregate for AITDM)

$$TCR_i = \beta_0 + \beta_1 AITDMs_i + \beta_2 PC_i + \beta_3 P(AITDMs_i \, x \, PC_i) + \epsilon_i \quad \text{.....EQN 3}$$

$$TCR_i = \beta_0 + \beta_1 AITDMs_i + \beta_2 PF_i + \beta_3 P(AITDMs_i \, x \, PF_i) + \epsilon_i \quad \text{.....EQN 3}$$

Where:

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

TCR = Tax Compliance Rate; AAD = Automated Anomaly Detection; DIAP = Data Integration Across Platforms; PAT = Predictive Audit Targeting; RTRT = Real-Time Reporting Tools; AITDMS = aggregate construct (AI-based Tax Detection Mechanisms); PC = Privacy Concern; PF = Perceived Fairness; ε = error term.

3.4 A-Priori Expectation

Based on theoretical and empirical literature, H1 to H4 and H6 are expected to be positive; while H5 expected to be negative.

3.5 Data Analysis Techniques

Data were analysed using descriptive statistics and Partial Least Squares Structural Equation Modelling.

4.0 Analysis of results and discussion of findings

Data Presentation

Table 2 presents the demographic profile of the respondents, summarised using frequencies and percentages. A total of 65 respondents were female, accounting for 50% of the sample. There were 65 male respondents, who accounted for 50% of the sample. This means that the sample was well balanced in terms of gender. Regarding age, 38 respondents were between the ages of 33-40 years, and this forms 29.23 percent of the respondents. Though 29 respondents fell in 40-50 years (26.15%), 24 respondents were in the 18-25 years category (18.46). Only 3.85% were above 50. It means that they will have an adult workforce, which has financial obligations. Similarly, 80 respondents held undergraduate degrees (61.54%), while 34.62% had postgraduate qualifications. 3.08% had a diploma certification while 0.77 of the respondents had a secondary school certificate. This shows a highly educated gig-worker population.

In the same vein, 59 respondents (45.38%) worked on two platforms. 28.46% worked on one platform, while 26.15% worked on three or more platforms. This indicates diversified income sources. Similarly, respondents were engaged in different gig sectors. While 46 respondents did not specify, representing 35.38% of the sample, 29 respondents were digital content creators (22.31%). Of the sample, 22 respondents were freelancers, accounting for 16.92% of the sample. 20 respondents engaged in delivery services, while 13 respondents were into ride-hailing. This accounts for 15.38% and 10% of the sample, respectively. The sample indicates diverse segments of the gig economy.

Table 2. Demographic Information of Respondents

Demographic Information	Details	Frequency	Percentage	cumulative
Age	Below 17 years	-	-	
	18 - 25 years	24	18.46	18.46
	26 - 32 years	29	22.31	40.77
	33 – 40 years	38	29.23	70
	40 – 50 years	34	26.15	96.15
	Above 50 years	5	3.85	100
Gender	Male	65	50	50
	Female	65	50	50
Education	Primary/Secondary	1	0.77	0.77
	Diploma/Certificate	4	3.08	3.85
	Undergraduate	80	61.54	65.38
	Postgraduate	45	34.62	100
Online Platform	One	37	28.46	28.46
	Two	59	45.38	73.85

	Three or more	34	26.15	100
Percentage of total monthly income from GIG	Less than 25%	17	13.08	13.08
	25% - 50%	29	22.31	35.38
	51% - 75%	23	17.69	53.08
	76% - 100%	61	46.92	100
Type of gig work	Ride-hailing	13	10	10
	Delivery	20	15.38	25.38
	Freelancing	22	16.92	42.31
	Digital content creation	29	22.31	64.62
	Others	46	35.38	100
Total		130	100	

Source: Author's Computations

Descriptive Statistics

Table 3 presents descriptive statistics for the tax compliance rate (TCR), automated anomaly detection (AAD), data integration across platforms (DIAP), predictive audit targeting (PAT), real-time reporting tools (RTRT), personal concern (PC) and perceived fairness (PF). Automated Anomaly Detection (AAD). AAD's mean value of 4.08 suggests that most gig workers agree that anomaly detection tools are used in tax monitoring. The standard deviation of 0.68 suggests moderate variability. Skewness of –0.58 indicates a left-skewed distribution with higher agreement levels. The kurtosis value of 3.15 implies normal distribution.

Similarly, the mean score of 4.19 for DIAP indicates positive perceptions. The skewness of –0.24 indicates slight left skewness. A kurtosis of 2.61 shows moderate peakness in the distribution. With a standard deviation of 0.63, responses are moderately spread. In the same, Predictive Audit Targeting (PAT) also recorded high positive responses, with a mean of 4.22. This suggests a strong belief in AI-powered audit selection. The standard deviation of 0.63 indicates moderate variability. The skewness of –0.29 reveals slightly more high-end responses, while kurtosis (2.50) indicates a normal distribution.

Also, Real-Time Reporting Tools (RTRT) show moderately high agreement, with a mean of 3.93. The distribution reveals that respondents agreed with the presence of real-time reporting tools. The standard deviation (0.60) indicates moderate spread. Skewness of –0.35 again indicates more responses at the high end. The kurtosis (3.54) reflects a slightly more peaked distribution than normal. Although respondents acknowledge real-time reporting, perceptions are less strong.

The mean of Tax Compliance (TC) stands at 4.01. This shows that the level of compliance among gig workers is mostly high. The standard deviation of 0.50 demonstrates the same attitudes of the respondents to compliance. Skew is -0.06, which implies that the distribution is almost symmetrical and kurtosis is 2.42, which implies that it is a relatively flat distribution. In the meantime, Privacy Concerns (PC) has a mean of 4.10. This indicates that the issue of data confidentiality, surveillance, and monitoring is of great concern to the respondents. Its standard deviation is 0.79 which is quite big. The value of skew (-0.61) represents a skewed distribution towards the left. The value of kurtosis of 2.71 is moderately concentrated. Also, the mean score of Perceived Fairness (PF) is 3.96. This represents a moderate high level of agreement that the tax management of gig workers is fair. The spread of views is moderate as the standard deviation is 0.61. The skew (-0.50) indicates that the responses were more skewed to high. The value of kurtosis of 3.42 shows that the distribution is more peaked meaning that respondents are consistent.

Table 3. Descriptive Statistics of Study Variables

Variable	Obs	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
AAD	130	4.084615	.6798585	2	5	-0.58314	3.1468

DIAP	130	4.187179	.6349074	2.333333	5	-0.23697	2.6134
PAT	130	4.217949	.6276867	2.666667	5	-0.28972	2.4989
RTRT	130	3.925641	.5975335	2	5	-0.35143	3.5442
TC	130	4.006731	.503455	2.875	5	-0.06229	2.4212
PC	130	4.096154	.788965	2	5	-0.60754	2.7114
PF	130	3.963462	.606898	2	5	-0.49786	3.42229

Source: Researchers' Computation

4.3 Correlation Analysis

Correlation analysis has found out that the variables of the study have significant interrelationships. Automated Anomaly Detection (AAD) has strong, positive, statistically significant correlations with Data Integration Across Platforms (DIAP) with correlation coefficient p-value of 0.001 when the correlation coefficient of AAD is 0.6714. PAT and AAD have a correlation coefficient of 0.5922 with a p-value of 0.001. Whereas, Real-Time Reporting Tools (RTRT) have correlation coefficient of 0.6072 and p-value of 0.001, and Tax Compliance (TC) have 0.6334 and p-value of 0.001. This means that the gig workers view more sophisticated systems of anomaly detection, integration of the platform information, predictive audits, and increased compliance with tax. On the same note, DIAP is positively related with PAT, RTRT, Privacy Concerns (PC) and TC. This implies that cross-platform data sharing helps to enforce the mechanisms, enhance compliance, albeit with greater awareness of privacy. Similarly, Predictive Audit Targeting (PAT) proves to be high association. It has a significant correlation with RTRT ($r = 0.3582$, $p < 0.001$), PC ($r = 0.5091$, $p < 0.001$), and TC ($r = 0.6331$, $p < 0.001$). This indicates that it is at the heart of AI-based enforcement and that it affects the taxpayer behaviour significantly. Moreover, there are relations of considerable correlation between Real-Time Reporting Tools (RTRT) and PAT ($r = 0.3582$, $p < 0.001$), Perceived Fairness (PF) ($r = 0.3879$, $p < 0.001$), and TC ($r = 0.5267$, $p < 0.001$). This underlines the significance in ensuring fairness as well as compliance. Also, Privacy Concerns (PC) has moderate and significant positive relationships with AAD ($r = 0.2569$, $p < 0.01$), DIAP ($r = 0.2527$, $p < 0.01$), PAT ($r = 0.5091$, $p < 0.001$) and TC ($r = 0.4448$, $p < 0.001$). This means that gig workers raise the issue of data privacy, but these concerns do not translate to preventing compliance. Once again, Perceived Fairness (PF) has a weak and significant correlation with AAD ($r = 0.2173$, $p < 0.05$), DIAP ($r = 0.2476$, $p < 0.01$), RTRT ($r = 0.3879$, $p < 0.001$) and TC ($r = 0.2585$, $p < 0.01$). This means that the perception of fairness is increased in case AI systems are regarded as consistent, transparent and fairly implemented.

Table 4. Correlation of the Study Variables

	AAD	DIAP	PAT	RTRT	PC	PF	TC
AAD	1.0000						
DIAP	0.6714*	1.0000					
	0.0000						
PAT	0.5922*	0.5776*	1.0000				
	0.0000	0.0000					
RTRT	0.6072*	0.5819*	0.3582*	1.0000			
	0.0000	0.0000	0.0000				
PC	0.2569*	0.2527*	0.5091*	0.1551	1.0000		
	0.0032	0.0037	0.0000	0.0782			
PF	0.2173*	0.2476*	0.1279	0.3879*	-0.0149	1.0000	
	0.0130	0.0045	0.1470.	0.0000	0.8667		
TC	0.6334*	0.4942*	0.6331*	0.5267*	0.4448*	0.2585*	1.0000
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0030	

Source: Author Compilation

4.4 AI-Driven Detection of Tax Evasion in the Gig Economy: Implications for Compliance.

Table 5 summarises the structural model results. This shows the effect of the AI-driven detection mechanism on tax compliance. Automated Anomaly Detection shows a significant positive path coefficient of 0.376 and a p-value of 0.004. This indicates that the more gig workers perceive greater use of automated anomaly detection tools by tax authorities, the more likely they are to comply with tax obligations. Also, at a coefficient of 0.400 and a p-value of 0.001, Predictive Audit Targeting exhibits a strong effect on tax compliance. This suggests that the use of AI-enabled systems enhances compliance behaviour.

In contrast, Data Integration Across Platforms (DIAP) demonstrates a weak and statistically non-significant effect at a coefficient of −0.050 and a p-value of 0.701. Although gig workers recognize platform-to-platform data sharing, this mechanism does not meaningfully influence their tax compliance decisions. Similarly, Real-Time Reporting Tools (RTRT) show a non-significant impact on compliance at a coefficient of 0.129 with a p-value of 0.307. This indicates that the mere availability of real-time reporting tools does not translate into higher compliance. Generally, these suggest that detection and predictive audits influence tax compliance in the gig economy.

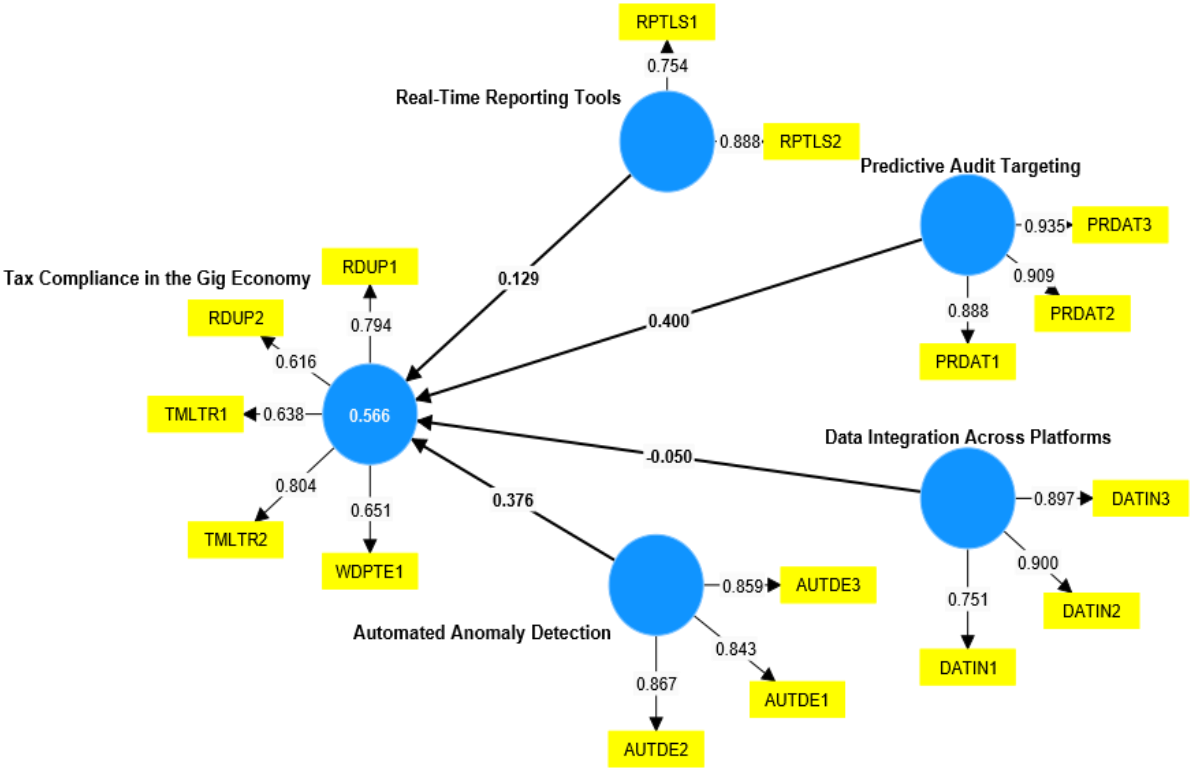


Table 5. Effect of AI-Driven Detection on Tax Compliance

Constructs	Path Co-efficient	T-Statistics	P-Values
Automated Anomaly Detection -> Tax Compliance in the Gig Economy	0.376	2.921	0.004
Data Integration Across Platforms -> Tax Compliance in the Gig Economy	-0.050	0.384	0.701
Predictive Audit Targeting -> Tax Compliance in the Gig Economy	0.400	3.883	0.000
Real-Time Reporting Tools -> Tax Compliance in the Gig Economy	0.129	1.021	0.307
Tax Compliance in the Gig Economy (R-square, R-square Adjusted, and Q^2)	0.566	0.552	0.482
F-Square (Effect Size)- Automated Anomaly Detection	0.125		
F-Square (Effect Size)- Data Integration Across Platforms	0.002		

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

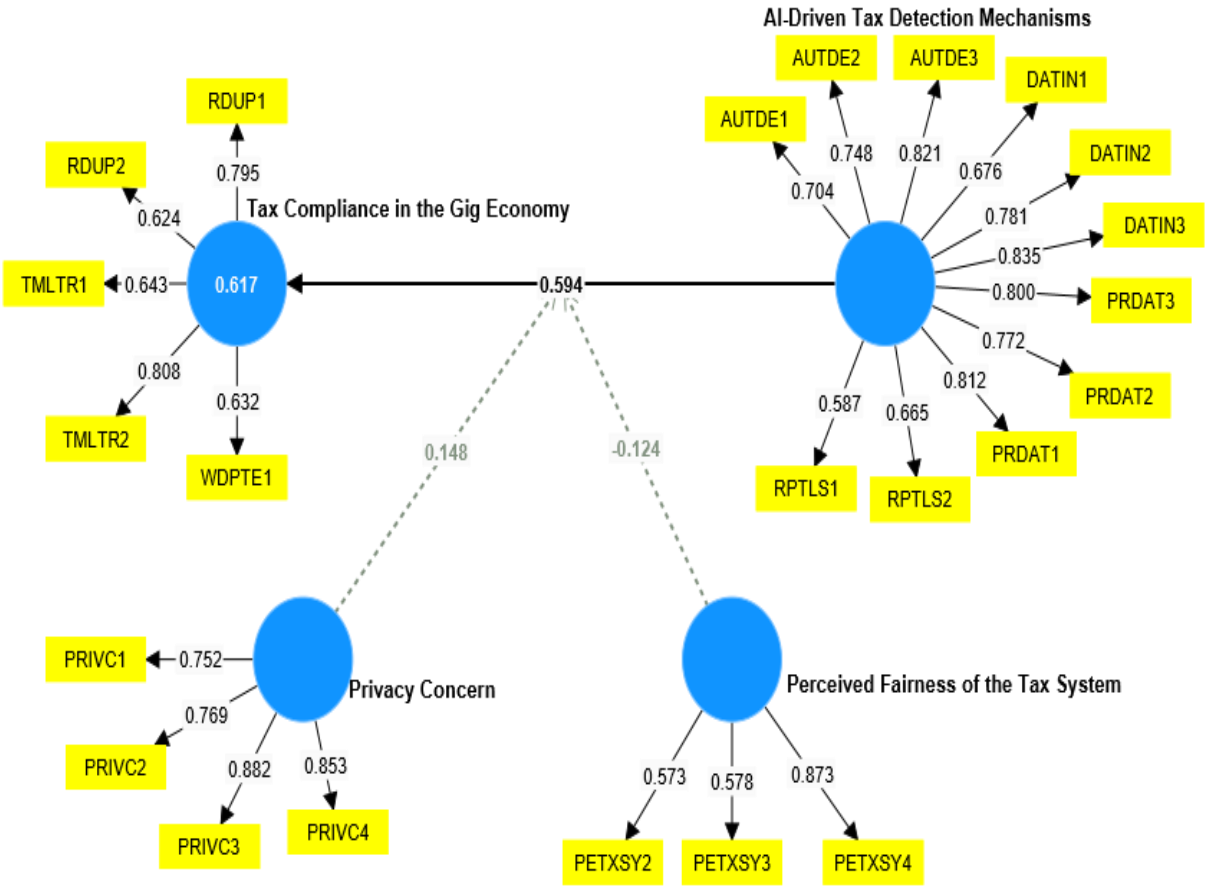
F-Square (Effect Size)- Predictive Audit Targeting	0.172		
F-Square (Effect Size)- Real-Time Reporting Tools	0.020		
SRMR	0.090		
NFL	0.688		
RMSE	0.736		

Source: Author's Compilation

4.5 AI-Driven Detection of Tax Evasion in the Gig Economy: Implications for Compliance, Privacy, and Fairness

The moderation analysis examined whether privacy concerns and perceived fairness influence the relationship between AI-driven tax detection mechanisms, and ultimately tax compliance among gig workers. At a coefficient of 0.148 and a p-value of 0.060, this shows that privacy concerns exert an insignificant positive moderating effect. This suggests that as privacy concerns increase, the positive relationship between AI-driven detection mechanisms and compliance becomes stronger. In this context, gig workers who are more concerned about data surveillance may exhibit higher compliance. However, since this effect lacks statistical significance, privacy concerns cannot be regarded as a strong moderating factor in influencing tax.

Similarly, the moderating role of perceived fairness also shows a weak and statistically insignificant effect at a coefficient of –0.124 and a p-value of 0.089. The negative coefficient implies that increased perceptions of unfairness weaken the influence of AI-driven detection tools on tax compliance. However, since the moderating effect is statistically insignificant, perceptions of fairness do not substantially influence the relationship between AI enforcement and tax compliance behaviour. Overall, these suggest that although gig workers may express concerns about privacy and fairness, these attitudes do not significantly affect the effect of AI-based enforcement. Instead, compliance appears to be primarily driven by the deterrent effect of technology, rather than by subjective perceptions of fairness and privacy. The path diagram reveals that automated anomaly detection has an impact on tax compliance among employees of the gig-economy. This highlights the expanding nature of smart enforcement machinery in defining taxpayer behaviour.



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Table 6. Moderating Effect of Privacy and Fairness

Constructs	Path Co-efficient	T- Statistics	P-Values
Privacy Concern x AI-Driven Tax Detection Mechanisms -> Tax Compliance in the Gig Economy	0.148	1.881	0.060
Perceived Fairness of the Tax System x AI-Driven Tax Detection Mechanisms -> Tax Compliance in the Gig Economy	-0.124	1.699	0.089
Tax Compliance in the Gig Economy (R-square, R-square Adjusted, and Q^2)	0.608	0.592	0.537
F-Square (Effect Size)- Privacy Concern	0.054		
F-Square (Effect Size)- Perceived Fairness of the Tax System	0.024		
SRMR	0.112		
NFL	0.588		
RMSE	0.6945		

Source: Author's Compilation

DISCUSSION OF FINDINGS

The significant effects of AAD and PAT align closely with the Slippery Slope Framework's power dimension: both raise perceived detection probability and thereby deter underreporting among gig workers whose income is otherwise opaque. The findings are consistent with Fan et al. (2024), Rahman et al. (2024), and Beer et al. (2020). Notably, the results support the deterrence pathway over the administrative efficiency pathway proposed by Zumaya et al. (2021) and Islam et al. (2025) — since efficiency gains would not produce the observed behavioural response at the individual level. The strong PAT effect also suggests that Christiansen's (2024) asymmetry (targeting works on unintentional, not intentional, non-compliance) may be less pronounced in the Nigerian gig context, where low baseline enforcement means even strategic evaders respond to a credible rise in detection probability.

The non-significant DIAP and RTRT findings are theoretically informative rather than merely null. Under TAM, both mechanisms may suffer from low perceived usefulness or ease of use among gig workers who do not see how integrated data or automated reporting reduces their compliance burden — a plausible reading in a context of limited digital literacy and weak platform-side reporting infrastructure. Alternatively, DIAP and RTRT may operate through structural opportunity removal rather than perceived deterrence; if gig workers are unaware of integration or do not experience reporting as automated, the behavioural effect is absent even where the technical capability exists. This divergence from Gudavalli (2022) and Jin et al. (2023) is best explained by contextual differences in institutional trust and digital infrastructure — consistent with the study's developing-country framing.

The non-significant moderation results are theoretically meaningful given the competing predictions set out in Section 2.4. For privacy concerns, the positive but non-significant coefficient ($\beta = 0.148$) leans toward the deterrence prediction rather than the reactance prediction: privacy concerns, if anything, slightly strengthen the AI–compliance relationship, suggesting that surveillance salience may signal enforcement seriousness rather than trigger resistance. This is consistent with Martin et al. (2022) but contrary to Neuman (2023) and Akinrinola et al. (2024). For perceived fairness, the negative but non-significant coefficient ($\beta = -0.124$) leans toward the crowding-out prediction rather than the Slippery Slope prediction: where enforcement is highly salient, fairness perceptions may not moderate compliance, consistent with Braithwaite (2017) and Gangl et al. (2019).

Together, these results suggest that compliance in the Nigerian gig economy is driven predominantly by coercive power rather than normative trust — a finding with direct implications for the Slippery Slope Framework's

assumption that sustainable compliance requires balance between the two. In low-trust, low-baseline-enforcement contexts, power may dominate trust in the short run, even if this is not sustainable in the long run.

4.7 Limitations of the Study

The study uses self-reported, cross-sectional data, so findings represent statistical associations rather than causal effects, and social desirability bias may inflate reported compliance. The sample (130) is modest and purposive, limiting generalisability. The Tax Compliance AVE (0.481) is marginally below threshold, indicating a need for measure refinement. Finally, the moderation analysis uses the aggregate AITDMs construct; mechanism-specific moderation (e.g., privacy × data integration, fairness × predictive targeting) remains untested and is a promising direction for future research.

CONCLUSION AND RECOMMENDATION

This study examined how AI-driven tax detection mechanisms affect tax compliance among gig workers, and whether privacy concerns and perceived fairness moderate that relationship. Automated anomaly detection and predictive audit targeting significantly increased compliance, supporting the deterrence pathway of the Slippery Slope Framework. Data integration and real-time reporting did not, suggesting that structural opportunity removal without perceived deterrence may be insufficient to change behaviour. Neither moderator reached significance, but the direction of coefficients is theoretically informative: privacy concerns leaned toward strengthening compliance (deterrence over reactance), while fairness perceptions leaned toward null moderation (crowding-out over trust-building).

Tax authorities should prioritise investment in automated anomaly detection and predictive audit targeting. Before scaling data integration and real-time reporting, they should address barriers to perceived usefulness and ease of use. Even where fairness and privacy did not significantly moderate compliance, transparent and privacy-respecting system design remains important for sustaining long-run legitimacy — particularly given that the study's findings suggest current compliance is power-driven rather than trust-driven. Future research should adopt longitudinal designs, larger and more representative samples, objective compliance measures, improved tax compliance measurement to raise AVE above 0.50, and mechanism-specific moderation tests.

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Questionniare

Section A: Demographic Information

1. Age: Below 17 years [ ] 18-25 years [ ] 26-32 years 33 – 40 years [ ] 40 – 50 years [ ] Above 50 years[ ]
2. Gender: Male [ ] Female [ ]
3. Education level: Primary/Secondary [ ] Diploma/Certificate [ ] Undergraduate [ ] Postgraduate [ ]
4. Number of platforms you earn from regularly. One [ ] Two [ ] Three or more [ ]
5. How long have you been working in the gig economy? Less than 6 months [ ] 6–12 months [ ] 1–2 years [ ] More than 2 years [ ]
6. On average, what percentage of your total monthly income comes from gig work? Less than 25% [ ] 25% - 50% [ ] 51% - 75% [ ] 76% - 100% [ ]
7. Type of gig work: Ride-hailing (Uber, Bolt, Lyft) [ ] Delivery (Glovo, DoorDash, Jumia Food) [ ] Freelancing (Fiverr, Upwork, PeoplePerHour) [ ] Digital content creation (YouTube, TikTok, etc.) [ ] Others [ ]

Section B: Independent Variable – AI-Driven Tax Detection Mechanisms

Automated Anomaly Detection

1. Tax authorities use advanced technology to detect unusual patterns in gig workers' income. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
2. Automated anomaly detection increases the likelihood of detecting unreported income. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
3. I am more likely to comply with tax rules because anomalies will be flagged. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]

Data Integration Across Platforms

1. Tax authorities can now combine data from multiple gig platforms to monitor income. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
2. My income from different platforms can be linked and shared with tax authorities. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
3. Integration of platform data increases my willingness to report my full income. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]

Predictive Audit Targeting

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1. AI helps tax authorities target gig workers who are most likely to evade taxes. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
2. The risk of being selected for an audit makes me more likely to comply with tax laws. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
3. Predictive audit targeting is an effective deterrent for underreporting income. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]

Real-Time Reporting Tools

4. Gig platforms provide automatic reporting of my income to tax authorities. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
5. Real-time reporting tools make it easier for me to file taxes on time. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
6. Tax reporting has become automatic or simplified. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]

Section C: Dependent Variable – Tax Compliance in the Gig Economy

Accuracy of Reported Income

7. I report all my gig income accurately to the tax authorities. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
8. I sometimes underreport my income to reduce tax liability. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]

Timeliness of Tax Filing

9. I usually file my tax returns on time. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
10. AI-based reminders help me meet tax deadlines. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]

Reduction in Underreporting

11. Automated systems have reduced my tendency to underreport income. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
12. Gig workers underreport their earnings. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]

Willingness to Disclose Platform Earnings

13. I am willing to disclose my earnings from all platforms when filing taxes. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
14. I feel discouraged from disclosing my income because of the complexity of tax rules. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]

Section D: Moderating Variables

Privacy Concerns

15. I am concerned that my gig platform income data could be misused. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]

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16. I feel uncomfortable with tax authorities collecting my digital transaction records. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
17. AI-based monitoring of gig income exposes my personal privacy. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
18. Concerns about data privacy reduce my willingness to comply with tax laws. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]

Perceived Fairness of the Tax System

19. The tax system treats gig workers fairly. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
20. Tax burdens are equitably distributed. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
21. Tax enforcement practices are unbiased. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]
22. A fairer tax system induces me more to comply voluntarily. Strongly Disagree [ ], Disagree [ ], Neutral [ ], Agree [ ], Strongly Agree[ ]