THE ROLE OF ORGANIZATIONAL DRIVERS IN ARTIFICIAL INTELLIGENCE ADOPTION IN MONITORING TAX COMPLIANCE AT THE KRA

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Citation: Kivuti, J. W., Minja, D. (2026). The role of organizational drivers in artificial intelligence adoption in monitoring tax compliance at the KRA. *International Academic Journal of Arts and Humanities*, *9*(10), 12-20.

ABSTRACT

Kenya Revenue Authority has embarked on adopting AI technologies in order to make its tax compliance monitoring procedures more modern and minimize cases of tax evasion. Nevertheless, the continued tax evasion, the underreporting, and non-filing makes one ask whether these technologies are adopted and were implemented effectively. This research examined the role of organizational drivers in artificial intelligence adoption in monitoring tax compliance at the KRA. The survey was directed by Technology-Organization-Environment (TOE) framework Theory. The target population comprised 852 individuals, consisting of 732 compliance staff and 120 Business Systems and Technology, Enterprise Management (BSTEM) staff in the Nairobi region that were at the heart of the tax compliance operations. Stratified sampling based on Yamane formula was used to sample 272 participants because of representativeness and data saturation. So as to analyze quantitative data, descriptive and inferential statistics were applied, whereas qualitative data of interviews and open-ended answers were analyzed on a thematic basis. A descriptive type of research design was used. Quantitative and qualitative information was gathered via structured and semi-structured questionnaires as well as interview schedules. The results demonstrate that an R-value of 0.729 establishes a solid positive association between the independent factors (technological drivers, organizational drivers, and environmental drivers) and the dependent variable (artificial intelligence adoption in monitoring tax compliance at the Kenya Revenue Authority). The research shows that technological drivers, which include system efficiency, data processing capabilities, and analytics tools, have the greatest impact on AI adoption. Staff capacity and internal policies and management support also serve as essential factors that determine successful execution of organizational objectives. The study recommends that KRA should enhance its technological infrastructure through continuous staff training and capacity development and better internal coordination while developing AI initiatives that match changing regulatory and policy requirements to achieve complete AI adoption success in tax compliance monitoring.

Key Words: Organizational Drivers In Artificial Intelligence.

INTRODUCTION

One of the most crucial components of a tax system is tax compliance since, in the absence of it, the system's integrity is jeopardized, the revenue authorities must employ more resources, and raising tax revenues is sufficient. There is a tax system that includes tax legislation, tax policy, and tax administration to assist taxpayers in following tax laws and regulations (Oeta, 2017). When a tax system is in place, people and organisations are forced to provide the government a portion of their revenue in the form of taxes (Marti 2000). According to Silvani (1992), encouraging voluntary compliance is the goal of tax administration. According to James and Alley (2004), tax compliance is the desire of people and other taxable entities to follow the goals and rules of tax administration and legislation without the need for enforcement actions.

The OECD (2008) defines tax compliance as the need to register for taxation, submit returns punctually, accurately declare tax liabilities, and remit taxes promptly. The justification for overseeing tax compliance stems from the fundamental objective of enhancing general conformity to revenue regulations. Compliance refers to adherence to the law, whereas non-compliance denotes a departure from legal standards. The failure to fulfil tax obligations, whether on purpose or accidentally, is known as non-compliance (James, 2004). Monitoring tax compliance, identifying and deterring criminal activity, and offering services and education to assist taxpayers in fulfilling their tax responsibilities with the least amount of complexity and compliance burden are the primary duties of tax administrations (Munawar et al. 2016). For maximizing the utilization of new technologies, the OECD (2016) advised all organisations, including tax authorities, to adjust to technological improvements and, if needed, change their services and distribution.

Artificial Intelligence (AI) is a collection of technologies that give intelligent systems human-like capabilities including learning, improving, calculating, making judgements, and being creative (Mhlanga, 2023). Advancements in AI technology, its acceptance, and its ramifications for organisations, individuals, society, and economies have been hastened by sophisticated technological adjustments and breakthroughs in hardware and software. AI has the latent to accelerate economic development and development while also improving the quality of data and statistics, allowing poor countries to overcome certain traditional challenges (Zafar & Villeneuve, 2018; Susar & Aquaro, 2019). The utilization of AI technologies like deep learning, expert learning systems, machine learning, and optical character recognition, in conjunction with other technologies, improves the efficiency

of managing tax-related problems and the efficacy of monitoring tax-related risks (Mpofu, 2024). Because of the political, social, economic, environmental, and AI infrastructure settings of developing nations, the use of AI in tax administration is linked to governance issues and other AI-related concerns that may be more noticeable there (Zhou, 2019). Artificial intelligence assume a critical role in comprehending and forecasting taxpayer behaviour by offering profound insights into taxpayer actions, revolutionizing conventional compliance procedures (Rahman et al., 2024). AI algorithms can identify how behavioural patterns can assist tax officials in determining if taxpayers will observe with tax rules or whether there is a chance that they would dodge compliance by using sophisticated statistical software and machine learning. The projections are based on historical data, terms of payment, trends in revenue disclosure, and economic variables such as anticipated discovery risk (Dashe and Asada, 2023; Rahman et al., 2024).

Indonesia detects fraud using DJP-AI, an AI-enhanced platform. To handle the data of the mined taxpayers in tax returns and other transactions, the platform uses machine learning. This improves tax collection, lowers tax evasion, and boosts tax compliance. The AI National Strategy reflects the national government's desire to achieve technological advancements, which is why Indonesia is now modernising its tax system (Saragih et al., 2023).

In South Africa, the SARS (South African Revenue Service) introduced a tax management service powered by artificial intelligence (AI) that enhanced tax compliance within the country. By leveraging AI within this platform, data analytics and other anticipatory risk management services allowed SARS to recoup around R210 billion from their efforts against illegal economic activities and tax fraud (Moodley, 2024). This is vital for enforcing tax compliance and enlightening the efficacy of tax administration (Mpofu, 2024).

An AI-powered system was put in place by the Rwanda Revenue Authority (RRA) to improve tax, registration, tax return and declaration filing, settle tax payment requirements, and employ natural language processing to identify potential tax fraud and evasion (Twesige et al., 2020). Furthermore, the East African Community utilizes the RECTS (Regional Electronic Cargo Tracking System) to monitor goods passing through Kenya and into nations like Rwanda, Uganda, and the Democratic Republic of the Congo (Julius & Christabel, 2020).

The deployment of AI in tax administration is being driven by a number of factors, including technological, organizational, and environmental factors, which all influence how well it works in practice. Relative advantage, complexity, and compatibility may all be viewed as technology drivers; they determine how effective the new systems are when KRA implements them in day-to-day operations. One major reason these tools were embraced is that they provide a competitive advantage, since they were shown to be more efficient, precise, and effective at detecting fraud than the manual techniques that people were using previously. Complexity refers to how easy it is for staff people to use and get acquainted with the tools, whereas compatibility determines if the technologies truly fit with existing tax systems and procedures (Zhang et al., 2023). Chong and Olesen (2017) believe that compatibility, technical preparation, perceived indirect advantages, organizational learning culture, and regulatory backing are all connected aspects. This survey broadens our understanding of how technology is utilized to enhance sustainability, but it still emphasises private environmental initiatives rather than highlighting the organisational and technological aspects that lead to the usage of AI for tax compliance monitoring. Gangwar, Date, and Ramaswamy (2015) found that factors such as relative advantage, complexity, compatibility, management support, organizational readiness, and training and education all had a significant impact on the perceived usefulness and ease of use of AI-powered systems. These researchers provided invaluable insight into the variables influencing technology adoption; however, they only examined how a single type of technology was adopted in the private sector, rather than focusing on the institutional, technological, and environmental factors required for AI implementation to monitor tax compliance.

Organizational innovation is driven by strong management support, committed leadership, and an innovative culture, whereas readiness facilitates adoption. Access to funds also influences how much KRA can continue to support and accelerate its technological developments (Patel and Sharma, 2022). According to Maestro and Rana (2024), adoption is mostly driven by leadership support, technology preparedness, and external pressure, with constraints such as cost, data security, and talent shortages. However, most of this study is theoretical and focused on specific organizations. Alsheibani et al. (2018) discovered that favorable external conditions, supporting leadership, and technology readiness are all critical for effective adoption. However, that research focused mostly on corporate adoption in the private sector and provided little insight into the public sector environment.

Monitoring tax compliance involves the appraisal of the effectiveness of taxpayers in fulfilling their duties. It can be evaluated using three main indicators which are tax filing, payment, and risk profiling. Compliance in tax filing is the degree to which taxpayers file correct and promptly filing returns and it is one of the basic indicators of compliance with tax laws. With effective AI systems, KRA will be able to automatically identify late or incorrect filings, which will enhance overall compliance monitoring (OECD, 2021). The payment compliance is concerned with whether taxpayers will pay the right amount of tax within the required deadlines. Payment systems integration has facilitated easier payments tracking, reconciliation of taxpayers records, and underpayment/non-payment cases (Kangave et al., 2022). In its turn, risk profiling implies the application of predictive analytics and data-driven models in order to pinpoint taxpayers that are more likely to be found non-compliant. Through transaction data and behavioural patterns, KRA will be able to prioritize audits and use their enforcement resources more efficiently (Munyua & Muturi, 2020).

Saptono et al. (2023) investigated how the quality of the e-tax system impact tax compliance intentions among certified tax professionals in Indonesia, utilizing electronic filing and e-Form services that promote accurate and timely tax submission and payment. Nevertheless, the paper fails to demonstrate the impact that AI adoption drivers have on tax filing. Tarus (2025) examines the compliance of big taxpayers in the North Rift region of Kenya with automated

tax systems and concludes that tax compliance is favorably correlated with the components of the systems such as online filing and reporting. However, it ignores organisational, technological, and other factors that impact KRA's adoption and integration of AI. Kibona and Goyayi (2025) examine how e-filing affects voluntary tax compliance in Kinondoni tax region, Tanzania, particularly with regard to filing behaviour and timely tax requirement payment. It also fails to cover technological, organizational and environmental drivers of adoption, which creates a gap.

KRA is a parasternal that was created on July 1st, 1995, under chapter 469 of Kenyan legislation. In addition to providing financial support to the G.O.K., it also carries out tasks including revenue assessment, collection, and accounting. Additionally, it handles any revenue-related tasks that the Cabinet Secretary may assign to the National Treasury and offers advice on revenue collection and administration (KRA, 2021).

KRA has increasingly embraced AI technologies to modernize its tax compliance monitoring processes and reduce instances of tax evasion (Business Daily Africa, 2024). The KRA has implemented AI solutions in customs, where machine learning algorithms assist in risk profiling and cargo scanning at the Port of Mombasa, flagging high-risk goods and suspicious imports (Patel & Sharma, 2022). In order to enhance tax compliance and reduce tax evasion, KRA also launched and improved iTax, an AI-supported platform for identifying possible tax evaders (Oeta, 2017). iTax examines data from taxpayers' bank accounts and transactions using machine learning. This makes it possible for the revenue authorities to identify taxpayers who understate their tax burden or avoid taxes by analysing their income and expenditure habits. Further, AI-enabled predictive analytics are now used in the revenue assurance unit to identify sectors or businesses at high risk for non-compliance (Business Daily Africa, 2024). As noted by Akinrinola et al. (2024), despite progress in automating tax administration processes, there remain deficiencies in statistical analysis, large volumes of data, data integrity, and tax compliance. It is essential to comprehend the elements that affect the implementation of AI in monitoring tax compliance in Kenya.

Statement of the problem

Adoption of AI solutions has become essential to improving the effectiveness and precision of tax compliance monitoring on a global scale (Zhang et al., 2023). The usefulness of AI in fraud detection, risk profiling, and compliance enforcement is documented in an expanding body of research, but the most researches concentrate on technology results rather than the circumstances that facilitate successful adoption. Zhang et al. (2023) emphasise the efficacy of machine learning models in detecting anomalies, but they neglect to examine the organisational capability and environmental constraints of the public agency systems. Likewise, Similarly, Patel and Sharma (2022) explored the efficiency benefits of using AI in India without addressing the institutional and legislative challenges that tax authorities may face. Wang and Liu (2023) and Jones and Lee (2024) study the use of AI in public administration by governments in wealthy nations, but they do not explore the contextual elements related with AI adoption in underdeveloped countries. Nembe et al. (2024) do not examine the dynamics of adoption by national taxes, although discussing the usage of AI in international taxation. This study highlights the dearth of empirical data about the organizational, technological, and environmental elements of AI deployment in Kenyan tax compliance monitoring. By analyzing how these variables impact the KRA's adoption and efficient use of AI-enabled tax compliance monitoring tools, this paper fills this gap.

The levels of tax compliance in Kenya are remain appalling, despite KRA's investments in digital and AI-driven solutions to increase efficiency, transparency, and accuracy in tax administration. The availability of technology is insufficient to guarantee efficient compliance monitoring, as evasions, underreporting, and non-filing have demonstrated. The body of previous research is focused on functionality and performance results of the systems, and very little empirical focus is given to the circumstances that can influence the process of adoption, integration, and utilization of the technologies in the tax administrations (Jones and Lee, 2024). There is inadequate evidence on the drivers influencing AI adoption in tax compliance monitoring at KRA. The current research addressed this gap by empirically examining the drivers of AI adoption at KRA and how they affect the effectiveness of monitoring tax compliance.

Objective of the Study

To establish the role of Organizational drivers in AI adoption in monitoring tax compliance at the KRA.

REVIEW OF RELATED LITERATURE

Monitoring Tax Compliance

Monitoring tax compliance is a significant element of good tax control that attempts to make taxpayers fulfill duties and at the appropriate time and in the right manner. It entails the systematic collection, authentication as well as handling of taxation associated data with a view of detecting anomalies, implement tax laws and diminish instances of tax evasion (OECD, 2021). Thanks to the expansion of the digital tools like the electronic tax system and predictive data analytics, the tax authorities have now the opportunity to conduct compliance with a greater precision and effectiveness, which previously heavily depended on the physical inspection and manual audits (Zhang et al., 2023).

Islam et al. (2025) examine how AI might affect tax compliance using predictive analytics and natural language processing, paying special emphasis to how it affects taxpayer behaviour and administrative efficiency. The study highlights how AI may improve fraud detection, streamline processes, and automate services for taxpayers. It is based on behavioural economics and cognitive psychology. It is abstract in style and concentrates more on the ethical concerns of algorithmic prejudice and data privacy, despite effectively examining instances of global problems in the US, Europe, and India. The institutional and contextual factors of AI deployment in the context of public tax administration are not well studied. This study bridges the information gap by examining the factors impacting KRA's use of AI to check tax compliance.

Tarus (2025) in his study investigates the level of compliance of major taxpayers in North Rift region of Kenya on automated taxation. The study relies on

regression analysis and a survey technique to identify a preferred relationship between elements of the system such as online reporting and filing and tax compliance. However, it does not consider the institutional elements that affect the adoption and the assimilation of AI by KRA. This research fills the gap by concentrating on technological, organizational and external drivers that impact the operative deployment of AI technology in public sector tax compliance monitoring at KRA.

Saptono et al. (2023) analyse how the quality of e-tax systems impact tax compliance intention among certified tax professionals in Indonesia, focusing on electronic filing and e-Form services that support accurate and timely filing and payment. They employ hierarchical multiple regression and administer online surveys to 650 e-Filing users and 492 e-Form users, based on the DeLone and McLean IS success model. They discover that user happiness, which in turn intercede the linkage between system quality and tax compliance intention, is greatly increased by information, system, and service quality as well as anticipated savings in compliance expenses. The study does not examine the elements that impact the adoption of such technologies, but it offers valuable insight into how system quality and user happiness impact filing and payment intentions. In contrast to this study, it does not look at how organizational, technological, and environmental elements impact KRA's use of AI for tax compliance monitoring.

Tuyishimire and Murorunkwere (2024) examined the topic of big data analytics to optimize the tax compliance monitoring of the VAT system in Rwanda. They examined such key variables as VAT underreporting, machine learning model, and firm characteristics like size, industry, and type of taxpayer. The methods of machine learning applied to the study to predict underreporting include logistic regression, decision trees, and random forests. The data set that will be analyzed consists of VAT audits from 2014 through 2019. While this research is a great source for gathering knowledge about prediction models, one can observe that there is no analysis of the wider environment that includes organization and technology that could be used when introducing machine learning into the taxation system. This particular oversight seems to be the gap being filled by this research, where the main purpose is to find out what drives AI adoption in monitoring tax compliance in KRA.

Kibona and Goyayi (2025) investigate how e-filing affects voluntary tax compliance in Tanzania's Kinondoni tax zone, with a focus on filing behaviour and timely settlement of tax due. The authors apply the Theory of Planned Behaviour and the Technology Acceptance Model in their positivist/quantitative study, which includes surveys of 185 sampled users of the e-filing system using the Yamane formula and the simple random sampling approach. Regression analysis of data collected via Likert scale questionnaires shows that factors such as the e-filing system's accessibility, user-friendliness, and reliability/secure operation are major predictors of voluntary tax compliance, specifically the timeliness of the process and prompt tax payments. Although the research has significant explanatory power, there is a gap that emerges from treating the electronic system as a given and focusing solely on taxpayer perceptions. Thus, the present KRA study aims to fill this gap by focusing on adoption factors.

Hamza et al. (2025) studied the impact of electronic payment systems on tax compliance. The survey looked specifically at how digital payment techniques may be used to improve tax processing speed and accuracy. The researchers conduct a structured review of the literature on electronic payments, analysing both theoretical and empirical research on the topic of accountability and transparency, to investigate how aspects such as the ability to follow a trail, better record keeping, and increased convenience can foster compliance. While this work deepens understanding of how digital payment channels affect taxpayer behaviour, it does not address AI supported payment monitoring, automated risk profiling of payment patterns or the internal adoption dynamics within tax administrations. The current study therefore extends this line of work by examining, within KRA, the technological, organizational and environmental drivers that impact the AI adoption infused digital tools for monitoring filing, payment and overall tax compliance.

Kabaka (2019) investigates how Kenyan tax compliance is affected by the iTax system. Important factors including taxpayer registration, tax return verification, and enforcement are identified in the study. Kabaka polled major taxpayers in the Domestic Taxes division of KRA using a descriptive survey design. Results indicate that through enhanced registration, verification, and enforcement, iTax has had a favourable impact on compliance. Nevertheless, organizational and environmental drivers influencing the AI adoption in public sector tax systems are not examined in the study. This study bridges the gap by concentrating on the other drivers including organizational and environmental.

Organizational Drivers in Monitoring tax compliance

Tornatzky and Fleischer (1990) aver that organizational context encompasses an organization's various features, such as its size, communication methods, organizational structure, and the available internal slack resources. The organizational factors in this study include management support, organizational readiness, and financial resources.

Maestro and Rana (2024) looked at the organisational, technological, human, and external aspects that affect firms' adoption of AI. In order to determine the factors that promote and hinder AI integration, they methodically examined earlier research using the Diffusion of Innovations (DOI) Theory, the TAM, and the TOE framework. Their findings showed that external pressures, technology preparedness, and leadership support are important adoption drivers, whereas cost, data security, and skill shortages are impediments. The research is however very theoretical and focused on the privately owned businesses. This paper bridges this gap by using the TOE framework on an empirical basis in a setting that is in a public sector, KRA.

Radhakrishnan et al. (2022) examined the organizational and external factors influencing artificial intelligence adoption across twenty international companies through semi-structured interviews. The researchers concluded that leadership dedication, organizational culture, access to expert staff, and inter-departmental cooperation were among the enablers of an effective adoption of AI. It also disclosed that information silos, change reluctance, and doubt of the payback reflected backward progress. Although the study offers interesting information regarding organizational

processes and leadership functions in the implementation of AI, it is a global study of the private companies. It is this gap that this research will fill by exploring the effect of similar organizational elements on the adoption and utilization of AI in tax compliance monitoring in Kenya.

Alsheibani et al. (2018) investigated the essentials that impact the execution of artificial intelligence in companies, concentrating on organizational, environmental, and technological factors. The research utilized a mixed-method strategy that incorporated the Diffusion of Innovations (DOI) Theory and the TOE framework to establish a framework for AI adoption by conducting interviews with experts and surveying businesses. The results have shown that the effective adoption is affected by a mix of positive leadership, sufficient technological maturity, and desirable external factors. The research was however mainly concerned with corporate-level adoption within general business settings, which does not provide much knowledge on the public sector settings. The research fills this gap by using the TOE paradigm to examine how organisational, technological, and environmental variables affect KRA's deployment of AI solutions for tax compliance monitoring.

METHODOLOGY

This survey embraced a descriptive research technique to demonstrate the link between factors, namely how implementing AI technologies influences operational efficiency and the accuracy of tax compliance at KRA. It relied on quantitative data acquired through well-organized questionnaires, but it also included qualitative viewpoints obtained through interviews, allowing the research to cover a wide range of topics while maintaining a more nuanced understanding of what was happening.

This study targets a population of 852 comprising of 732 compliance officers and 120 staff from Business Strategy, Technology & Enterprise Modernisation (BSTEM) unit at the Kenya Revenue Authority Nairobi Region. Monitoring tax compliance AI tools are primarily used by the compliance staff which allows them to give their first-hand experience in terms of its functionality, usability and challenges. Their experiences and perceptions are essential for assessing how organizational, technological, and environmental factors affecting the successful adoption and implementation of these tools at KRA. Staff members with backgrounds in BSTEM are in a unique position to offer insights on KRA's long-term goals for institutional preparedness, AI integration, and alignment with larger reform projects.

Stratified sampling was utilized in this investigation since it worked best with homogenous populations. Unlike simple random sampling, which offered each population an equivalent opportunity of being involved in a sample, stratified sampling used intervals (Saunders, Lewis & Thornhill, 2019). A representative sample of 272 respondents was arrived at.

The study gathered primary data via a structured questionnaire. The questionnaire was structured based on the various study variables including factors driving AI adoption and monitoring tax compliance. Additionally, the questionnaire sourced for qualitative data through relevant open-ended questions to enhance the quality of the data. The choice of the questionnaire was because of its ability to be self-administered, achieve uniformity, and reduce bias (Saunders et al., 2019). Additionally, the study also conducted interviews with managers in the 2 departments (Compliance Unit and BSTEM).

The quantitative data collected was analysed utilizing descriptive and inferential statistics. The mean and the standard deviations for the quantitative data were calculated to help in describing the collected data. Inferential statistics were done using regression model, analysis of variance, and t-tests. These enabled the survey to explore the connection between drivers of AI adoption and monitoring tax compliance at KRA, as well as establish the extent to which these drivers influenced adoption of AI for monitoring tax compliance at KRA. The qualitative data collected was analyzed utilizing the content analysis.

RESULTS

The researcher gave 272 questionnaires to the chosen responders drawn from the Compliance Unit and the Business Systems, Technology and Enterprise Management (BSTEM) departments at KRA. The study achieved a response rate of 91.2% because participants returned 248 completed questionnaires which researchers considered a highly satisfactory result. The study results match Gephart and Saylors (2020) recommendations which state that researchers can analyze data with a 50% response rate while 60% response rate represents good results and 70% response rate shows excellent outcomes.

A review of demographic information indicated that on gender distribution, indicated that most participants in the study were male with 149 respondents accounting for 60.1% of the total sample while 99 female participants represented 39.9% of the 248 total participants. High percentage of male respondents reflects the overall gender distribution in technical departments in KRA, where male members have predominantly occupied technical positions due to historical reasons. Data on age distribution indicated that the largest group of responders belongs to the age group of 31-35 years (35.1%, n=87) followed by those who are in the 26-30 years age group (29.8%, n=74) and 36-45 years age group (20.2%, n=50). There were smaller percentages of individuals in the age groups of 18-25 years (10.1%, n=25) and 46 years and above (4.8%, n=12). Data on levels of education indicated that most participants possess a Bachelor's degree which accounts for 48.8% of the sample (n=121) while the second largest group holds a Master's level (29.8%, n=74) and the third largest group holds a Diploma (12.9%, n=32) and the final group holds a PhD (8.5%, n=21). The high proportion of respondents with Bachelor's and Master's degrees indicates a strong educational foundation which enables them to use AI tools. Data on familiarity with AI indicated that 52.4% of respondents identified as either very familiar with AI tools (35.1%, n=87) or extremely familiar (17.3%, n=43) while 29.8% (n=74) showed moderate knowledge of the tools. Only 17.7% showed slight (12.9%, n=32) or no knowledge of the subject (4.8%, n=12). The high level of awareness among users demonstrates that KRA effectively established basic digital skills through its AI training and awareness programs in its various departments.

Organizational Drivers in AI Adoption in Monitoring Tax Compliance

Participants were requested to rate their agreement with various statements regarding organizational factors using the five-point Likert scale. Table 1 shows the results which were obtained by calculating the mean and standard deviation values.

Table 1: Results on Organizational Drivers

Statements	Mean	Std. Dev
The management at KRA actively supports the adoption and use of AI tools for monitoring tax compliance.	3.94	0.741
KRA provides adequate training to staff on how to use AI tools effectively in their daily compliance monitoring tasks.	3.68	0.823
The organization has sufficient financial resources to support the implementation and maintenance of AI systems.	3.53	0.854
The leadership at KRA encourages innovation and the use of new technologies to improve tax compliance monitoring.	3.86	0.762
There is clear communication from management regarding the objectives and benefits of adopting AI tools.	3.72	0.791
Employees at KRA are well prepared and willing to adapt to new technologies in their work processes.	3.64	0.807
The organizational structure at KRA facilitates collaboration between departments using AI tools for compliance monitoring.	3.59	0.839
KRA's internal policies and procedures support the effective utilization of AI tools for compliance and audit activities.	3.77	0.773
Average scores	**3.72**	**0.799**

Research Data (2026)

Table 1 provides insights into respondents' perceptions of organizational drivers which impact AI adoption at KRA. The mean scores range from 3.53 to 3.94, with an aggregate average of 3.72 and a standard deviation of 0.799, indicating moderate to strong agreement across all eight items among the 248 respondents. The standard deviations of various items show that staff members experienced different levels of organizational readiness to implement AI technology.

Respondents most strongly agreed that management at KRA actively supports the adoption and use of AI tools for monitoring tax compliance (Mean = 3.94, Std. Dev = 0.741). The study results show that leadership dedication to AI adoption functions as a primary factor which organizations need to develop their artificial intelligence capabilities. Senior management who publicly support AI programs demonstrate to employees that the organization considers these programs to be important.

A senior management interviewee echoed this view, stating: *'The Commissioner General's office has been instrumental in championing the digital transformation agenda. Without that top-level visibility, it would be difficult to mobilize the resources and institutional will needed for AI integration.'*

The statement that KRA's leadership encourages innovation and the use of new technologies received a mean of 3.86 and standard deviation of 0.762, suggesting strong agreement. Rogers (2003) shows that an organization's leadership needs to be innovative because this quality affects how new technologies spread through the organization. The internal procedures and policies of KRA which permit AI usage received a rating of 3.77 with a standard deviation of 0.773 because people agreed that these regulations create a favorable environment for AI adoption throughout the organization.

Management's communication regarding the goals and advantages of utilizing AI tools is evident (Mean = 3.72, Std. Dev = 0.791), however the higher standard deviation suggests varying experiences of this communication throughout departments. This supports Radhakishann et al. (2022) who assert that transparent communication within an organization is critical in aligning staff expectations to the goals associated with deploying AI.

One middle manager in the Compliance Unit commented: *'We hear about new systems being launched, but sometimes the rationale and expected operational changes are not communicated early enough to the frontline teams, which creates some uncertainty.'*

Respondents agreed that KRA provides adequate training to staff (Mean = 3.68, Std. Dev = 0.823) and that employees are well-prepared and willing to adapt to new technologies (Mean = 3.64, Std. Dev = 0.807). The higher standard deviations on these items show that staff members from various departments experience different levels of support in their work environments. Mahesh, Vijayapala and Dasanayaka (2018) emphasize that targeted, role-specific training is critical for maximizing technology adoption outcomes, particularly in data-intensive environments.

The statement that organizational structure facilitates inter-departmental collaboration using AI tools recorded the lowest mean of 3.59 and highest standard deviation of 0.839 which showed moderate agreement but produced significant score differences. Ghani, Ariffin and Sukmadilaga (2022) state that organizational structures block cross-functional collaboration which organizations need to implement effective AI-driven compliance monitoring. The statement concerning KRA's financial resources for AI implementation recorded a mean of 3.53 and standard deviation of 0.854 the lowest and most dispersed scores in this section suggesting that budget constraints remain a notable concern. Mpofu (2024) shows that developing-country revenue administrations face AI adoption obstacles because of their insufficient financial resources.

Respondents widely acknowledged the critical role of management support in facilitating AI adoption. One departmental head stated: *"Top management has been very supportive in terms of championing digital transformation, which has motivated staff to embrace AI tools in their daily operations."* This support has been reflected in policy direction, resource allocation, and strategic prioritization of digital initiatives.

Despite this, several organizational challenges persist. A respondent from the Domestic Taxes Department noted:

"There are still gaps in staff training, and not all employees feel confident using the systems to their full potential." Others cited inadequate funding for system upgrades, limited cross-departmental collaboration, and resistance to change among some staff as barriers to effective AI implementation.

To enhance adoption, respondents suggested increased investment in capacity building, continuous professional training, improved internal communication, and stronger collaboration across departments. One manager emphasized: *"Regular training and knowledge-sharing forums would go a long way in ensuring that all staff are aligned and capable of leveraging AI tools effectively."*

AI Adoption in Monitoring Tax Compliance at KRA

The study measured AI adoption levels utilized for tax compliance monitoring at KRA as its dependent variable. Participants were requested to rate their agreement with nine statements on a five-point Likert scale. The standard deviations and means were computed, and the results are presented in Table 2.

Table 2: Results on AI Adoption in Monitoring Tax Compliance

Indicators	Mean	Std. Dev
The utilization of AI tools has improved the accuracy and timeliness of tax filing at KRA.	3.96	0.743
Taxpayers are more likely to file returns on time due to enhanced tax monitoring systems.	3.74	0.781
The integration of AI tools has improved the accuracy of payment tracking and reconciliation.	4.01	0.712
KRA's AI systems effectively identify cases of delayed or incomplete tax payments.	3.88	0.754
Risk profiling tools have enhanced KRA's ability to detect potential tax evasion and non-compliance.	4.09	0.721
Predictive analytics and data-driven insights have improved audit targeting and compliance interventions.	4.04	0.736
AI tools have reduced manual errors and increased transparency in compliance monitoring.	3.91	0.758
The overall effectiveness of KRA's compliance monitoring has improved since the adoption of predictive AI systems.	3.97	0.741
The use of AI technologies has strengthened KRA's ability to assess taxpayer behaviour and compliance trends.	4.03	0.728
Average scores	3.96	0.742

Research Data (2026)

Table 2 displays the views of respondents about the results of AI adoption for tax compliance monitoring at KRA, which were assessed by 248 respondents. All nine items showed strong agreement from participants whose mean scores about them ranged between 3.74 and 4.09, resulting in an overall average of 3.96 and standard deviation of 0.742. The results demonstrate that AI adoption has produced significant and visible advancements in KRA's compliance monitoring operations.

The KRA's ability to identify potential tax evasion and non-compliance has improved through the implementation of risk profiling tools which produced a high mean score of 4.09 with a standard deviation of 0.721. The findings of Rahman et al. (2024) show that AI systems which use risk profiling techniques achieve superior accuracy in identifying high-risk taxpayer groups when compared to traditional methods of sampling. The combination of predictive analytics with data-driven insights has improved both audit targeting and compliance interventions (Mean = 4.04, Std. Dev. = 0.736) while AI systems have enhanced KRA's capacity to monitor taxpayer conduct and compliance patterns (Mean = 4.03, Std. Dev. = 0.728). Organizations should implement predictive analytics for tax audit selection because Jones and Lee (2024) demonstrate that the technology has transformed developed economies while emerging markets begin to adopt it.

The usage of AI tools has enhanced payment tracking accuracy which leads to better reconciliation results (Mean = 4.01, Std. Dev = 0.712), while the implementation of AI technology has improved all aspects of compliance monitoring for organizations (Mean = 3.97, Std. Dev = 0.741). The implementation of AI tools has enabled organizations to achieve better tax filing results through improved accuracy and timely submissions (Mean = 3.96, Std. Dev. = 0.743), while AI tools decreased human errors and enhanced system transparency (Mean = 3.91, Std. Dev. = 0.758). The research conducted by Saragih et al. (2023) demonstrates how AI integration brings operational advantages to tax modernization efforts in Indonesia.

KRA's AI systems effectively identify cases of delayed or incomplete tax payments (Mean = 3.88, Std. Dev = 0.754), and taxpayers are more likely to file returns on time due to enhanced monitoring systems (Mean = 3.74, Std. Dev = 0.781), the latter recording the lowest mean. The results show that taxpayer behaviour changed only slightly because AI systems improved KRA's internal monitoring which needs more development to decrease taxpayer non-compliance. This evidence supports James and Alley (2024) who demonstrate that sustained enforcement visibility throughout time directly improves compliance through deterrence mechanisms.

CONCLUSIONS

The study concluded that organizational drivers play a critical facilitative role in the adoption of AI at KRA. The organization achieved positive results for AI integration because its leaders showed commitment to digital transformation and their institutional policies supported this work while the employees maintained an open attitude toward digital transformation. The organization faces several challenges because its staff lacks the necessary skills and training resources while financial support remains limited and different departments fail to work together. The organization needs to establish stronger support systems which will help it achieve its strategic goals through effective operational implementation. The research

demonstrates that the Kenyan Revenue Authority uses artificial intelligence for tax compliance monitoring through three different technological, organizational, and environmental factors which drive their operations. The research shows that technological elements function as the main drivers which enable artificial intelligence to achieve its optimal performance through advanced analytics and machine learning technologies that enhance both efficiency and accuracy while supporting better decision making during compliance activities. The research shows that technological improvements depend on three conditions which must be satisfied to achieve optimal results: system usability, infrastructure compatibility, and equitable access across departments. This research shows that technological sophistication does not guarantee optimal performance because it depends on system usability and infrastructure compatibility and equitable access across departments.

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