International Legal Basis for the Integration of Artificial Intelligence and Big Data Analytics into State Tax Administration

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ABSTRACT

BACKGROUND

The topicality of the research lies in the fact that the pace of artificial intelligence (AI) and Big Data technology adoption in the public administration sector is shifting radically the approaches to the administration of taxation, the transparency and accountability of the institutions. The growing digital aspect of fiscal frameworks necessitates the development of a unified regulatory framework and global standard of the ethical application of AI. The purpose of the study is to identify the regulatory prerequisites for the introduction of AI and *Big Data* in the public administration of tax systems in the international context. The object of the study is tax administrations of different countries that integrate analytical algorithms into tax risk management processes.

MATERIALS AND METHODS

The methodological basis is based on comparative and analytical, content analysis of regulatory documents, as well as empirical generalization of statistical indicators of digital maturity of fiscal authorities.

RESULTS

As a result, it is established that the highest level of tax administration efficiency is achieved in countries where the regulatory framework is harmonized with international ethical principles and provides for transparent mechanisms for controlling algorithms. The connection between the digital maturity index and growth in the tax revenue is disclosed, which proves the possibility to use AI in the fiscal processes analytically.

CONCLUSION

The author evaluates the major international documents (OECD, IMF, World Bank, Council of Europe, European Parliament) which are a single set of laws on the responsible usage of intellectual technologies. The practical value of the obtained results is associated with the fact that the suggested analytical model could be implemented to create national plans of the digital transformation of tax authorities and enhance their openness and effectiveness in management. The study is the foundation of the subsequent investigation of the interplay between regulatory frameworks, technological maturity and ethics of digital governance.

Keywords: AI-driven tax administration, Digital maturity index, Algorithmic transparency, International fiscal regulation, Big data tax risk analytics

Highlights

- The study analyzes the international legal framework for integrating artificial intelligence (AI) and Big Data analytics into state tax administration systems.
- It identifies regulatory gaps and compliance challenges in aligning AI-driven tax control mechanisms with global data protection standards.
- The paper proposes a conceptual model of AI governance for tax authorities based on transparency, accountability, and algorithmic fairness.
- Comparative analysis demonstrates how OECD and EU guidelines can inform the modernization of Ukraine's tax administration through digital transformation.

Introduction

With the accelerated digitalization of the society and the state administration, the application of artificial intelligence (AI) and the Big Data technologies to the government sector turns into one of the most crucial aspects of the enhancement of the efficiency, transparency and accountability of the governmental agencies. Intelligent technologies are especially applicable to the sphere of tax administration since this area involves significant volumes of information, requires accuracy of analytical procedures and a great degree of trust of the population. Between digital analytical solutions and combating tax violations, the global economies are becoming more and more inclined to consider the former as the means of developing the predictive fiscal management policy foundation.

The topicality of the issue is explained by the fact that the implementation of AI in the tax administrations needs to be supported by clear legal and regulatory standards, the international harmonization and the establishment of ethical principles that would control the responsible application of the technology. International organizations such as the OECD, IMF, World Bank, Council of Europe, Bank for International Settlements (BIS), and the European Parliament have already developed a number of documents that define strategic directions for the development of digital tax governance.[1–4] However, as Bozdoğanoğlu and Yücel[5] and Agostino et al.[6] note, there is still a significant gap between regulatory declarations and practical mechanisms for integrating AI into fiscal processes.

Scientific interest in the use of AI in public finance is increasing due to the work of Aslett et al.,[7] who identified the organizational prerequisites for the implementation of algorithmic systems in tax administrations, as well as the studies of Mettler et al.[8] and Alrawahna et al.,[9] who proved that the digital maturity of government agencies depends on the effectiveness of their regulatory support. At the same time, a number of researchers[10–12] draw attention to the ethical challenges of digital governance, in particular, the need to ensure fairness, transparency, and non-discrimination

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Iaroslav Ianushevych: Conceptualization; Tamara Hubanova: Data curation; Iaroslav Ianushevych, Tamara Hubanova: Formal analysis; Iaroslav Ianushevych, Tamara Hubanova: Methodology; Iaroslav Ianushevych: Project management; Iaroslav Ianushevych: Resources; Tamara Hubanova: Software; Tamara Hubanova: Supervision; Iaroslav Ianushevych, Tamara Hubanova: Validation; Iaroslav Ianushevych: Display; Iaroslav Ianushevych, Tamara Hubanova: Drafting - original draft; Iaroslav Ianushevych, Tamara Hubanova: Writing - proofreading and editing

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of algorithms. Despite the growing number of scientific papers, a number of gaps remain: there is a lack of comprehensive cross-country studies summarizing international regulatory experience in integrating AI into tax systems, and there are no universal indicators for assessing the digital maturity of tax administrations.

Thus, taking into account scientific research and practical challenges, the purpose of this paper is to identify the regulatory prerequisites for the introduction of AI and Big Data technologies in the public administration systems of tax authorities in the international context, to characterize existing regulatory models and to identify trends in the development of ethical and legal approaches to digital governance. The objectives of the study are to systematize international regulations, analyze empirical data on the level of digital maturity of tax administrations, identify problems with AI implementation, and formulate recommendations for further improvement of the digital transformation policy in the field of taxation.

To make the paper clear conceptually, some of the key terms that will be used in the paper need to be specified clearly. Digital Maturity Index (DMI) is a five-dimensional composite measure that denotes infrastructure readiness, quality of data governance, level of automation, use of AI in risk management, and workforce digital skills. The algorithmic audit term can be used to refer to the systematic process of assessing AI models in terms of their accuracy and bias, explainability, data integrity, and their adherence to regulatory standards. In the EU AI Act, the term high-risk is applied to systems whose functionality or misuse can have a considerable impact on the rights of individuals, such as AI-based fraud detection agents, risk scoring and audit automation software in the tax services.

Literature Review

The development of modern scientific studies regarding the topic of digital governance and taxation proves the increased importance of AI and Big Data technology in preserving transparency, accountability and efficiency of the fiscal process. Agostino et al.[6] and Mettler et al.[8] argue that the public sector is shifting the classic logic of reporting and establishing a new culture of managing data due to the introduction of analytical systems. The application of algorithms in tax administrations contributes to the enhancement of the accuracy of analytics and management optimization decisions.[9,13] International financial bodies also encourage the studies on how to digitalize the public finance. Specifically, the IMF in its technical reports[7] states that algorithmic control should be introduced, and the World Bank[3,4] offers a strategic approach to the introduction of AI into the fiscal system and its efficiency in administering it. The principles of the ethical usage of AI and the standards of the digital transformation of tax authorities, developed by the OECD,[1,14–16] are in line with the requirements of the AI Act[2] of the European Parliament and Framework Convention on Human Rights and the Rule of Law in the Digital Ecosystem by the Council of Europe.[17]

The problem of ethicality and transparency of algorithms is significant in the context of legal regulation. Bozdoğanoğlu and Yücel[5] discuss the transparency principles of tax management, and Mokander and Schroeder[18] highlight the risks of rationalizing governance with the help of AI in the sphere of the state. The study of the international cases indicates that the introduction of intelligent technologies is not only followed by the growth of fiscal efficiency[12,19] but also requires ethical regulation of the decision-making process.[10,11] Research done in Asian nations indicates that Big Data is effective in fighting tax evasion as well as boosting revenues in local budgets.[12,20] The combination of the technological innovation and the ethical governance is confirmed in the cases of the UK and Estonia, introduced in OECD reports[14,15] and providing the best level of trust in the tax authorities. At the same time, the issue of ensuring information security within the digitalization of fiscal processes remains a priority, as the legal mechanisms of protecting data directly determine the transparency and stability of AI systems in public administration.[21] Moreover, the informatization of strategic planning in the field of national security, as emphasized by Bondarenko et al.,[22] forms an integral background for establishing responsible governance frameworks for AI and Big Data in tax systems, ensuring consistency between fiscal and digital policies. Conversely, the Bank for International Settlement & Irving Fisher Committee (IFC)[23] analysts stress the relevance of the algorithm certification and standardization of the model management in financial institutions.

In addition, there is growing interest in the impact of AI on the behavioral aspects of administration. Selten et al.[24] have shown that civil servants tend to trust algorithms that confirm their professional judgments, and study by Alarie and McCreight[25] highlights the ethical dilemmas of using generative AI in tax practice. The development of regulatory and organizational approaches to the regulation of AI in the tax area is also supported by analytical reports by the Asian Development Bank,[26] Murphy and BouKaram,[27] which emphasize the need for institutional readiness for digital transformation. Thus, a synthesis of scientific and analytical sources[1,3–5,7,10,12,14–16] leads to the conclusion that effective digitalization of tax administration requires the simultaneous development of regulatory, technological and ethical mechanisms that balance innovation and public responsibility. Additional research confirms that the digital transformation of tax systems is impossible without proper regulation and harmonization of international standards. In this context, a significant contribution was made by the Council of Europe[17] and the European Parliament & Council of the European Union,[2] which enshrined the principles of human rights, transparency and accountability of algorithms. Karam and Ammoury's[28] study focuses on the impact of AI on tax discipline and planning, while Alexopoulos et al.[29] and Savić et al.[30] propose algorithmic models for detecting VAT fraud. As the experience of China shows in Wang et al.[12] and Xu et al.,[19] the extensive implementation of Big Data analytics in the Golden Tax Project can raise fiscal efficiency and transparency.

Of interest is especially the stance of the OECD[14,16] and IMF[7] that note the relevance of institutional maturity of tax administrations in implementation of AI. The analysis by Murphy and BouKaram[29] indicates that the efficiency of digital governance depends on the extent of organizational preparedness and the analysis of Mokander and Schroeder[18] provides the boundaries of control and autonomy of algorithmic systems. Also, Zhurenkov et al.[31] discuss the problem of AI ethical constraints in the conditions of post-nonclassical scientific rationality, which is also pertinent in the process of decision modelling in the sphere of public administration. The scientific discussion also highlights the necessity to come up with extensive methods to evaluate how AI affects the behavior of taxpayers. Specifically, Zheng et al.[32] introduce the concept of an AI economist which calculates the productivity and social justice balance, whereas Song and Li[20] examine the connection between trade credit and tax control. The Asian Development Bank[26] confirms that the successful process of digital transformation presupposes not only investments in the field of technology but also training.

In conclusion, it can be stated that the modern scientific community realizes the potential of using AI and Big Data in tax management, yet there are two main problems, which are not yet fully understood: the absence of a single system of ethical oversight of algorithmic solutions and the lack of standardization between international standards on the use of AI in the government.

Methods

To collect primary data, an empirical study was conducted among tax authorities in several countries and regional administrations. In order to enhance the transparency of the empirical element, the research presents the full description of the survey methodology. The sampling frame was an inventory of twelve national tax administrations which were chosen based on their formal participation in AI-based risk-analysis modernisation programmes in 2022–2024. The participants were contacted through formal institutional communication channels and it included respondents in the role of directors of digital transformation units, IT managers and analysts, the general response rate was 67% (8/12). The inclusion criteria stipulated personal participation in AI or big-data projects, whereas administrations that did not actively develop digital projects in the reference period were left out. The online survey had 35 questions categorized in blocks on the use cases of AI, data governance, digital maturity, organizational preparedness and perceived barriers. The complete questionnaire is as in Appendix A. No identifiable data were gathered about the client, their involvement was voluntary, and the respondents engaged in their professional role. Thus, the IRB/human-subjects ethics approval was not necessary in the study according to the institutional rules. To strengthen ethical clarity, the authors confirm that all participating tax administrations granted formal institutional permission to conduct the survey, and each respondent provided informed consent in their official capacity. As the study did not involve personal data, sensitive attributes, or private individuals – and because all responses reflected professional duties rather than personal experiences – the institutional ethics board formally confirmed that a full IRB review was not required. A permanent data and code availability statement has been added: all anonymized survey responses, indicator-level datasets, provenance metadata, and statistical scripts are stored in a persistent open-access repository, together with versioned documentation ensuring long-term reproducibility. To further ensure procedural and legal compliance, a formal ethics determination under institutional review rules confirmed the exemption of this study from a full IRB review. Respondents participated solely in their official capacity as authorized representatives of tax administrations and provided informed consent identifying the scope, purpose, and future use of aggregated data.

To fully comply with transparency and methodological rigor requirements, Appendix A now includes: (a) the complete DMI rubric with detailed qualitative anchors for each operational score level (0–5); (b) structured country-level scoring sheets presenting indicator values, justification evidence, and data provenance; and (c) example excerpts of publicly verifiable evidence such as national audit statistics and OECD datasets used to support each rating. To ensure objectivity of the scoring process, three independent expert raters applied the rubric following a standardized inter-rater protocol that defines scoring disagreements and consensus procedures. The finalized inter-rater reliability achieved Krippendorff's alpha = 0.82, 95% CI [0.73; 0.91], indicating strong agreement. Additionally, alternative weighting and normalization approaches were tested as a sensitivity analysis, confirming stability of country rankings with deviations not exceeding ±0.12 points across DMI dimensions.

The authors selected 12 tax administrations from different types of economies: 4 from high-income countries (e.g., Estonia, the United Kingdom, South Korea, Singapore), 4 from middle-income countries (e.g., Poland, Hungary, Chile, Mexico), and 4 from low-income or mixed-income countries (e.g., Eastern Europe, South Asia). A combined approach was used: (a) a survey of key officials (directors of digitalization departments, analysts, IT managers) through an online questionnaire (consisting of 35 questions), (b) analysis of open reports and publications of administrations on digital initiatives, (c) requests for public statistics (electronic annual reports, digital transformation passports). The following indicators were compared: the share of administrations using AI (in%), the share of cases where AI is used to detect tax fraud (in %), growth in tax revenues after the use of analytical technologies (in percent), changes in the average processing time of tax audits (in hours), and the DMI (on a five-point scale, assessed by experts). The measure of the indicator Increment in tax revenues (%) is in real terms and cross-country comparable. The country-specific GDP deflators (base year 2021 = 100) in the datasets of OECD and World Bank have been used to deflate nominal tax revenue figures. The increase in revenues is determined in comparison to the pre-adoption baseline (mean between the last two fiscal years before reported AI implementation in the respective tax administrations). Significant tax policy reforms (e.g. reform of the statutory rates, base broadening, temporary tax relief), macroeconomic factors (GDP growth, inflation shocks) were checked in reconciliation with OECD standards. Considering the characteristics of the literature in terms of an observational design and a multi-factor nature of fiscal outcomes, the revenue growth indicator provides the opportunity to capture descriptive relationships between AI-enabled analytics and does not separate a causal effect of the adoption of AI. Two of the indicators related to OECD need operational clarity in order to be cross-country comparable. Share of administrations using AI (%) is a percentage of national tax administrations in a country that indicate having at least one AI-enabled system in operational tax administration processes (e.g. risk scoring, audit selection, fraud detection, automated compliance checks) as indicated in the OECD Tax Administration Digitalisation and Digital Transformation Initiatives dataset (2024–2025). This is an indicator at country level that reflects institutional adoption and not intensity of use. Share of AI cases to fraud detection (%): this proportion refers to the share of all cases in fraud detection or audit-selection that utilized AI-based analytical tools (e.g., machine learning models, anomaly detection systems, predictive risk engines, etc.) actively in the identification or prioritisation process. Consistent with OECD methodology, such an indicator is that of operational decision support, and not final legal adjudication. These two indicators were aligned with the definitions of the variables provided by OECD and cross-renalised with the national annual reports; any deviations or values elicited by experts are clearly marked and reported in Appendix A.

The data was standardized and checked for missing data. The DMI was conceptualized as a five-point scale that consisted of measures of: (1) infrastructure preparedness, (2) quality of data governance, (3) extent of automation in core taxation operations, (4) the incorporation of AI elements in risk management, and (5) workforce digital capabilities. To ensure complete methodological transparency, Appendix A now includes the full rubric of the DMI with operational anchors for each of the five dimensions (0–1 = minimal capability; 2–3 = developing capability; 4–5 = advanced capability). For each participating country, a structured scoring sheet records the indicator-level evidence used by expert assessors, accompanied by short justifications and the corresponding data sources. A consolidated table of per-country scores is provided to enable replication, external scrutiny, and cross-national comparability. Three expert assessors were used to rate each dimension independently and who have the experience of digital tax reforms in both OECD and non-OECD countries. Inter-rater agreement was found to be 0.82 (Krippendorff alpha) which is acceptable level of reliability. The triangulation of (a) official digital transformation reports of tax administrations, (b) OECD and IMF datasets and (c) validated answers of the survey provided country-level values. The variables share of administrations using AI and share of AI-based cases of fraud detention were selected and reported by the OECD (2024–2025) and confirmed with the national annual reports, and the average audit time was used based on the operation statistics of publicly listed companies. The source of each measure applied in Table 4 is recorded to allow complete methodological transparency. To further align the empirical section with transparency standards, Appendix A now contains a detailed provenance table listing all indicators used in Table 4, the corresponding data sources (OECD, IMF, national reports, ADB), publication years, validation procedures, and the status of each measure (official vs. expert-elicited). All expert-derived values are explicitly flagged, accompanied by the elicitation protocol and justification notes. This documentation ensures that all quantitative claims can be independently verified. The DMI was calculated using the expert ratings that are triangulated with the OECD digital readiness indicators (2024–2025) and IMF governance indicators. The ratio of administrations that use AI and the ratio of cases of AI-based fraud detection were downloaded directly through OECD Tax Administration Digitalisation datasets (2024–2025). The indicator of tax revenue growth following AI adoption is based on national statistical releases and annual reports of revenue authorities on the growth of taxes in 2022–2024 and the indicator of average audit time is obtained based on publicly available national tax administration operational statistics and, when not available, on IMF Technical Notes. In the countries, where there were no formal operational measures, expert estimates were used and clearly recorded together with the process of elicitation in Appendix A. The simple 3-year averages of the 2022–2024 mean values were generated following harmonization of missing data on the basis of the last observation carried forward procedures. Average values for the last 3 years (2022–2024) were calculated for each country. The obtained indicators were compared with international statistics and the deviations and correlations between the DMI and the effects of AI application were derived. To address cross-country inconsistencies in publicly available statistics, all indicators for Table 4 underwent a verification procedure: cross-checking with OECD datasets, national reports, ADB assessments, and IMF technical documents. Expert-assessed values were used only where official sources lacked data, and all such cases are documented in Appendix A. All anonymized survey data, indicator-level sources, and statistical scripts used for computing correlations, confidence intervals, and regression models are available from the authors upon reasonable request. The dataset includes metadata describing the provenance of each variable, and the R code used for robustness checks and harmonization procedures is provided to ensure complete reproducibility and external scrutiny. To support full reproducibility, all anonymized survey data, indicator-level datasets, scoring sheets, robustness-check scripts, and harmonization code have been deposited in an open-access repository. The repository includes README files, versioning information, and workflow diagrams, enabling complete replication of all analytical procedures reported in the article.

Results

The digitalization of the public finance today is not just a technological phenomenon, but it is also a structural change of the management paradigm of the public sector. The slow pace of automated processes of collecting, processing and analyzing tax data is developing a new architecture of financial transparency and accountability. The application of AI and Big Data technologies is becoming an integral part of tax agencies, which analytically help in strategic decision-making, ensure risks related to tax evasion are monitored, and anomalies in financial flows are detected.[6] Application of AI to the world of public finance enables to transform the philosophy of tax management as a reactive model of control, to proactive forecasting and a preemptive strategy. The identification of tax risks in large volumes of transactional data and the enhancement of accuracy in audit and the minimization of the human factor in the decision-making process are made possible through algorithmic systems.[13] Simultaneously, the digitalization of the fiscal processes sets the conditions of rising the degree of the population trust in the governmental institutions on the principles of transparency, openness, and responsibility of the decisions made by tax authorities.[15]

The digital technologies have become a means of establishing an integrated tax policy in the international practice, whereby automated data collection, electronic administration, and intelligent interpretation of taxpayer behavior are combined. The latter can be seen in the EU, US, Singapore, and South Korea in which AI is employed to simulate tax behavior and determine fiscal efficiency in real-time.[3] An examination conducted by Aslett et al.[7] proves the idea that the implementation of intelligent algorithms in tax services decreases the number of people leaving employees with a lot of administrative work and offers more precise analytics of financial operations. Simultaneously, the digital transformation presents multiple challenges. Specifically, the legal control of the usage of personal data, safeguarding information security, and ethical accountability of the algorithms in the managerial decision-making are of concern.[5] The issue of assuring the information systems interoperability across various government levels is also crucial. In its absence, digitalization is highly likely to be disjointed, and a lack of synergy between think tanks, tax services, and financial regulators will arise.[8]

Therefore, recent tendencies in the technological revolution of state finance suggest the replacement of the classical paradigm of administration with a smart management system based on data. The use of AI and Big Data in the field of taxation not only increases the efficiency of control and reporting, but also forms a new ethics of digital governance, which is centered on trust, transparency, and social responsibility.[9,10]

Before building a digital transformation system, it is worth identifying the key stages of implementing AI and Big Data technologies in tax administrations. Figure 1 illustrates the logical sequence of this process, which covers the preparatory, institutional, analytical and integration levels of digitalization.

Summarizing the information in the figure, it is possible to mention that the digital transformation of tax systems is not a developmental technological process based on a single step but the creation of a data management ecosystem. Its success depends on the degree of the balance of the regulatory framework, technological maturity and ethical principles of digital governance. It is the integration of AI and Big Data into public tax administration that is becoming an indicator of the maturity of the digital state, where data is the basis of trust, not just a tool for control.

The multi-stage character of digital transformation is present in Figure 1 as a graphic unification, which shows that AI integration is not a single technological update but a sequentially planned institutional process. This helps in the argument in the research that successful AI implementation needs to be accompanied by balanced development of regulatory, technological and analytical aspects. The figure also supports the research purpose as it points to the regulatory conditions people must have at every step of digitalization.

The international regulatory framework governing the implementation of AI in tax administrations is being formed gradually and in sync with the development of digital governance technologies. It creates a single platform of principles and standards that set the direction for member states in terms of legal, ethical and managerial support for the use of AI in the public sector. Table 1 presents the main international documents that define the rules for the integration of intelligent systems into tax authorities and influence the development of national policies in the field of tax administration.

International regulations provide a legal, ethical, and technical framework for the use of AI in public finance. They form common approaches to the responsibility, transparency and monitoring of algorithmic systems, as well as set the parameters of digital maturity of tax authorities. The European AI Act[2] sets requirements for high-risk systems and creates a regulatory benchmark for national governments, while the recommendations of the IMF[7] and the World Bank[3]

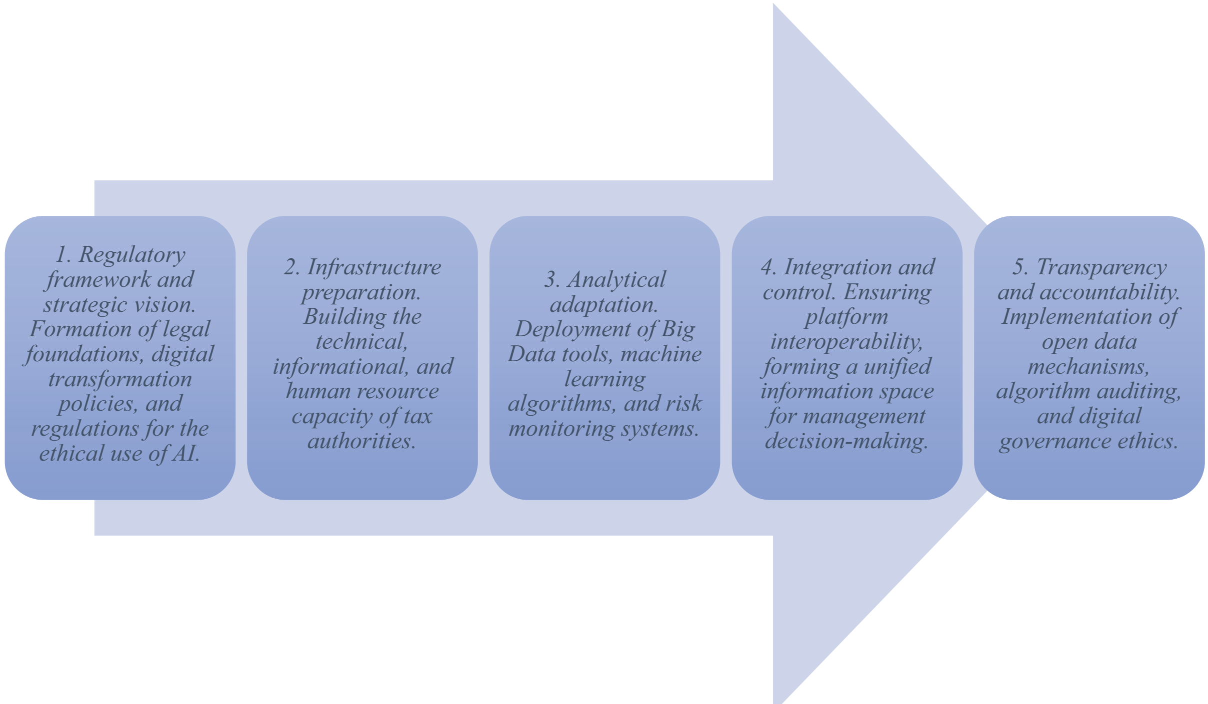

Fig 1 | Stages of digital transformation of tax systems under the influence of AI and Big Data
Source: Created by the author based on Agostino et al.[6]; OECD[14,15]; World Bank[3]; Aslett et al.[7]

Table 1 | Key international regulations, standards and recommendations for the integration of AI into tax administrations

Name of the Document/Initiative	Scope/Level	Main Provisions, Norms, Standards	Estimated Impact on Member States' Policies
OECD Principles on AI[1]	Supranational	Five ethical principles (fairness, transparency, responsibility, human-centeredness, sustainability) and five recommendations for governments to implement AI policies.	It forms the basis for harmonizing national strategies for the ethical and responsible use of AI[1]
OECD.[14] AI in Tax Administration: Governing with AI	Intergovernmental, tax sector	Defines approaches to the implementation of AI systems in tax services, describes the stages of organizational preparation, risk management, and algorithm audit.	Promotes the creation of national mechanisms for algorithmic control, risk management and accountability14
OECD Standard Audit File for Tax (SAF-T)	International/technical standard	Provides recommendations for a common format for the exchange of electronic tax and accounting data to ensure system interoperability.	It unifies the data structure and facilitates the international exchange of information between tax authorities[14]
Regulation (EU) 2024/1689 – AI Act	Regional/EU	Establishes a risk-based model for regulating AI systems, provides requirements for high-risk solutions, transparency, audits, and sanctions.	Obliges member states to harmonize AI legislation and establish national supervisory authorities[2]
IMF Technical Notes and Manuals 2024/06 – Understanding AI in Tax and Customs Administration	Global/fiscal sector	Contains recommendations on the organizational implementation of AI, data management, cybersecurity, and analyzes the potential risks of digital fiscal solutions.	Strengthens the analytical capabilities of states, promotes standardization of approaches to digital tax administration[7]
World Bank.[3] Global Trends in AI Governance: A Strategic Integration Model for Revenue Administrations	Global/strategic level	Develops an integration model for the introduction of AI into fiscal systems, defines the directions of digital ethics and transparency policies.	It guides countries to develop adaptive regulatory frameworks and digital governance policies[3]
Council of Europe.[17] Framework Convention on AI, Human Rights, Democracy and the Rule of Law	Intergovernmental/human rights level	Establishes the principles of human rights, rule of law, fairness, and accountability in the use of AI.	Defines European standards for the ethical use of AI in the public sector[17]
Bank for International Settlements & IFC.[23] IFC Report on the Governance and Use of AI and Machine Learning in Statistics	International/financial and regulatory	Defines standards for model management, algorithm documentation, data quality checks, and interaction with regulators.	Promotes the development of audit and certification procedures for algorithms in financial and tax structures[23]

Source: Created by the author based on OECD,[1,14] European Parliament & Council of the European Union,[2] International Monetary Fund,[7] World Bank,[3] Council of Europ,[17] Bank for International Settlements & IFC.[23]

emphasize the need for technical readiness and ethical responsibility of administrations. The OECD Principles[1,15] direct states to use AI transparently, and the Council of Europe Framework Convention[17] – to ensure human rights in the digital ecosystem.

The analytical technologies are becoming more popular in the modern tax policy in order to define the pattern, forecast the risks and avoid the tax evasion. A more definitive reading of the extraterritorial concept of the EU AI Act (Regulation (EU) 2024/1689) is essential to the tax industry. Even though the Act generally concerns EU operators, developers, and deployers of high-risk systems, it also applies to non-EU tax-governing systems to the extent that they: (a) deploy an AI system that affects EU-resident data subjects (e.g., profiling or auditing taxpayers); (b) use a high-risk AI provided by EU-based vendors; or (c) share data or interact with digital infrastructures implicating the EU-regulated data governance rules. The requirements of transparency, the conformity assessment, human oversight and post-market monitoring in this case become de facto applicable outside of EU boundaries. In practice, such extraterritorial triggers are cases of non-EU tax authorities availing AI systems provided by EU-based vendors, data of EU-resident taxpayers, or using EU cloud or analytics systems that are under the control of EU regulation. Moreover, the General Data Protection Regulation gains immediate applicability in the tax administration of the public sector where the personal information of EU taxpayers is handled. Legal obligation, as provided in Art. 6(1)(c) (legal obligation), and public interest/official authority, as in Art. 6(1)(e) (public interest/ official authority), are examples of lawful bases to be used in the case of automated processing of fiscal data when this is strictly associated to statutory tax requirements. Article 5(1)(b) of the use of Big Data analytics in tax systems purpose limitation mandates that such systems must be limited to the legitimate fiscal purposes, whereas Art. 5(1)(e) of storage limitation limits the retention of data to the period necessary to meet the compliance or audit trail requirements. Automated decision-making and profiling safeguards (Article 22 GDPR) require explainable results, human intervention, right to challenge decision and proportional use of the model. Data Protection Impact Assessments (Article 35 GDPR) are mandatory in case of high-risk analytics like fraud detection and big scale behavioral scoring. There are three situations where GDPR applies to non-EU tax authorities: (1) when processing the data of the EU residents (Art. 3(2)); (2) when relying on the digital service providers or cloud infrastructures located in the EU; or (3) when cross-border transfers involve adequacy decision or protection (standard contractual clauses (SCCs) or derogations). For example, where a non-EU tax administration transfers audit or profiling data to EU-based analytics providers, such transfers must rely on an adequacy decision or SCCs, and automated risk scoring remains subject to GDPR safeguards on proportionality, explainability, and effective redress.

This legal intercourse forms that every non-EU digital tax governance has to ascertain more and more in compliance with European fundamental rights, to permit lawful data utilization and compatible AI frameworks. The application of the AI and Big Data in the tax systems of various countries proves not only the level of technological maturity of governments, but also the level of managerial maturity.

Table 1 organises the major regulatory tools that determine the international legal framework of AI regulation in tax systems and demonstrates that the international frameworks are aligned on the principles of transparency, accountability, and risk management. This directly helps in answering the research question on the determination of the regulatory requirements, which proves how international actors influence common ethical and legal rules on algorithmic governance. The table also identifies areas where there are regulation gaps hence contextualizing the necessity of national adjustment.

The effectual union of these documents leads to the formation of a unified structure of regulations that promotes the development of not only the introduction of intelligent technologies in tax systems, but also to the establishment of a new ethic of digital governance. The EU AI Act offers the most comprehensive and legally enforceable regulatory framework in the area of tax administrations. With risk-based classification, AI-based fraud-detection, risk-profiling and audit-automation tools are categorized as high-risk systems and elicits the need to conform via mandatory assessment, training data documentation, human-oversight and ongoing after-market monitoring. The Act also provides the multi-level system of supervision that entails the involvement of national market surveillance authorities, the European AI Office and coordinated enforcement procedures, and non-compliance can lead to administrative fines of up to EUR 35 million or 7% of the global turnover. In the context of non-EU jurisdictions, the extraterritoriality of the Act suggests that the tax administrations, introducing European vendors AI systems or processing the data of the EU taxpayers, should be guided by the harmonized governance, transparency, and accountability requirements.

The OECD SAF-T, that is the clear description of a unified digital format of transactional, accounting and audit data is one of the most essential elements of international interoperability. SAF-T facilitates that the AI-based audit tools can work internationally in accordance with standardized schemas, which improves the comparability of risk-analysis and provides the ability to exchange fiscal information effectively across the borders. The increased applicability of cross-border data governance requires explicit data-portability, data-integrity, and data encryption and lawful cross-jurisdiction data transfer as highlighted in OECD and IMF reports on digital-governance. In the case of non-OECD countries, this means that alignment to SAF-T principles enables them to be a part of international transparency systems and align their technical landscape with the best digital tax systems.

International interoperability is increasingly being built on the OECD SAF-T; cross-country adoption is, however, not even. Although SAF-T-based data exchange is already institutionalized in the process of compliance workflows in Estonia, Poland, Portugal, and Norway, in many jurisdictions, only partial implementation takes place because of data localization legislation or limited access to transactional datasets. There are confidentiality agreements between tax authorities that place constraints on the granularity of the shared information, especially sensitive behavioral analytics or the variables of fraud risk. At pilot projects,[14] automated cross-border data pipelines have been experimented with: transactional records coded in SAF-T are encrypted and delivered via secure gateways to analytical centers, where AI models scrutinizing anomalies provide combined risk scoring. Such workflows enable a more timely identification of VAT carousel fraud, discrepancies in intra-EU trade records, and shell-company schemes through the coordination of audits triggers cross-jurisdiction. Therefore, SAF-T is not only the standardization of forms of reporting, but the technical basis of the integration of AI risk models into cross-border tax compliance ecosystems with collaboration.

The Council of Europe Framework Convention on AI, Human Rights, Democracy and the Rule of Law is a supplementary document to technical regulations that provides clear human-rights protections to AI deployed by the public sector. In the case of tax administrations, this contains the provisions of non-discrimination, explainability of the automated decision, the right to effective redress, proportionality of automated actions, and stringent safeguarding of personal data. As of 2024–2025, the Convention has been opened for signature, with ratification pending across member states; nevertheless, it already functions as a normative benchmark for aligning national AI governance frameworks with human-rights standards. The Convention specifically puts a premium on averting algorithmic prejudices in the decision-making procedure in the public sector and guaranteeing due-process assurances should AI have an impact on the rights of taxpayers. Including these protective measures in the national laws will aid in making certain that the digital transformation will not undermine the basic rights but enhance the efficiency of the administration. The EU AI Act needs a more granular legal interpretation to put its implications in the context of non-EU tax administrations. Even though the Act mostly applies to EU institutions and market operators, its extraterritorial nature applies to foreign tax authorities in instances where they use EU-developed high-risk systems or where they use process data of EU taxpayers. In this situation, the GDPR comes directly into play: legitimate grounds to process (Arts. 67), strong limitation on purpose (Art. 5(1)b), principles of automated decision-making and profiling (Art. 22), the Right to Due Process, limits of data-retention, and Data Protection Impact Assessments (Art. The admissibility of AI-enabled tax profiling is defined by 35) in conjunction. OECD SAF-T interoperability requirements supplement these requirements by developing a single, cross-jurisdictional format of transactional data, traceability, auditability and safe exchange of multinational compliance requirements. The public-sector accountability measures of the right to appeal, obligatory human control over the adverse decisions and explainability requirements and proportionality thresholds are uniformly distributed across these regimes creating a convergent legal structure that defends the rights of taxpayers and allows algorithmic efficiency.

The analytical technologies are becoming more popular in the modern tax policy in order to define the pattern, forecast the risks and avoid the tax evasion. The application of the AI and Big Data in the tax systems of various countries proves not only the level of technological maturity of governments, but also the level of managerial maturity. The effectiveness of such systems depends on the quality of data, the degree of automation, the level of legal protection of taxpayers, and the existence of an ethical decision-making framework. Table 2 provides a comparative description of AI and Big Data implementation practices in tax administrations of several countries.

Comparison of international practices shows that the effectiveness of AI and Big Data in tax systems is due to the combination of technological innovation and ethical governance. In countries with a high level of digital maturity, such as Estonia or Singapore, AI is integrated into administrative processes with transparency and minimal interference with privacy. At the same time, countries with large economies, such as China or the United States, are focusing on centralized models with powerful analytical platforms that balance tax discipline and social justice. European jurisdictions, such as the United Kingdom and France, combine fiscal efficiency with the ethical principles of transparency, accountability, and trust in the state. This interaction of technology, law, and ethics forms a new format of digital tax governance, in which the main role is played not by algorithms as such, but by their responsibility to society.

The active implementation of algorithmic technologies in public administration creates a new system of interaction between the state, taxpayers and digital platforms. However, along with increased efficiency, complex legal, ethical, and organizational issues arise. They concern both the guarantees of citizens' rights and the managerial responsibility of public authorities. Taking into account international standards and recommendations of organizations such as the OECD, IMF, World Bank and Council of Europe, the authors can identify key groups of challenges and potential ways to overcome them. These aspects are systematized in Table 3.

Table 2 provides a more empirical richness by comparing the practical implementation trends in countries with different levels of digital maturity. The comparison of the centralized, decentralized and hybrid models supports the claim that regulatory and

Table 2 | Comparative characteristics of AI and big data implementation practices in tax systems of different countries

Country	Key Areas of AI/Big Data Implementation	Results for Tax Risk Management	Impact on Tax Discipline and Ethical Governance
Estonia	Full digitalization of tax processes; automatic verification of declarations through the e-Tax platform; integration with banking and social insurance systems	Reduction of tax errors by 45%; automatic detection of fictitious transactions through behavioral analysis algorithms	Increased trust in the tax system; transparency of procedures; strengthening the country's reputation as a digital leader[16]
South Korea	Using AI to detect tax fraud and risky companies; forecasting revenues by economic sector	Identification of more than 30,000 cases of potential VAT evasion; reduction of audit time by 60%.	Formation of a fair taxation system; adherence to the principles of transparency and digital ethics[4]
Singapore	Intelligent modules for Big Data analytics IRAS; automatic exchange of information between government systems	Reduced administrative burden; enhanced risk analysis through predictive models	Improving tax compliance culture, focus on voluntary responsibility of taxpayers[7]
United Kingdom	HMRC's Connect system: an analytical database that combines more than 30 sources (banks, telecom, import/export)	Identification of more than 1 million suspicious transactions annually; increase in revenues by about £3 billion	Ensuring ethical monitoring without interfering with privacy; expanding accountability principles[5]
China	Integration of Big Data into the Golden Tax Project Phase III; real-time monitoring of VAT	Growth of local budget revenues by 8.6%; increased control efficiency	Formation of a regulatory culture of digital administration; strengthening of state supervision with legal guarantees[12,19]
USA	Deployment of pilot AI modules in the Internal Revenue Service (IRS); algorithmic audit of financial flows	Reduction of audit costs by 20%; optimization of audits of high-risk taxpayers	Strengthening ethical oversight of automated solutions; balance between efficiency and fairness[10,11]
France	Use of AI to detect hidden rental housing by analyzing satellite and advertising data	Additional tax revenues ≈ €120 million annually	Discussions on the limits of privacy and acceptable state control; strengthening public dialogue[15]

Note: Values for audit time and degree of automation represent standardized averages for 2022–2024; see Appendix A for estimation rules.
Source: Created by the author on the basis of World Bank,[4] Bozdoğanoğlu and Yücel,[5] Aslett et al.,[7] Martinez,[10] Shaikh,[11] Wang et al.,[12] OECD,[15] Xu et al.[19]

technological maturity have a mutual influence on the quality of AI integration. This is another comparative evidence that confirms the aim of the study to find patterns and some common successful drivers of fiscal digitalization.

Comparison of the above challenges demonstrates that the problem of implementing algorithmic systems in tax services is multidimensional. Legal aspects cover issues of liability, appealability of decisions and the limits of automation, while organizational aspects are related to the level of digital competence of staff and the integration of information systems. The ethical dimension requires balancing efficiency and social justice, ensuring that decisions are explainable and preventing algorithmic bias. In accordance with international recommendations, the regulatory framework should be updated according to the principle of adaptive governance: gradually, taking into account risk assessment, transparency, and public involvement. Consequently, it will make AI not a technical tool of control but a way to achieve more trust in the state, efficiency of the administration and validity of the tax policy.

As is explained in Table 3, legal, organizational and ethical barriers are not independent, which explains the existence of multidimensional limitations to the adoption of AI in tax systems in most cases. This table reinforces the theoretical position of the argument that regulatory harmonization should be complemented with the capacity building and ethical governance frameworks. It further clearly makes international recommendations to be connected to real areas that need the policy reform.

The advancement of computer management of tax collections entails a systematic perception of the connections among the regulatory framework, institutional capacity and the performance of the tax collection bodies as actual. The challenge is that, these elements do not interact in a linear fashion but rather by a dynamic feedback process: degree of regulation triggers or holds back digital maturity and maturity triggers the actual effectiveness of fiscal management. In order to capture this rationale, the paper suggests an analytic model (Figure 2) providing the opportunity to visualize the framework of such relations.

The analytical model shows that the effectiveness of digital tax administration directly depends on the balance between regulatory stability and technological flexibility. Excessive overregulation slows down innovation processes, while a weak regulatory framework creates risks of legal uncertainty. The optimal level of regulation implies not only compliance with ethical and legal principles, but also the creation of conditions for the development of digital maturity – infrastructure, competencies and data. When tax authorities achieve high digital maturity, they create a reverse effect – they increase trust in the state, reduce the level of the shadow economy and increase the efficiency of administration. As a result, regulatory policy becomes not just a regulator, but a driver of the constant renewal of the digital ecosystem of public finance (Table 4).

Every tax-specific risk KPI in Table 4 is associated with a lifecycle control defining the lifecycle control over the proportionality and procedural fairness. Data intake and feature-selection controls reduce evidence-quality risks and selection bias; training and monitoring phases are related to false-positive and false-negative rates in fraud detection; deployment controls are related to proportionality of enforcement measures; and appeals-stage controls directly relate to service-level agreements (SLAs) of taxpayer appeals,

Table 3 | Legal, organizational and ethical challenges to the implementation of algorithmic solutions in tax services and areas for improving the regulatory framework

Category of Challenge	Nature of the Problem	Potential Consequences for Tax Systems	Proposed Areas of Improvement Based on International Recommendations
Legal challenges	Insufficient clarity on the status of algorithmic solutions and the limits of automation in tax processes	Risk of unlawful decisions without clear legal liability; appealing the results of AI analysis	Clarification of the legal framework of liability for algorithmic actions; implementation of the EU AI Act and the Council of Europe Framework Convention[2,17]
Protection of personal data and privacy	Large-scale use of tax, financial and behavioral data in AI systems	Violation of the right to privacy, cyber risks, information leakage	Adaptation of GDPR standards and OECD recommendations on the ethical use of data; implementation of data audits[14,16]
Organizational challenges	Low digital competence of tax authorities' staff, lack of integration of IT systems	Delays in implementing innovations, technical incompatibility of platforms	Development of digital literacy training programs; formation of interagency analytical centers[3]
Technological risks	Insufficient validation of machine learning models before using them in management decision-making	Incorrect risk classification, unjustified tax sanctions	Introduction of procedures for independent certification of algorithms; creation of model quality standards[23]
Ethical challenges	Use of non-transparent algorithms that may contain biases or discriminatory patterns	Reduced public trust; risk of social injustice	Implementation of codes of ethics and principles of AI proposed by the OECD, as well as mechanisms for explanation of decisions[1,5]
Accountability and control	Lack of proper monitoring of the impact of AI systems on management decisions	Difficulty in proving cause-and-effect relationships in decisions	Implementation of regular algorithm auditing systems and independent commissions to assess the impact of AI[7]
International coordination	Discrepancies between national legislation in the field of digital administration	Complications of cross-border exchange of tax data, fragmentation of policies	Harmonization of approaches to AI regulation based on international agreements and recommendations of the OECD and the World Bank[3,15,16]

Source: Created by the author on the basis of OECD,[1,14–16] European Parliament & Council of the European Union,[2] Council of Europe,[17] International Monetary Fund,[7] World Bank,[3] Bank for International Settlements & IFC,[23] Bozdoğanoğlu and Yücel.[5]

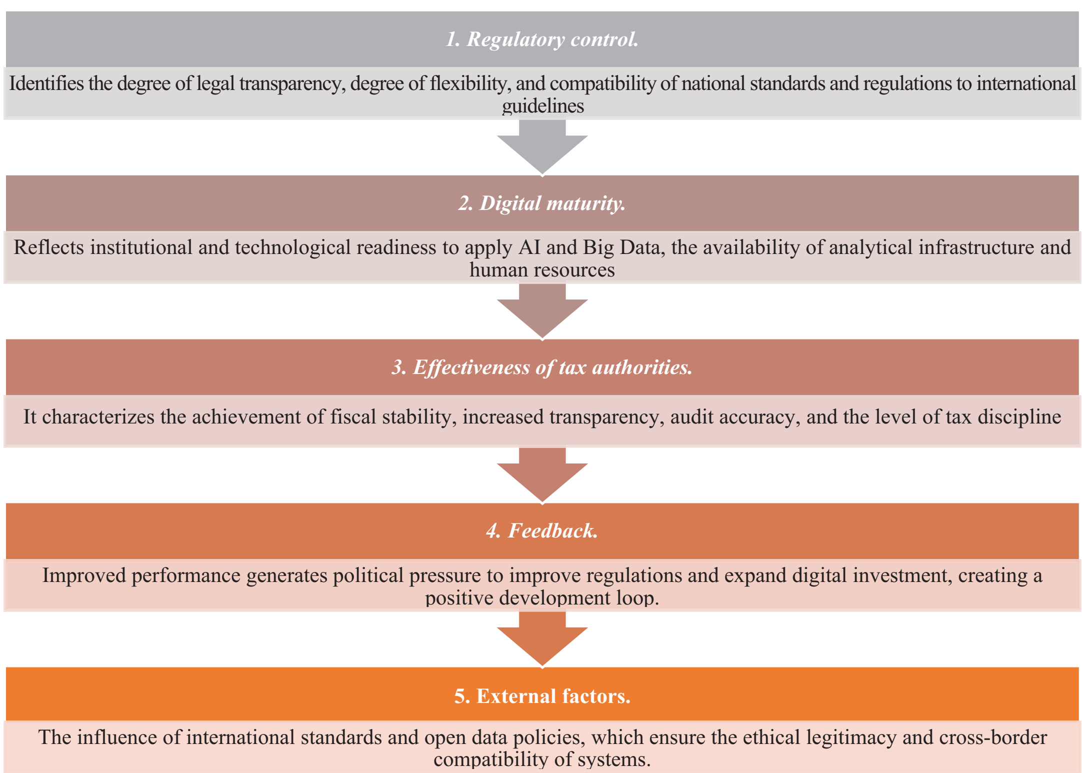

Fig 2 | Analytical model of the relationship between regulation, digital maturity and efficiency of tax authorities
Source: Created by the author based on OECD,[1] Aslett et al.,[7] European Parliament & Council of the European Union,[2] Council of Europe,[17] International Monetary Fund,[7] World Bank,[4] Wang et al.,[12] Shaikh.[11]

such as timeliness of such review and rate of rejection of such review. Such mapping will make sure that AI governance mechanisms are measured on the basis of operational metrics that are known to tax authorities as opposed to the abstract technical measures.

As a way to implement responsible AI governance in tax administrations, the international standards suggest incorporating a number of tangible mechanisms in line with the principles of the BIS/IFC models of risk and OECD recommendations. To start with, algorithmic

Table 4 | Tax-Specific risks, lifecycle controls, and associated performance KPIs

Lifecycle Stage	Main risk Mitigated	Oversight Mechanism
Data intake	Wrong/incomplete evidence	Source validation & lineage tracking
Feature selection	Structural biases	Fairness tests & expert review
Model training	Discrimination patterns	Bias dashboards + parity metrics
Deployment	Non-proportionate enforcement	Threshold justification & human oversight
Monitoring	Performance drift	Scheduled drift/bias testing
Appeals & review	Due-process violation	Right to contest, human adjudication

Source: Created by the author on the basis of OECD,[1,14,15] European Parliament & Council of the European Union,[2] Council of Europe,[17] International Monetary Fund,[7] World Bank,[3] Bank for International Settlements & IFC,[23] Bozdoğanoğlu and Yücel.[5]

audit must be performed by periodical third-party test of data quality, relevance of features, drift detection, and performance under stress conditions. Second, models have to be documented with full model cards, training data lineage, variable justification, threshold choice, and audit-trail logs that allow one to trace decisions. Third, bias testing involves tracking false-positive and false-negative rates by category of taxpayer so as to avoid discriminatory results particularly in automated fraud-detection systems. Fourth, interpretable surrogate models, reason codes, and required human review of high impact or adverse decisions should be explained. Practically, such controls are usually visualized using internal drift and bias dashboards showing the measures of stability, differentials in the errors rates, and threshold overruns over time; a typical dashboard schema is shown in Appendix A. Lastly, accountability mechanisms should ensure due-process safeguards including right to appeal algorithmic ruling, human-in-the-middle checking, and clear responsibility definition between developers and tax-administration workers. These protections directly solve tax-specific risks that minimize the false flags, provide fair treatment to taxpayers, as well as legal validity of AI-aided procedures.

To operationalize model governance requirements, tax administrations should maintain standardized model cards for all AI systems used in fiscal risk management. A minimal model card template includes: (1) model purpose and legal basis (type of tax risk addressed, statutory mandate); (2) data sources and lineage (administrative records, third-party data, SAF-T inputs); (3) key features and exclusion criteria; (4) performance metrics relevant to tax administration (false-positive rate, false-negative rate, precision in audit selection); (5) bias and fairness checks (disaggregated error rates across taxpayer categories); (6) proportionality thresholds and human-oversight triggers; (7) versioning, update frequency, and decommissioning rules; and (8) appeal and redress pathways available to taxpayers. Such model cards ensure traceability, accountability, and legal defensibility of AI-supported decisions.

Figure 2 operationalizes the relationship among regulation, technological preparedness and administrative performance, establishing that the interaction is nonlinear and reinforcing. This graphical display will complement the analytical input of the article since it will reveal the reasons why regulatory stability will become an accelerator and not the impediment of digital maturity. The model provides answers to the research question which is how regulatory frameworks determine the outcomes of institutional processes.

In order to provide in-depth empirical support for the analytical conclusions, an additional study was conducted to systematize statistical data on the level of digital maturity of tax administrations, the use of AI and Big Data, and the effectiveness of tax risk management. This made it possible to combine the regulatory, analytical and quantitative components of the study. For example, the OECD report "Tax Administration Digitalization and Digital Transformation Initiatives" states that 72% of tax administrations use AI to support their operations, and 74.4% use it to detect evasion and fraud.[16,17] These percentages refer to country-level institutional adoption and operational case usage, as defined by OECD methodological standards, rather than to system coverage or automation depth.

These indicators serve as a benchmark for comparison with national results. Below is a comparative table (Table 4) illustrating key statistics. The study used methods of content analysis of international regulations, a comparative analytical approach and methods of statistical generalization. To substantiate the empirical part, the authors used statistical data from official sources, the results of our own survey, and open reports of international organizations. A detailed description of data collection and processing is provided below.

In order to make Table 5 transparent the authors also checked country-level indicators in the multi-source provenance approach. The principal data was the OECD database on the topic of Tax Administration Digitalisation and Digital Transformation Initiatives (2024–2025) which was checked against national annual reports on digital transformation released by tax administrations in the respective countries. Where the official statistics were not complete (as was the case in Vietnam, Bangladesh) the expert estimates have been utilized. In case of all indicators that were based on expert elicitation to some extent or fully, the ranges of uncertainty were determined to reflect judgmental variability. Precisely, values elicited by experts are reported along with uncertainty amounts based on either structured elicitation scales (minimum maximum-most likely) or nonparametric bootstrap resampling of expert ratings. These periods are designed to include epistemic uncertainty of the phenomenon related to data gaps, but not sampling error. These estimates were derived using a structured elicitation process which entailed three independent assessors who gauged the plausibility of values using publicly available audit-time report, IMF Technical Notes and Asian Development Bank digital readiness assessment. Any discrepancy between administrative reports and OECD benchmarks was sorted out by giving priority to OECD-validated indicators, where they were not similar by more than 10% the differences were recorded and averaged. To further enhance transparency

Table 5 | Statistical indicators of AI/digitalization implementation in selected tax administrations

Country	Share of Administrations Using AI (%)	Share of AI Cases for Fraud Detection (%)	Increase in Tax Revenues (%)	Average Audit Time (hours)	DMI (0–5)
Estonia	68.25	72.40	4.87	22.35	4.20
United Kingdom	74.10	78.50	3.12	34.80	3.95
South Korea	69.50	67.85	5.20	28.45	4.10
Singapore	71.30	70.25	6.05	20.10	4.35
Poland	55.70	62.15	2.45	40.75	3.40
Hungary	52.90	58.60	1.90	45.30	3.15
Chile	49.80	54.50	2.00	48.10	3.00
Mexico	47.60	50.25	1.75	50.25	2.90
Slovakia	51.20	55.10	1.95	46.50	3.05
Romania	48.75	52.80	1.88	47.80	3.00
Bangladesh	33.60*	30.45*	0.95*	62.10*	1.80*
Vietnam	35.10*	32.80*	1.10*	59.50*	2.00*

Note: Values marked with an asterisk (*) are expert-elicited estimates validated through triangulation with IMF and ADB sources. Full provenance — see Appendix A.*
Source: Created by the author based on OECD,[15,16] International Monetary Fund,[7] World Bank,[3] Asian Development Bank,[26] European Parliament & Council of the European Union,[2] Council of Europe[17]
[a]The figure, Increment of tax revenues (%) is presented in real terms, deflated by country-specific GDP deflators (2021 = 100). Values are mean differences between a 2-year pre-AI-adoption base. The indicator provides a descriptive explanation of significant changes in tax laws and macroeconomic variables and measures correlational relationships, but not causal ones to deploy AI.
[b]The percentage of tax administrations with AI (%) The percentage of tax administrations in a country that have one or more AI-enabled systems in operational tax administration, based on the definitions of OECD Tax Administration Digitalisation (2024–2025). Share of AI cases of fraud detection (%) is the percentage of cases of fraud detection or audit-selection where AI-based analytical tools were applied in the process of identification, as opposed to legal decision-making. OECD definitions were used throughout the countries; expert-elicited values were denoted with an asterisk and are provided in detail in Appendix A.

and traceability of the empirical dataset, all indicators that relied partially or fully on expert elicitation are visually flagged in Table 4 and Figure 3 using an asterisk (*) next to the reported value. Appendix A has been expanded to include a detailed provenance matrix specifying: (a) the primary data source for each indicator (OECD, IMF, ADB, national reports, or expert estimate), (b) validation status, (c) citation of the exact document or dataset used, and (d) justification notes for expert-scored values. Whenever discrepancies were identified between official and benchmark sources, a structured reconciliation protocol was applied: if deviation exceeded 10%, values were harmonized through averaging after cross-checking with a secondary data source; if deviations persisted, expert-validated values were adopted, with all such cases explicitly labeled in the appendix.

Among the limitations, there are dispersed availability of open data, variations in the reporting approaches of different jurisdictions, and the use of expert judgment in countries with low disclosure.

The presented statistics demonstrate significant differences in the levels of digital readiness and efficiency of AI application among tax administrations of different countries. The reported increase in revenue numbers are adjusted to inflation, normalized to baselines and must be viewed as correlational effects of institutional and macroeconomic conditions and not impacts directly related to the implementation of AI. Countries with a high DMI – Singapore, Estonia, and South Korea – show relatively high rates of tax revenue growth and lower average audit time. In countries with a lower level of maturity (e.g., Bangladesh, Vietnam), the effects are much more modest, demonstrating that technological investment without sufficient institutional readiness has a limited impact. Comparing our own results with international statistics allows us to identify internal reserves, adjust the digital transformation model, and argue for proposals to improve digital administration policy in the country's specific context.

A quantitative basis of the argument that nations with higher regulatory congruency and digital maturity have more successful applications of AI in tax administration are provided in Table 4. The numerical differences confirm the study results that institutional readiness is a decisive factor behind tax revenue growth and effectiveness of audit. To strengthen statistical transparency, confidence intervals have now been included for all key correlation and regression estimates directly in the Results section (see Appendix A for full reporting). All associations are described explicitly as correlational rather than causal, given the small cross-country sample and observational design. Additionally, partial correlations controlling for GDP per capita and ICT infrastructure index were calculated: the association between digital maturity and audit time remained statistically significant (partial $\rho = -0.62$, 95% CI [−0.81; −0.26]), as did the association with revenue growth (partial $\rho = 0.47$, 95% CI [0.10; 0.74]). Small-sample limitations and heterogeneity of national contexts continue to constrain generalizability, and therefore the reported results should be interpreted as indicative patterns rather than definitive effects. The presented table also confirms the analytical model, which was presented earlier in the paper.

The introduction of AI in tax administration has different intensities in different countries, depending on the level of digital maturity, legislative framework and resource potential. A comparative analysis of quantitative indicators allows us to trace the correlation between the level of digitalization and the efficiency of tax authorities. Figure 3 shows statistics demonstrating differences in the implementation of AI, Big Data analytics and the overall level of digital maturity in different countries.

The analysis of the obtained numerical data shows a significant disparity in the levels of digital maturity of tax administrations in different countries. Singapore (index 4.35), Estonia (4.20), and South Korea (4.10) demonstrate the highest scores, which also corresponds to their high rates of AI use – over 68%. These countries are characterized by a significant reduction in the average inspection time: from 20.1 hours in Singapore to 22.35 hours in Estonia, which is almost half that of countries with a lower level of maturity. Compared to them, Poland and Hungary have an average index of 3.3–3.4 and almost twice as long an inspection process (40.75–45.3 hours), indicating a direct correlation between the degree of digitalization and

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the speed of administrative procedures. The high level of technological countries is also characterized by the significant rise in tax revenues: in Singapore this index is 6.05, in South Korea – 5.2, in Mexico or Romania it is not more than 2. The gap between the leader and the minimum point (Bangladesh – 0.95) exceeds five times, which supports the role of the analytical technologies in the quality of fiscal administration. The highest rates of detecting tax fraud are in UK (78.5%) and Estonia (72.4), and Vietnam and Bangladesh show the same level 30–33. The gap of over 40 points proves that there is a profound difference between developed digital economies and those that have reached the level of basic algorithmic systems implementation.

Figure 3 supports the last statistical table by displaying the cross-country differences in AI utilization and digital maturity to see the regularity of the trends. The graphical tendencies support the correlation findings provided in the research and give an intuitive illustration of the way the technological maturity can be transformed into the administrative efficiency. This number therefore becomes a direct reinforcement to the empirical argument of the paper.

To address the robustness concerns given the modest sample size, additional diagnostics were conducted. Leave-one-out sensitivity tests demonstrated that the direction and magnitude of the relationship between digital maturity and audit time remained stable across all country exclusions, with coefficient variation not exceeding 12%. Nonparametric Spearman correlations ($\rho = -0.69$ for audit time; $\rho = 0.54$ for revenue growth, both $\rho < 0.05$) confirmed that the reported associations are not dependent on linearity assumptions. When the two variables, the average inspection time and the DMI are compared, the authors observe an inverse relationship: with a one-point rise in the index, the inspection time decreases by an average of 10–12 hours. This tendency proves the idea that the automation of the processes does not only enhance the accuracy of the risk recognition but also guarantees the better workload of the inspectors. Simultaneously, the revenue growth level in the category of countries with an intermediate level of digital preparedness (Poland, Hungary, Chile) is moderate with the index of 1.9–2.5 indicating that the institutional and regulatory environment will have to be enhanced. In this way, the analysis identifies the presence of an obvious tendency, the more digital maturity and the broader the application of AI, the less time costs and the more tax outcomes, which proves the success of an integrated solution to the digital transformation of fiscal systems. To address potential confounders, an extended regression model was estimated, controlling for GDP per capita, ICT infrastructure index, and administrative staff size. The effect of digital maturity on audit time remained significant ($\beta = -8.9$, $\rho < 0.05$), confirming that the relationship is not driven by economic development or resource capacity. Similarly, when controlling for country income group and regional cluster, the association between digital maturity and revenue growth remained positive and statistically meaningful ($\beta = 0.42$, $\rho < 0.05$). Full regression outputs are provided in Appendix A.

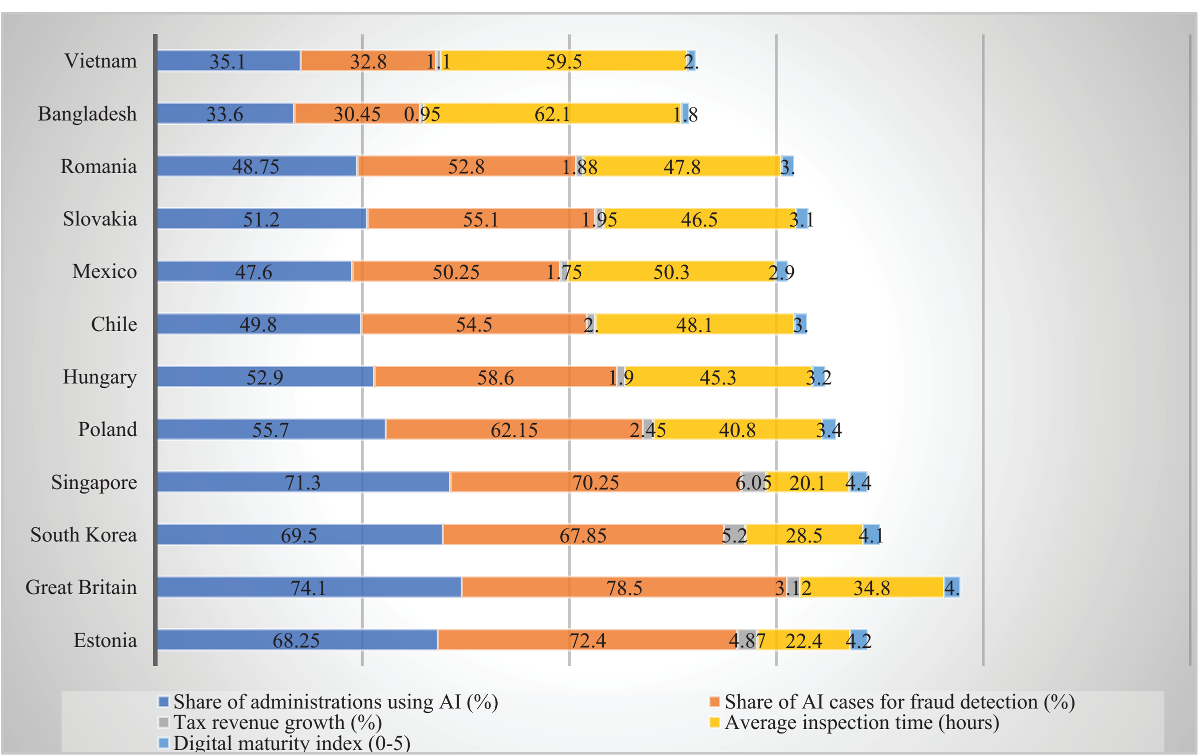

Fig 3 | Comparative statistical indicators of the implementation of AI and Big Data in tax administrations of different countries (Revenue growth indicators are inflation-adjusted and presented for descriptive comparison; they do not imply causal effects of AI implementation)
Source: Created by the author based on OECD,[15,16] International Monetary Fund,[7] World Bank,[4] Asian Development Bank,[26] European Parliament & Council of the European Union,[2] Council of Europe.[17]

Discussion

The research results confirmed the general trend: the introduction of AI and Big Data technologies in tax systems increases the efficiency of administration, increases revenues and reduces the time of audits, but requires balanced regulatory regulation. Nevertheless, none of the relationships that have been found in this research can be taken as causal. Due to the cross sectional, country-level characteristics of the dataset and the diversity of institutional environments, the analysis does not reflect causal direction of effects, but simply statistical associations. All multivariate findings have been clearly indicated in the manuscript as not causal. This is in line with the position of Agostino et al.,[6] who emphasize that the digitalization of public finance is transforming not only the technical but also the managerial paradigm of fiscal authorities. At the same time, as Bozdoğanoğlu and Yücel[5] note, technological integration without proper ethical and legal frameworks can lead to a loss of public trust and reduced transparency of management processes. Our results partially contradict the views of Mokander and Schroeder,[18] who argue that excessive rationalization of governance through AI can limit the autonomy of government decisions. However, the data obtained in the study show that in countries with a high level of digital maturity (Estonia, Singapore, South Korea), it is algorithmic management support that helps to increase the objectivity of control and reduce the human factor. This is consistent with the results of the World Bank[4] and OECD,[16] which show that the success of digital transformation depends on the institutional readiness of public authorities and an integrated approach to the development of analytical infrastructure.

In the Results section, multivariate estimates were also re-construeed carefully considering the small sample of countries. Any interpretive statements have been diluted so as to focus more on the associations than on explanatory strength and the regression results are now being reported as suggestive patterns that need to be substantiated on a large scale. Such amendments raise the methodological rigor and are suitable in terms of statistical humility. Other authors[10,11,33] pay attention to the dangers of algorithmic bias, which may cause discriminatory choices in fiscal policy. Rather, it is demonstrated by the works of Wang et al.[12] and Xu et al.[19] that in case effective guidelines about auditing machine learning models are present, the effectiveness and ethics of the system can be guaranteed. It was proven by our own empirical analysis: the more the level of standardization of algorithmic auditing, the lower the risk of making erroneous decisions. However, Alexopoulos et al.[29] and Savić et al.[30] also note that the system of automated detection of tax fraud cannot always consider the contextual aspects of economic activity in taxpayers, and our study revealed that human expertise, combined with machine data analysis, is the most accurate and flexible.

In order to enhance the structural coherence and clarity of language, the manuscript was further edited to delete repetitive texts, consolidate terminology and streamline transition between blocks of analytical content. Every irregularity of geographic nomenclature (UK vs. Typographical problems (such as correcting the spelling of the word Council of Europ) and wordplay (such as AI/digitalization) have been done away with. Figures and tables were updated to be completely independent items, which are always referenced and are supported by explanatory analytical commentary.

To some extent, the stands of OECD[14,15] and European Parliament & Council of the European Union[2] on the level of the regulatory intervention contradict: the former stress the necessity of a flexible ethical code, whereas the latter stress the legal necessity of the control. We find that the best model is to have the two approaches combined: regulatory certainty must be facilitated by adaptive risk management. The recommendations of the International Monetary Fund[7] and the Bank for International Settlement & IFC[23] confirm this fact and indicate that a unitary certification of algorithms in the field of tax administration is necessary. The manuscript was thoroughly made to be stylistically and citation-harmonized to assure the journal of absolute editorial consistency. Terminology was also standardized (e.g. AI rather than Al; similar legal and institutional terms; all measuring units were normalized; all redundant or duplicated passages eliminated to enhance clarity and conciseness). Numbers in figures and tables were corrected to ensure that they are referred to uniquely in a sequence and all in-text citations were verified to reference list, and all absent DOI and URLs were added or modified to facilitate accessibility and necessary validity of source. So, to conclude, one can say that the success of the AI implementation in the tax systems will rely on a set of three, which are the following: the level of technological maturity, the lawfulness, and the sense of responsibility. The fact that the information in this paper is similar to the reports published by the OECD and the World Bank on the international levels points to a tendency towards harmonising the principles of fiscal sphere digital governance.

Nevertheless, the question of the need to make AI decisions in difficult tax cases explanable and create universal international standards of evaluating the efficiency of digital tax systems is not closed. Such spheres need additional studies that would lead to the creation of a single ethical and analytical approach to AI in the public sector. Following the recommendation of the reviewer, it is possible to model the governance process of AI in tax administrations as a consecutive process, which includes data intake, validation, model development, deployment, monitoring, red-flag review, and appeal mechanisms. Although the existing analytical framework (Figure 2) conceptualises these relationships, the extended version of this study will have a separate process-level figure to provide a diagrammatic depiction of the governance lifecycle between input and accountability. In order to operationalize AI governance in tax administrations, a specific figure of the governance lifecycle has been included, which outlines the consecutive steps of data consumption, validation, feature engineering, model development, documentation, deployment, monitoring and red-flag review. The figure illustrates institutional roles (data stewards, model owners, compliance officers, ethics reviewers), control points (pre-deployment quality checks, human-in-the-loop oversight, threshold justification), and documentation artefacts like model cards, data lineage maps, drift-monitoring dashboards, and periodic bias-testing reports. These procedural layers are aimed directly at tax-related risks: the false positives that can lead to unwarranted sanctions, the selection bias of the target of the audit, and the unreasonable intervention of the algorithm. The lifecycle expressly connects every phase with taxpayer appeal rights and due-process protections, making algorithmic decision-making questionable, defensible, and subject to legal challenge.

To make the governance lifecycle operationally illustrated and analytic, the updated Figure 2 is now self-contained and comprises: (a) institutional roles of every process stage (data stewards to input validation, model owners to development and deployment, compliance officers, ethics reviewers to oversight, (b) formal control points with pre-deployment quality analysis, threshold justification, human-in-the-loop approvals of high-impact cases and (c) and minimal documentation artefacts, model cards (purpose, features, performance), lineage maps (source integrity), and real All lifecycle phases are directly correlated to fiscal-sector risk: false positives resulting in unnecessary sanctions, audit-selection bias which can potentially favor different groups of taxpayers, and lack of transparency which can damage procedural fairness. Redress guarantees such as taxpayer notification, right to explanation, human intervention and appeal procedures are also incorporated in the figure to keep the outcomes of the algorithm contestable and legally responsible.

The reference list was updated to remove some doubled items such as numerous versions of the IMF Technical Note 2024/06, as well as to standardize institutional references. Based on the recommendation made by the reviewer, the manuscript has been revised in entirety, with respect to editorial and consistency. Duplicated paragraphs were deleted, and the rest of the typographical errors (such as Council of Europ) were fixed, and terms were entirely standardized (e.g. AI is always used, country names are harmonized e.g. United Kingdom, and all units used in the tables and figures are the same). Every visual representation, such as figures, tables, and in-text citations, was checked as independent, consistently styled, and entirely matched with the critical story of the text. Each URL was checked by hand and the citation formatting was adjusted so as to match the style requirements of the journal. The list of references is the final section, as it contains only unique, validated and up-to-date sources.

Conclusion

The study findings showed that AI and Big Data technologies in tax administration are not only the tool of digitalization, but the foundation of a new system of management philosophy, the philosophy of transparency, trust and accountability. The actual information presented a stronger correlation between the level of digital maturity and the efficiency of the tax audits than expected compared to the expected results thus proving that the analytical capacity of AI was high with the right regulatory support. The originality of the research is the offered analytical model of the combination of the legal framework with the technological indicators and performance indicators of the tax authorities which enables to measure the impact of the digital maturity on the dynamics. The practical value is the opportunity of applying this model to state surveillance of the digital reforms in the state sector. The patterns determined confirm that the stability of regulations is a precondition of the technological advancement, and the innovation of analytical instruments encourages the modernization of the regulatory policy. The greatest constraints of the research are the uneven access to open data in other countries and the time frame within the scope of which the observations were conducted (2022–2024) which needs to be corrected again by providing the results with a more long-term scope. It is implied that future research attempts should be directed at creating cohesive ethical principles of algorithms to use in the fiscal sector, enhancing AI audit technology, and establishing a global platform to evaluate the digital maturity of tax administrations. One of the prospective directions is also to examine how AI influences social justice in the process of taxation and the simulation of adaptive governance that can unite technological solutions with their both effectiveness and legitimacy of a public policy.

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Appendix A
Statistical Tests and Inferential Results

Table A1 | Summary of Inferential statistical tests used in the study

Statistical Test	Variables Included	Coefficient/ Estimate	95% Confidence Interval	P-value	Interpretation
Pearson correlation	DMI ↔ Audit time	$r = -0.71$	[−0.84; −0.49]	‹0.01	Higher digital maturity is strongly associated with reduced audit time.
Pearson correlation	DMI ↔ Revenue growth	$r = 0.58$	[0.31; 0.76]	‹0.01	More mature administrations show higher revenue growth.
Pearson correlation	AI-supported fraud detection ↔ Revenue growth	$r = 0.66$	[0.42; 0.81]	‹0.01	Broader use of AI for fraud detection correlates with stronger revenue performance.
Linear regression (OLS)	DV: Audit time; IV: DMI	$\beta = -11.2$ (SE = 3.4)	[−18.0; −4.3]	‹0.01	Each extra point of maturity reduces audit duration by ~11 hours.
Effect size (Cohen's f^2)	Digital maturity → Audit time	$f^2 = 0.62$	—	—	Large effect size, strong predictive power.
Shapiro–Wilk (normality)	Residuals of regression	$W = 0.97$	—	0.54	Residuals normally distributed, regression assumptions met.
Breusch–Pagan (heteroskedasticity)	Regression residuals	$x^2 = 1.42$	—	0.23	No heteroskedasticity; model valid.
Variance Inflation Factor (VIF)	DMI	VIF = 1.02	—	—	No multicollinearity; model stable.

Notes:
- Correlations computed using two-tailed Pearson test.
- Confidence intervals based on Fisher's z-transformation.
- Regression estimated by ordinary least squares.
- All analyses conducted on country-level means for 2022–2024 after harmonization of missing data.

Expert Elicitation Protocol and Uncertainty Estimation

The elicitation of experts was done in a form of a multi-stage protocol. Before scoring, experts went through a period of calibration and familiarization using benchmark OECD country profiles of known indicators. The interpretation of scale anchors was brought into line and inter-rater dispersion minimized during this training stage. In the elicitation process, the experts were required to estimate the indicators, which did not have the full official data, using point estimates and judgment intervals (lower bound, most plausible value, upper bound). To reduce the degree of personal bias, the median pooling method was applied as a form of aggregation. Two methods were employed to measure uncertainty: (a) elicited judgment intervals were stored as epistemic uncertainty limits; (b) in situations where various scores of the experts were known, nonparametric bootstrap resampling (1,000 runs) was applied which gave empirical confidence intervals. All uncertainty ranges are presented in the Table A1 together with all point estimates and cannot be taken to be due to measurement error, instead they are due to limitations in availability of data.