U4 ANTI-CORRUPTION RESOURCE CENTRE

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Harnessing artificial intelligence for anti-corruption

An update of emerging evidence on benefits and challenges in prevention, detection and investigation

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Artificial intelligence (AI) is increasingly being applied to anti-corruption efforts, offering significant opportunities and introducing new challenges. Evidence from academic studies and public policy applications shows that AI can strengthen prevention by predicting corruption risks and "hotspots" in public fund allocation, as well as by deterring petty corruption through simplified procedures and citizen access to accurate information. Emerging uses include awareness raising and integrity training.

In detection, AI has been used to analyse political integrity datasets and satellite imagery, enabling the identification of risky tenders, fake bidders, conflicts of interest and environmental harms linked to corruption. Though less tested in investigations, AI demonstrates strong potential in evidence gathering and large-scale document review.

Evidence on AI use in monitoring and evaluating national anti-corruption strategies remains limited, but related applications offer lessons for tracking commitments and assessing results. Public institutions are also embedding AI into established oversight workflows.

Key benefits include scalability, predictive capacity and the integration of heterogeneous datasets, while challenges stem from data quality issues, opacity of black-box models, institutional capacity gaps and privacy risks. Ensuring algorithmic transparency, regulatory safeguards and capacity building is essential for responsible deployment.

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Harnessing artificial intelligence (AI) for anti-corruption (2025)

Caveat

This Helpdesk Answer is an update to a previous version published in October 2025. This 2026 version of the paper includes new sections on the use of AI tools in the area of awareness raising, integrity trainings, monitoring and evaluation, and risk assessments. It also contains new information on recent initiatives and potential synergies between traditional anti-corruption instruments and AI-driven technologies.

Query

Please provide an update of the 2025 Helpdesk Answer about key benefits and challenges of using AI for corruption prevention, detection and investigation. Include sections on awareness raising, integrity trainings, monitoring and evaluation, risk assessments and existing initiatives and potential synergies between traditional anti-corruption instruments and AI-driven technologies.

Main points

- Key features of AI technologies include autonomous learning and task execution, leveraging advanced computing power and the ability to exploit novel data sources like satellite imagery. As such, applying these technologies to anti-corruption efforts can bring benefits such as the reduction of human error, the simplification of repetitive tasks and improved targeting and efficiency in gathering and analysing large datasets.
- Embedding AI – especially LLMs – into existing anti-corruption workflows to automate repetitive data tasks (e.g., converting PDFs to spreadsheets or tabular formats, classifying large datasets, extracting names/dates/entities) delivers immediate value at scale.
- These "mundane" uses of AI in anti-corruption efforts can free up scarce staff time and support activities to prevent (cleaner, richer indicators), detect (faster triage of red flags) and investigate (bulk evidence ingestion and entity extraction) corruption while maintaining a degree of human oversight and control.
- As such, there is a broad scholarly consensus that AI should complement existing anti-corruption workflows rather than replace them. Nonetheless, in addition to the "mundane" uses of AI, there are a growing number of cases of AI tools being developed as a dedicated products to deliver specific outputs in the domain of preventing, detecting and even investigating corruption.
- The potential of AI in corruption prevention has mainly been tested in two areas: (i) predicting corruption risks and "hotspots" in the allocation and disbursement of public funds and (ii) deterring lower-level corruption in public service delivery by simplifying procedures and improving access to accurate information for citizens.
- Preventive potential of AI is also visible in the domain of anti-corruption awareness raising and integrity training. Chatbots help citizens and officials understand integrity rules and reporting procedures, while emerging training applications use AI to develop practical scenarios and support ethical judgement. However, evidence of their effects on understanding and behaviour remains limited.
- Key benefits of AI in corruption prevention include scalability compared to traditional audits, meaning that state authorities can allocate their finite oversight resources in a more targeted and efficient manner, which can strengthen safeguards and heighten deterrence. Predictive methods can also help authorities intervene before damage occurs (e.g. before a procurement contract

is awarded). These tools can integrate heterogenous datasets and thereby help generate more robust corruption risk profiles.

- AI has also been applied in corruption detection, primarily to strengthen accountability and transparency through political integrity datasets and to use satellite imagery to detect corruption risks linked to environmental harm.

- Key benefits of AI in corruption detection include the ability of AI anti-corruption tools (AI ACTs) to detect high-risk tenders, fake bidders or conflicts of interest among public officials.

- While the potential of AI in corruption investigations has been tested far less, a handful of real-world public policy applications highlight potentially promising uses in evidence gathering and large-scale document review.

- Across prevention, detection and investigation, academic studies and public policy applications most commonly employ machine learning and deep learning techniques, though natural language processing (NLP) and generative AI – particularly LLMs – have also been applied.

- The use of AI tools as part of corruption risk assessments cuts across prevention, detection and investigation, with applications particularly widespread in public procurement. By combining administrative data, extracting information from documents and identifying suspicious patterns, AI tools can help authorities flag risks before contracts are awarded, prioritise audits and select allegations or investigative leads for further scrutiny.

- Evidence on AI use in the appraisal, monitoring and evaluation of national anti-corruption strategies remains limited. Applications in procurement oversight, electoral pledge tracking and public policy evaluation nevertheless show potential to organise administrative data, track commitments and synthesise evidence for evaluations, with human oversight remaining central to assessing implementation and results.

- Public institutions are increasingly embedding AI into established audit, procurement and investigative workflows to prioritise reviews, identify suspicious patterns and retrieve relevant information. Linking administrative datasets and combining institutional expertise through partnerships can strengthen these applications. However, evidence of improvements in efficiency remains stronger than evidence of their effects on corruption.

- There are potentially sizeable challenges and drawbacks to the application of AI technologies to anti-corruption efforts. Across the areas of prevention, detection and investigation, key challenges are similar: data quality issues, algorithmic opacity, regulatory lag, lack of institutional capacity, inclusivity gaps, and concerns around privacy and fundamental rights.

- More fundamentally, data limitations and biases can affect the reliability and accuracy of AI ACTs. In one instance from the UK, apparent shortcomings of an AI tool used by the Serious Fraud Office to support its investigations has resulted in past convictions being questioned on procedural grounds, underscoring the importance of rigorously testing the accuracy of AI ACTs before deployment.

- Perhaps most importantly, any shortcomings in training data can compound skewed historical patterns. If corruption is already under-detected in transaction data and AI models are trained

only on the limited cases that are identified, the models will become good at detecting those identified positive cases. However, this also reinforces the blind spots, making it harder for the system to detect the many cases that went unnoticed in the first place.

- Moreover, while AI can reduce traditional opportunities for corruption by limiting human discretion, this can also create new risks. If an AI system is flawed or manipulated, it could systematically misclassify cases or misallocate resources at scale before errors are detected. Transparency International (2025) has proposed the concept of "corrupt uses of AI" to cover instances in which AI systems are abused by entrusted powerholders for private gain. This heightens the need for robust oversight, continuous monitoring and transparent algorithmic audit trails to ensure accountability.

- To ensure responsible deployment of AI in anti-corruption efforts, beyond promoting algorithmic transparency and accountability, it is essential to close institutional and regulatory gaps and invest in sustained capacity building initiatives.

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Background

Artificial intelligence (AI) is an umbrella term covering a wide array of technologies and applications, from predictive analytics in finance to autonomous robots in manufacturing, and from medical-image analysis to language translation services. While definitions vary by discipline and use case, most agree on three core features: the ability to sense or interpret an environment; to learn from data; and to act with some degree of autonomy toward specific objectives. For example, the OECD (2024) defines an AI system as:

> "a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment."

Given AI's many forms and applications, no single, universal definition exists, so this description captures the essential elements where most definitions converge (Jones 2023; Zinnbauer 2025).

The field of AI dates back to the mid-twentieth century, with early work on symbolic reasoning in the 1950s, but its pace of innovation has markedly accelerated in the 2020s with the development of generative AI, thanks to advances in deep learning architectures (e.g. transformers), the explosion of digital data and growing computing power (Roy 2023; Zinnbauer 2025) (see Figure 1). This surge is particularly evident in the development of large foundation models and the technologies that build upon them, such as generative AI.[1] These tools leverage unsupervised or semi-supervised training[2] on vast unlabelled datasets to learn broad patterns before fine-tuning in relation to specific tasks (e.g. GPT-5, LaMDA). This represents a paradigm shift that has unlocked new capabilities in text, image, code and multimedia generation (Roy 2023; Jones 2023).

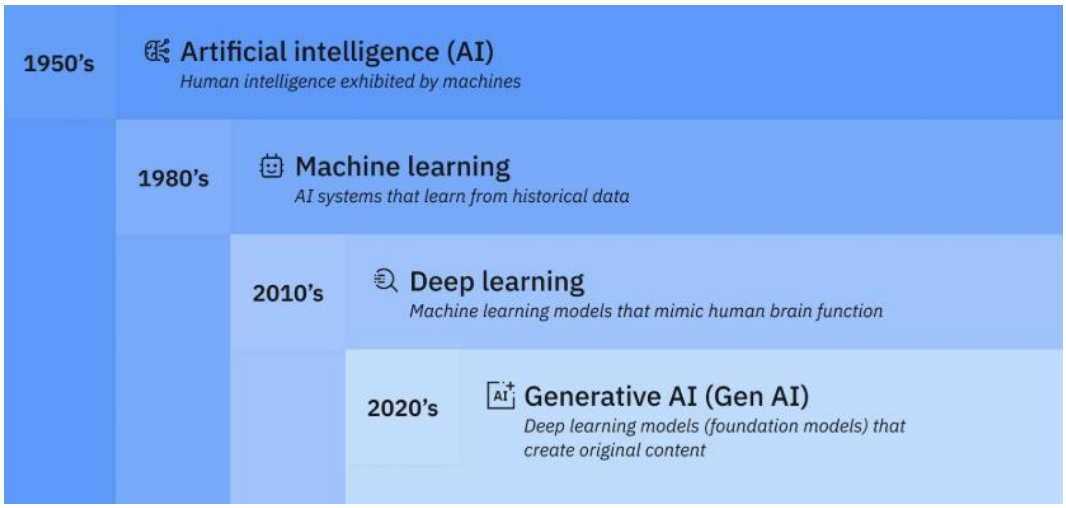
[1] For example, GPT-3.5 and GPT-4 are families of Open AI's GPT foundation models that are trained on a massive amount of text data used to power ChatGPT.

[2] Unsupervised training refers to where an AI model is given only unlabelled data and tasked with discovering hidden patterns or structure in the data without human-provided labels. Semi-supervised training refers to where an AI model is given a small amount of labelled data and a large amount of unlabelled data to improve the model's ability to perform a task, such as classification.

The dramatic growth in both private and public sector support for AI development reflects this momentum. In 2024, generative AI initiatives secured US$33.9 billion in global private investment, an 18.7% increase over 2023, underscoring firms' eagerness to commercialise foundation models and related tools (Maslej et al. 2025). In 2025, total investment in AI reached US$581.69 billion, almost 130% increase from 2024 (Sajadieh et al. 2026: 178).

Governments have likewise ramped up policy and regulation engagement. For instance, US federal agencies issued 59 AI-related regulations in 2024 – more than twice as many as in 2023 – spanning guidance on risk management, data governance and permissible uses of AI in critical sectors (Maslej et al. 2025), though many of these were later repealed in early 2025 by the Trump administration (Wheeler 2025). In September 2025, Italy became the first EU member state to pass an AI law, intended to complement EU-level regulation (Sajadieh et al. 2026: 329).

Figure 1: The evolution of AI since the 1950s



Source: Stryker and Kavlakoglu 2024

The complex and evolving nature of corrupt practices can make AI-driven solutions appear attractive (Gerli 2024). Research shows that AI has been successful in some traditional anti-corruption areas, including procurement integrity and anti-money laundering, in both preventing and detecting corruption (Zinnbauer 2025). The ability of AI tools to process vast amounts of data, make connections across numerous datasets and learn from data to identify patterns indicative of corruption can aid in the identification of cases for targeted audit as well as the detection of high corruption risk procurement contracts (e.g. López-Iturriaga and Sanz 2018; Mazrekaj et al. 2024; Fazekas et al. 2023; Wacker et al. 2018; García Rodríguez et al. 2022). As such, AI anti-corruption tools (AI ACTs) have been increasingly adopted by governments and private sector organisations around the world. For instance, a bot called Alice has been

developed by the Office of the Comptroller General in Brazil to help curb corruption in public procurement (Gerli 2024). For more details on Alice, see page 43 in Annex 1.

However, available inventories suggest that only a small share of the AI tools documented in public administration have a direct anti-corruption function. For example, drawing on data from the EU Public Sector Tech Watch platform, Petriashvili (2026) identifies only 47 tools with a direct anti-corruption function among 1,640 documented AI tools. Similarly, Petriashvili and Piotrowski (2026: 726) report that, in 2024, only 8% of the tools listed in the US Federal AI Use Case Inventory were specifically designed for anti-corruption functions.

However, alongside its promise, AI also introduces significant challenges. First, data reliability and algorithmic bias can arise when models are trained on incomplete, unrepresentative or low-quality datasets, leading to unfair or inaccurate outcomes (Köbis et al. 2022a; Raghavan 2020, Transparency International 2025: 4). Second, inclusivity gaps persist because AI development teams and training data often lack diversity, which can amplify existing social inequities (Leech et al. 2024; Maslej et al. 2025; Transparency International 2025: 4). Third, information asymmetry and opacity in AI decision-making – commonly associated with "black-box" models – undermine transparency and accountability, making it difficult for practitioners and affected communities to understand or challenge AI-driven actions (Odilla 2023, 2024; Transparency International 2025: 4; Zinnbauer 2025). These issues – alongside others discussed in this Helpdesk Answer, such as ethical concerns about surveillance and consent – must be carefully managed if AI ACTs are to achieve their intended impact.

This Helpdesk Answer takes stock of emerging evidence in the academic and policy literature on the benefits and risks of AI ACTs and is structured as follows. The next section explains key AI technologies: machine learning (ML), deep learning, natural language processing (NLP), computer vision (CV) and generative AI (Gen AI). The section after that first introduces how AI can enhance existing anti-corruption work by being embedded into current workflows to augment rather than replace human judgement. The answer then surveys the existing evidence of benefits and risks of using AI ACTs for the prevention, detection and investigation of corruption.

Subsequent sections examine AI-supported risk assessment across these functions and explore applications in the appraisal, monitoring and evaluation of national anti-corruption strategies, drawing lessons from related fields. The Helpdesk Answer also reviews existing initiatives and opportunities to combine established anti-corruption instruments with emerging AI technologies. It concludes with a discussion of broader challenges for deploying AI in anti-corruption efforts.

The annex tables identify the AI technologies used in each example. These include machine learning (ML), of which deep learning is a subset, as well as natural language processing (NLP), computer vision (CV) and generative artificial intelligence (gen AI). The tables also name model types such as convolutional neural networks (CNNs) and large language models (LLMs). For a fuller explanation of these technologies and their anti-corruption applications, see Resimić (2025: 9-13).

General benefits and challenges of using AI in anti-corruption efforts

This section first situates AI within the broader evolution of information and communications technologies (ICT) that have been applied to anti-corruption efforts, ranging from early e-governance platforms and electronic procurement systems to today's advanced analytics and predictive tools (Aarvik 2019; Zinnbauer 2025). It then outlines the key benefits and challenges of applying AI tools in anti-corruption contexts.

From digital technologies to contemporary AI systems in anti-corruption

Over the past two decades, the anti-corruption field has increasingly adopted digital technologies to enhance transparency, citizen engagement and oversight (Zinnbauer 2025). Early initiatives focused on e-government systems and the digitalisation of public services, which streamlined administrative processes, reduced waiting times and were empirically shown to lower corruption risks (Shim and Eom 2008; Andersen 2009; Elbahnasawy 2014; Gurin 2014). In parallel, crowdsourcing platforms, whistleblowing portals and open-data dashboards empowered citizens and journalists to monitor procurement, asset declarations and legislative votes in real time (Kossow and Dykes 2018; Kossow and Kukutschka 2017). More recently, blockchain has been piloted to create tamper-proof records of public contracts and financial flows, offering stronger audit trails (Hariyani et al. 2025).

Yet every wave of ICT innovation has brought its own risks. Digital channels can be exploited for illicit transactions on the dark web, crypto-based money laundering or the manipulation of citizen feedback systems (Adam and Fazekas 2018). Today, artificial intelligence represents the next frontier: AI systems can sift through millions of records to flag anomalous bids or suspicious transactions and automate facial recognition or satellite-image monitoring of public works. Early evidence suggests AI can significantly improve detection rates in public contracting and anti-money laundering efforts (Aarvik 2019; Zinnbauer 2025).

However, as with many previous technologies, AI also introduces challenges – such as data quality and bias, algorithmic opacity and uneven access to computing

resources – that must be carefully managed to ensure these tools strengthen, rather than undermine, integrity and accountability.

General benefits of using AI in anti-corruption

Key features of AI systems that can be beneficial to anti-corruption efforts include:

- **Autonomous learning and task execution at scale**: After initial programming and inputs from humans, AI systems can independently train on datasets to execute tasks that once required intensive human effort (Köbis et al. 2022a). Deep learning models using neural networks automatically detect complex patterns and relationships across millions of data points, enabling them to flag subtle corruption indicators that human analysts could miss. For example, research shows that AI ACTs can detect corruption risk zones and predict embezzlement by processing vast volumes of documents and records (Köbis et al. 2022a; López-Iturriaga and Sanz 2018; de Blasio et al. 2022).

- **Leveraging advanced computing power**: modern AI thrives on the exponential growth in computing capacity, which allows it to ingest and process massive datasets in near real time (OECD 2025a). This makes it possible to track complex corruption schemes such as the use of shell company networks, aggregate data from disparate sources and run predictive analytics that highlight where bid rigging or embezzlement is most likely to occur (Köbis et al. 2022a; OECD 2025a). High-performance computing also enables rich and detailed visualisations of complex financial flows to uncover hidden relationships and money trails (OECD 2025a).

- **Fewer human interventions**: unlike human decision-makers, AI, in principle, operates without personal interests, theoretically limiting opportunities for conflicts of interest (Köbis et al. 2022a). By automating decision flows and removing discretionary human steps, AI reduces the number of interactions where petty corruption can occur (Köbis et al. 2022a). However, this reduction in human involvement also means fewer natural audit checks: if an AI system is compromised – through biased training data, for example – there may be no human operator to notice or correct it. In such cases, a corrupted AI could systematically misclassify or misallocate resources at scale before anyone realises something is wrong (Köbis et al. 2022b; Zinnbauer 2025). Thus, while fewer human interventions lower opportunities for traditional corruption, they heighten the importance of robust oversight, continuous monitoring and transparent algorithmic audit trails to detect and respond to any AI system failures or manipulations (Kossow et al. 2021).

- **Capability to integrate novel and disparate data sources**: AI can potentially detect instances of corruption that would be hard to uncover using traditional research methods and tools. For instance, AI systems can leverage large geospatial datasets and satellite imagery to expose corrupt practices in hard-to-reach areas. Deep learning models, for example, have been used to spot illegal road construction linked to deforestation, monitor unauthorised mining and map land grabs by using satellite imagery and deep learning (Labbe 2021; Hausermann et al. 2018; Laurance 2024). These capabilities boost transparency and can empower civil society and local watchdogs with micro-level detail on where illicit activities are occurring, even in remote areas (Zinnbauer 2025; Labbe 2021).

General challenges of using AI in anti-corruption

Key general challenges include:

- **Data reliability and bias**: AI-driven anti-corruption tools are only as good as the data they consume, yet many datasets used in anti-corruption contexts are often incomplete, inconsistent or biased (Köbis et al. 2022a; Zinnbauer 2025). Biases may result from poor quality data (missing values, errors from the data gathering stage) or personal biases of those involved in developing AI systems (Odilla 2024). Both academic studies and public policy AI ACTs analysed in this Helpdesk Answer note the issue of limitations in public expenditure data like public procurement (Fazekas et al. 2023; Katona and Fazekas 2024) and corruption investigation/conviction data (Gallego et al. 2021). These limitations, which include missing data, interoperability challenges, difficult-to-process data formats, as well as deeper concerns like the "selective labelling problem"[3] (see Gallego et al. 2021; Gallego et al. 2022) negatively affect the reliability of AI-driven tools for identifying corruption risks.

  For instance, the project MARA in Brazil, which uses ML to develop individual level corruption scores for civil servants based on previous conviction data, has faced criticism that it simply reinforces existing patterns and biases (Nicaise and Hausenkamph 2025). This is because it was trained only on individuals who were caught and punished, which may exclude undetected corrupt behaviour and focus disproportionately on those civil servants from agencies with robust internal oversight, which consequently overlook broader systemic corruption (Nicaise and Hausenkamph 2025;

[3] The selective labelling problem happens when AI models are trained only on the cases that were caught and labelled (e.g., prosecuted corruption cases), which introduces bias.

Köbis et al. 2022a; Odilla 2024). Data poisoning – deliberate tampering with training data by bad actors – poses another concern, especially for systems that rely on continuously updated online data (Ugale and Hall 2024: 45).

Therefore, it is important to invest in transparency initiatives aimed at ensuring the maintenance of high-quality, unbiased, open government and open data repositories (Zinnbauer 2025: 15). The experience of the Tribunal de Contas (TdC) in Portugal in using AI for developing audit risk models offers several useful lessons on how to improve data quality. First, enhancing data validation mechanisms, which may involve automating the cross-referencing of datasets with other external sources to automatically flag inconsistencies before they can affect the analysis. Second, enforcing data quality and consistency standards across public sector institutions to enhance more efficient use of such data (Hlacs and Wells 2025: 22).

- **Algorithmic challenges and capture**: even the most sophisticated AI models can produce false positives (e.g. wrongly flagging innocent officials) and false negatives (e.g. failing to detect actual corruption). False positives risk reputational harm if AI-generated risk scores or alerts are made public without human verification (Köbis et al. 2022a). Conversely, false negatives can erode trust in AI tools: if a large corruption scandal slips through automated checks, the public may suspect that those in power have tampered with the AI system to hide wrongdoing (Köbis et al. 2022a).

  At the broader level, the weaknesses in the training data can compound blind spots (false negatives). If corruption is already under-detected in transaction data and AI models are trained only on the limited cases that are identified, the models will become good at detecting those identified positive cases. However, this also reinforces the blind spots, making it harder for the system to detect the many cases that went unnoticed in the first place.

  Transparency International (2025) has proposed the concept of "corrupt uses of AI" to cover instances in which AI systems are abused by entrusted powerholders for private gain. This could involve officials trying to game the system. For example, if an official knows what type of behaviour or data would be flagged as a "corruption risk", they could pass on or sell this information to people to help them avoid these supposedly systematic and comprehensive checks. Rather than gaming the system, manipulations can also involve influencing the design of the AI system itself. For instance, algorithmic capture can occur in e-procurement as a one-time manipulation of the AI system by power holders, resulting in narrow politically connected interests reaping long term benefits (Köbis et al. 2022b: 8).

- **Need for human oversight**: effective deployment requires the right balance between AI autonomy and human oversight (Köbis et al. 2022a). Many of the international standards and principles of using AI that have been emerging focus on this aspect. For example, a recently published AI Playbook for the UK Government (2025) calls for a meaningful human control at the right stages, including ensuring that humans validate any high-risk decisions influenced by AI (Principle 4). Governance frameworks – such as the OECD AI Principles and the EU AI Act – also mandate human oversight and thresholds for AI autonomy in high-risk contexts, reinforcing that AI should augment, not replace, human decision-making (OECD 2019; EC 2024).

- **Institutional readiness and regulatory lag**: AI effectiveness in anti-corruption contexts critically depends on the broader institutional, legal and oversight environment in which these AI systems operate (Ubaldi and Zapata 2024). In many jurisdictions, these enabling conditions lag far behind the pace of AI innovation, particularly with the rapid deployment of gen AI since 2022. National and supranational stakeholders have warned that the absence of clear governance frameworks, procurement standards and operational guidelines increases risks of misuse, bias and rights violations (OECD 2019; Ubaldi and Zapata 2024). For example, the EU's AI Act (2024) treats many AI tools as high-risk, thereby obliging AI providers to establish a risk management system, conduct data governance (e.g. ensuring that training, testing and validation datasets are sufficiently representative) and allow for human oversight, among other requests (Future of Life Institute 2024). Yet, in many developing countries, such safeguards are absent or only partially implemented, meaning that AI systems can be deployed without adequate accountability mechanisms in place. In Albania, critics questioned who would bear legal responsibility for procurement decisions influenced by Diella, an AI Chatbot introduced as a virtual minister in 2025 to tackle corruption, and how bidders could challenge those decisions, highlighting the need for first consolidating legal framework and developing methodology for monitoring the efficiency of such systems (Gjoka 2026; Washington Post 2025). Experts also raised concerns about data quality and whether Albanian institutions had the technical capacity to protect sensitive information, audit the system and assess its effectiveness (Gjoka 2026).

- **Inclusivity gaps**: AI systems' development and training datasets often lack diversity, reinforcing the existing digital divide, which can flow into data, model design and deployment. Women and marginalised communities remain underrepresented among AI professionals, and there is a lack of high-quality training data representing these groups (Zinnbauer 2025). For instance, women are estimated to make up only 29% of AI professionals (Constantino 2024). Moreover, while AI and computer science education is

expanding, gaps in access persist as it remains limited in many African countries due to existing infrastructure challenges, including issues as fundamental as access to electricity (Maslej et al. 2025). Considering that most current AI systems are controlled by commercial actors in the Global North (Laforge 2024), they are unlikely to be tailored to the needs of the Global South (Zinnbauer 2025: 15). This increases the risk of discriminatory outcomes and has implications for anti-corruption efforts (Raghavan 2020; Leech et al. 2024; Maslej et al. 2025). For example, when AI tools are trained on historical "sanctions" or enforcement data, they can reproduce who was already visible to oversight and who was not, thereby amplifying disparities (see Odilla 2024). At the same time, "low-data environments" – common in many countries in the Global South where governance data is patchy – pose additional challenges, since this increases the likelihood that AI ACTs will be trained and rely on datasets with significant gaps or biases (for example, official data that primarily reinforces government narratives) (Foti 2025). This underscores the need to prioritise local data and triangulate information, while strengthening human oversight and ensuring transparency by involving independent experts and civil society actors in AI tool development (Foti 2025).

- **Information asymmetry and opacity**: many AI models, especially deep learning, are "black boxes", producing outputs without transparent explanations (Köbis et al. 2022b: 10). This opacity is compounded by the fact that both the training datasets and the model architectures are often proprietary – created and maintained by private, for-profit vendors – placing them beyond the reach of public scrutiny, although the quality gap between closed and open models have reportedly been shrinking (Pillay 2024). Moreover, this raises acute accountability concerns: if an AI tool generates erroneous or unfair outcomes, it is unclear who should be held accountable: the private developer whose opaque model produced the error or the government body that chose to integrate and act upon those outputs? (see Sanderson et al. 2023).

  On the one hand, the opacity arises from the technical nature of the models, which makes it inherently difficult to interpret results.[4] On the other, it is exacerbated by deliberate secrecy by governments about the AI systems they deploy, as seen with SyRi in the Netherlands and the "Zero Trust" programme in China (Algorithm Watch 2020; Borgesius and van Bekkum 2021; Chen

[4] For a recent discussion about how AI solutions not only inherit but also transform longstanding methodological and measurement challenges in anti-corruption field, like validity, accuracy, data bias and replicability, see Gnaldi and Odilla (2026).

2019). The challenge of interpretability and explainability[5] is also evident to LLMs, considering the breadth and variety of data fed into these models (Ugale and Hall 2024). Therefore, it becomes challenging to trace the connection between input data and the outputs of these models, making it more difficult for citizens to understand how a decision was made and to appeal those decisions to protect their own rights and interests (Ugale and Hall 2024: 41). Although there are no easy solutions to these challenges, Ugale and Hall (2024: 41) note that governments have explored the use of decision trees to illustrate the link between the AI systems' results and explanations of how they were reached and have issued explainable AI toolkits, while some academics have introduced a taxonomy of explainable techniques for LLMs (Berryhill et al. 2019; Zhao et al. 2024; Government of the Netherlands 2024).

Without clear governance frameworks, public administrators may be tempted to defer liability to vendors, while developers may evade responsibility by invoking technical complexity. The EU AI Act (2024) and OECD's AI Principles (2019) both emphasise the need for transparency, explainability and shared accountability, requiring that high-risk AI systems include human controls, detailed documentation of training data and mechanisms for contesting decisions (EC 2024; OECD 2019, 2025).

[5] When describing interpretability and explainability, it is important to note that while relatively interpretable models such as random forests or regularised regressions can provide feature-level explanations (i.e., highlighting which variables contributed most to a given prediction), these models are highly sensitive to small changes in the dataset. As a result, their "explainability" is limited: they may clarify how the model arrived at a particular prediction, but they tell us much less about the interaction of factors that produced a given outcome.

AI and anti-corruption

This section first discusses how AI can enhance existing anti-corruption work by being embedded into current workflows to augment rather than replace human tasks and judgement. In practice, the most common, and immediately valuable, applications are the mundane[6] ones: using AI (especially LLMs) to automate repetitive tasks at scale. The section then reviews empirical evidence on the use of AI in the prevention, detection and investigation of corruption. For prevention and detection, it examines key themes, the AI technologies applied, central findings and the main benefits and challenges, drawing on academic studies and public policy applications. For investigations, where far fewer applications exist, the discussion focuses on the potential benefits and challenges of using AI tools, particularly in evidence gathering and document analysis.

"Mundane" uses of AI technologies in anti-corruption efforts

AI is proving valuable for governments, private firms and non-profits by automating "mundane" tasks that would otherwise consume scarce staff time or be virtually impossible to accomplish due to the vast volumes of data involved. With AI (particularly LLMs), prompts can be adjusted without building complex new programming pipelines, teams can quickly add stages to the existing pipeline and achieve strong accuracy on routine work that would be prohibitively time-consuming – or practically impossible – to perform manually at this scale. Typical examples range from translation, copy editing and project management tasks to converting PDFs into spreadsheets or structured tabular formats, classifying large datasets and extracting names, roles, dates and entities from unstructured text.

As noted later in this Helpdesk Answer, Transparency International UK's (n.d.) use of AI to classify lobbying records transformed vast records of lobbying meetings into an analysable dataset, freeing researchers to focus on substantive insights rather than manual data collection (for practical uses of this dataset see: Whiffen 2025).

Similarly, the Transparency International Global Health Atlas aggregates and structures diverse information on corruption in the health sector, creating a reusable

[6] This "mundane" layer is cross-cutting: it underpins prevention (cleaner, richer indicators), detection (faster triage of red flags) and investigation (bulk evidence ingestion and entity extraction), enabling experts to examine far more material with the same resources.

evidence base for investigations, advocacy and policy design (Transparency International Global Health 2025). These initiatives have demonstrated the usefulness of LLMs, ML and NLP based techniques to turn vast amounts of information into structured and regularly updated datasets.

Box 1. Civil society uses of AI in anti-corruption efforts: The experience of Transparency International UK

For several years, Transparency International UK has moved beyond theoretical work to deploy practical AI tools that turn vast, complex datasets into actionable evidence addressing public integrity challenges, from lobbying and conflicts of interest to public procurement corruption. In doing so, they have applied a range of AI techniques, including ML, NLP and gen AI.

Their Health Atlas project (discussed in the following section) uses LLMs in a multi-stage classification process. The system identifies articles relevant to corruption, classifies the specific type of corruption (e.g., bribery), and extracts key metadata like location and date, creating the world's largest repository of evidence on health corruption. In the project's early stages, they also analysed the data (using BERT sentiment analysis[7]) to distinguish between reports of corruption and articles detailing anti-corruption efforts.

Building on these capabilities, TI UK developed Tomni AI, a versatile platform that integrates retrieval-augmented generation. This allows users to ask natural language questions of vast document sets. This system uses a hybrid approach, combining vector-based semantic search with traditional keyword search (BM25) for accuracy, before an LLM synthesises the retrieved information into a coherent answer. Tomni AI is also designed as an agentic AI system, where a researcher can define a customed sequence of tasks – such as semantic chunking, data enrichment with user-defined red flags (e.g. extract when suspicious transactions are noted and their value), and named entity and relationship extraction (to automatically populate network maps from vast PDFs/leaks/investigations) – for the system to execute automatically on unstructured data.

[7] BERT sentiment analysis uses a model called BERT (Bidirectional Encoder Representations from Transformers) to understand and classify the sentiment of text, such as determining if a review is positive or negative. It leverages deep learning techniques to analyse the context of words in sentences, improving the accuracy of sentiment detection.

AI and prevention[8] of corruption

Key themes

The potential of AI technologies in preventing corruption has been tested primarily in two broad thematic areas:

- predicting corruption risks and corruption "hotspots" in the allocation and disbursement of public funds (Huber and Imhof 2023; Gallego et al. 2021; Decarolis and Giorgiantonio 2022; Rodríguez et al. 2022; Fazekas et al. 2023; Katona and Fazekas 2024; Mazrekaj et al. 2024)
- deterring lower-level corruption in the public sector, supporting informed decisions and reducing information asymmetries that increase corruption risks (Odilla 2023; Köbis et al. 2022a; TNRC 2024; Lisnichuk et al. 2026; Nestulia 2026).

Academic studies and public policy applications of AI ACTs demonstrate the potential of AI to identify corruption risks in public procurement contracting (e.g. Gallego et al. 2021; Odilla 2023; Katona and Fazekas 2024). Research also shows AI can effectively detect cartels and collusion in public contracting (e.g. Huber and Imhof 2023; Fazekas et al. 2023). Furthermore, empirical studies and public policy deployments highlight AI's potential to uncover conflicts of interest, either by identifying politically connected firms (Mazrekaj et al. 2024) or by classifying lobbying meetings and health corruption cases into various categories (Transparency International Global Health 2025; Transparency International UK n.d.).

AI has also been applied to simplify administrative procedures and improve public awareness of public service delivery, thereby reducing opportunities for petty corruption. A notable example is Justina del Mar, an NLP based chatbot developed by WWF Peru. It provides artisanal fishers and shipowners with instant, reliable answers about inspections, licensing, sanctions and reporting channels (WWF 2024). Built from phone surveys and consultations that mapped common questions and knowledge gaps then systematised with regulatory texts and information obtained from authorities, the tool provides plain-language guidance via simple menus or natural language queries (WWF 2024). By putting accurate rules and reporting channels directly into users' hands, it is intended to reduce opportunities for petty

[8] In this Helpdesk Answer, prevention involves those cases in which AI can identify corruption "hotspots", whereas detection covers the cases where AI can identify specific entities (i.e. public officeholders, firms, public procurement contracts).

bribery or extortion tied to information asymmetries and to strengthen transparency and trust between communities and authorities (WWF 2024).

Beyond citizen-facing information tools, AI can also support corruption prevention by helping public officials understand and apply relevant rules and procedures. One example comes from Ukraine, where DREAM, an open digital ecosystem for public investment management, has been at the centre of its Public Investment Management (PIM) reform (Nestulia 2026). DREAM connects various registers and supports project monitoring and data analysis, providing a single digital pipeline covering the full investment cycle, from project initiation and feasibility appraisal to implementation monitoring (Nestulia 2026).

Building on this infrastructure, the initiative sought to integrate AI to address the practical difficulties officials face in navigating complex legislation, procurement rules, financial requirements and donor conditions (Nestulia 2026). The underlying premise was that AI cannot yet replace public servants, expert judgment or political accountability, but can improve how knowledge is accessed, interpreted and applied. The DREAM AI Assistant was therefore developed to provide support within existing governance processes, helping officials prepare and appraise projects. Its initial phase in 2026 focuses on providing real-time guidance on PIM rules and project preparation, with plans to expand into quality assurance in 2027 and advanced investment modelling thereafter (Nestulia 2026).

AI technologies in corruption prevention

Most academic studies and public policy applications rely on machine learning (ML) techniques, ranging from traditional regressions to deep learning models (e.g. Fazekas et al. 2023; Gallego et al. 2022; García Rodríguez et al. 2022; Mazrekaj et al. 2024). Existing academic studies often employ linear models, such as lasso, and tree-based ensemble models, like random forests, while fewer use neural networks (e.g. López-Iturriaga and Pastor Sanz 2018).

Some initiatives also use natural language processing (NLP) techniques, which were shown to be especially useful in generating novel corruption risk indicators based on textual data from public procurement notices (e.g. Katona and Fazekas 2024). Moreover, Transparency International UK has been using gen AI (LLMs) for their projects on classifying lobbying meetings (Annex 1, Example #13) and healthcare related corruption stories (Annex 1, Example #12).

Across approaches, trade-offs emerge: interpretable models (e.g. traditional statistical models) facilitate transparency and policy adoption, while more complex

black-box models (e.g. neural networks) can increase predictive performance but risk resistance from oversight bodies due to their opacity.[9]

Central findings

Evidence from academic studies and practical deployments analysed in this Helpdesk Answer suggests that AI ACTs show promising results in preventing corruption. Most academic studies report that their models achieve high predictive performance in identifying corruption "hotspots" in public procurement, detecting collusive bidding patterns and flagging politically connected firms with the potential of predicting conflicts of interest (e.g. Katona and Fazekas 2024; Fazekas et al. 2023; Mazrekaj et al. 2024; Huber and Imhof 2023).

For instance, using NLP and ML algorithms to analyse the text in tender documents lifted single-bid prediction[10] from 77% to 82% in Hungary (Katona and Fazekas 2023), while ML models correctly predict over 85% of politically connected firms in the Czech Republic based solely on firm-level financial and industry indicators (Mazrekaj et al. 2024).

Key benefits and challenges

The key advantage of AI technologies for corruption prevention lies in their superior efficiency and scalability compared to traditional audits. By prioritising corruption risk "hotspots" for targeted audits, authorities can allocate their finite oversight resources more efficiently (Katona and Fazekas 2024; Fazekas et al. 2023). Complex models – such as gradient boosting or neural networks – can uncover subtle, non-linear patterns in procurement or financial data that simple rule-based systems or human auditors may miss (Chen 2019; Gallego et al. 2021). Predictive scoring also enables authorities to intervene before contracts are awarded, reducing losses from corrupt practices, such as in the case of the Alice tool in Brazil (Odilla 2023). Moreover, AI tools can integrate heterogeneous data sources – structured procurement records, corporate ownership registries, social network mappings and unstructured text – to create richer and more robust corruption risk profiles and identify more complex collusion and conflicts of interest patterns (Aarvik 2019; García Rodríguez et al. 2022; Mazrekaj et al. 2024; Zinnbauer 2025).

[9] There are also models that aim to combine interpretability with strong predictive performance. One notable example is the explainable boosting machine, a glass-box model with built-in interpretability: it is transparent by design, enabling users to understand its logic, while often achieving accuracy comparable to state-of-the-art black-box models (InterpretML n.d.; McGrail 2023; MinnaLearn n.d.).

[10] The number of tenders that received only one bid.

However, challenges persist. First, the opacity of black-box models such as deep neural networks limits interpretability, which can undermine public trust (Chen 2019). Second, there are still significant challenges with data quality, especially with regards to public procurement datasets (Katona and Fazekas 2024; Fazekas et al. 2023). Incomplete, inconsistent or biased datasets can produce misleading results, amplifying false positives or negatives. This is especially problematic with the use of corruption investigation/conviction data, which is prone to a "selective labelling problem" (see Annex 1, Example #9 below) (Gallego et al. 2021). Third, corrupt actors may adapt their behaviour once risk indicators become known, requiring periodic retraining with updated data to maintain model effectiveness (Fazekas et al. 2023). Finally, there are resource and capacity gaps: building and sustaining these systems requires technical expertise and institutional infrastructure that may be lacking in some public agencies. In citizen-facing tools, such as Justina del Mar in Peru, basic digital literacy among end-users is also a prerequisite for effective use (TNRC 2024).

For a list of examples of the application of AI ACTs in corruption prevention, see Annex 1.

Box 2. AI and awareness raising

AI tools are increasingly being used to explain integrity rules, direct people to reporting channels and make information about corruption cases easier to find. These efforts often take the form of chatbots. As the example of Justina del Mar in Peru illustrates, practical guidance on licensing, inspections and where to report misconduct can help people understand what officials are entitled to ask of them (WWF 2024).

Public institutions have developed similar tools to explain conflicts of interest and disclosure obligations to officials, while civic initiatives have used AI to help citizens follow corruption allegations involving elected officials.

These applications form a small part of a broader trend. Governments report growing use of AI across public services, with chatbots and workflow automation among the most common applications (Lundy et al. 2026, pp. 14-15). Evidence of the effectiveness of chatbots in anti-corruption awareness raising remains limited. Several initiatives are still at the design or testing stage, and little is known about whether they improve users' understanding of integrity rules or their ability to act on that knowledge.

In Latin America, Pit Policy Lab and GIZ are developing a Citizen Complaint Chatbot for audit institutions in Guatemala, Uruguay, Panama and the city of Buenos Aires, Argentina. The proposed chatbot would explain where and how to submit a complaint

and what information it should contain (PIT Policy Lab no date). The goal of this chatbot is to educate citizens about the appropriate methods, procedures and locations for submitting complaints to the Supreme Audit Institutions (SAIs). The design recommendations gathered from civil society and participating audit institutions highlight that users should be able to tell when they are receiving automated guidance. Other recommendations include making the chatbot accessible across devices and to people with limited digital skills, protecting users' anonymity and privacy, and explaining how the reporting process works by organising capacity building trainings (PIT Policy Lab no date).

In Argentina, the Anti-Corruption Office has used the TINA virtual assistant to make integrity guidance more accessible to citizens and public officials (Ministry of Justice 2026). In mid-2025, TINA incorporated a conflict-of-interest simulator explaining officials' obligations and how potential conflicts should be managed (Anti-Corruption Portal 2025). This functionality was then built into the existing national chatbot TINA, a virtual assistant developed by the Office of the Chief of the Cabinet of Ministers of Argentina. Building on these services, the Office and the Secretariat of Innovation, Science and Technology developed MIA-OA, an AI-powered conversational assistant operating through TINA (Ministry of Justice 2026). In addition to the conflict-of-interest simulator, TINA has also integrated a "Report corruption" functionality, providing citizens with a channel to submit information about potential corruption violations to the Anti-Corruption Office of the Ministry of Justice and Human Rights (Anti-Corruption Portal 2025). Still in testing as of September 2026, MIA-OA was designed initially to guide officials in completing their asset declarations, with plans to extend its coverage to other public-ethics obligations (Ministry of Justice 2026).

In Ukraine, Corruption Radar, an AI-powered tool for daily digest of corruption verdicts launched in 2025, automatically analyses newly published court rulings and generates short AI-produced summaries, which are then published to the Corruption Radar Telegram Channel (World Bank no date). The goal is to provide easier access to corruption cases to journalists, civil society organisations and the general public and offer visibility into lower-profile corruption cases that would otherwise go under the radar (World Bank no date; BRDO 2025).

In Kenya, a citizen-led initiative used AI to make information about corruption allegations involving politicians and public officials easier to access. During the 2024 anti-government protests, a Kenyan citizen created Corrupt Politicians GPT, a ChatGPT-based tool that allowed users to enter a politician's name and retrieve a summary of publicly reported allegations and case outcomes, including whether the individual had faced prosecution or had been cleared (Kimani 2024, Wekesa 2024, Karanja and Musili 2026).

Box 3. AI and integrity trainings

Integrity trainings often use practical scenarios to help public officials apply ethical standards to situations they may encounter at work (see OECD 2020). The expansion of AI applications has opened up opportunities to make integrity and compliance training more interactive and responsive to learners' needs, although their use in this area remains at an early stage.

Drawing on a learning content survey conducted among product user groups in December 2024, DiChiara (2025) highlights interest in AI-supported personalisation in ethics and compliance training. Respondents identified greater engagement, tailored content, more personalised feedback and assistance with questions as desirable features. In particular, 78% considered courses that assess learners' knowledge and adapt accordingly to be a potentially important future application of AI in their training. Respondents also expressed interest in conversational tools and AI-generated quizzes offering personalised feedback (DiChiara 2025).

In South Korea, the Anti-Corruption and Civil Rights Commission's (ACRC) 2026 training programme includes a three-and-a-half-hour exercise in which officials practise making integrity judgements with AI assistance (ACRC 2026; National Institute for Integrity and Rights Education no date). The 2026 Training on Integrity and Rights Competencies utilising AI and Data consists of various practical tasks of which integrity was one component. Another training relevant for integrity within this programme covers ethics and security in the public sector including issues like safe data input and management (ACRC 2026).

In Taiwan, the Ethics Office of the Taitung County Environmental Protection Bureau launched an interactive online guide in February 2026 to help public officials apply integrity rules in everyday situations, including receiving gifts, invitations to meals and requests for favours. The initiative emerged from an internal workshop on using AI in administrative work. The bureau's government ethics office used AI to help organise common scenarios and the reasoning needed to assess them, and to translate this into a web-based guide (Central News Agency 2026). Officials navigate a sequence of choices, receiving explanations and reminders at each decision point to help them consider the appropriate response. Government ethics staff reviewed and revised the content against existing rules. The guide processes users' selections locally in their browsers and collects or retains no personal data (Central News Agency 2026). It provides an initial self-assessment resource alongside formal consultation procedures, illustrating how AI can help institutions turn integrity rules into practical, accessible guidance for officials (Central News Agency 2026).

More broadly, there is growing emphasis on equipping public officials to use AI tools responsibly in their work. A recent OECD (Heyaca and Pallotta 2026) paper notes that institutions are embedding upskilling initiatives within their wider change management strategies to build a digital culture. Some have also established internal training academies to deliver targeted training in AI and data science (Heyaca and Pallotta 2026: 48). For example, the European Court of Auditors adopted a comprehensive approach to build staff competencies in AI. This combines formal training through general AI courses with “GPT cafés”, informal gatherings for discussing AI topics. Other components include a “knowledge node”, an online repository supporting self-directed learning, and functional forums, dedicated communication channels where staff can ask AI-related questions. Conferences also provide opportunities for staff to learn about AI developments and share good practices across institutions (Heyaca and Pallotta 2026: 48).

AI and detection of corruption

Key themes

The potential of AI technologies in detecting corruption has been tested in two broad thematic areas:

- strengthening public sector accountability and transparency by leveraging and connecting diverse political integrity datasets and embedding AI tools into traditional anti-corruption instruments, particularly in audits (Odilla 2023; Harutyunyan 2023; Chen 2019; Transparency International Ukraine 2025; Bosisio et al. 2021; Wacker et al. 2018; Gandhi et al. 2024; Heyaca and Pallotta 2026; Medina-Hernández et al. 2026)

- using satellite imagery to detect corruption risks linked to environmental harm (WWF 2023; Wageningen 2023; Hillsdon 2024; Labbe 2021; Paolo et al. 2024; Zinnbauer 2025)

In the first area, academic studies and public policy applications demonstrate AI's potential to detect corruption risks associated with firms and individual public officeholders. Tools focused on individuals have scrutinised asset declarations (Harutyunyan 2023), flagged wasteful spending (Odilla 2023), enhanced audit of government financial statements (Heyaca and Pallotta 2026) and detected conflicts of interest or irregular financial movements (Chen 2019). Firm-focused applications have assessed corruption risks in public procurement contracts (Transparency International Ukraine 2025; Medina-Hernández et al. 2026), flagged corporate ownership anomalies (Bosisio et al. 2021), detected fake suppliers (Wacker et al. 2018) and identified money laundering patterns (Gandhi et al. 2024).

For instance, the Tweetbot Rosie de Serenata was created to analyse reimbursement claims submitted by members of Brazil's congress (Köbis et al. 2022a). Originating from the grassroots anti-corruption initiative Operação Serenata de Amor (Operation Love Serenade), Rosie processes official spending data and flags suspicious expenses, such as cases where a congress member appears to have been in two locations on the same day and at the same time (Cordova and Gonçalves 2019). When a suspicious transaction is detected, Rosie automatically posts the finding on X, inviting citizens and legislators to confirm or refute the suspicion (Cordova and Gonçalves 2019).

In the second area, AI combined with satellite imagery has been used to detect illegal deforestation (WWF 2023; Wageningen 2023; Hillsdon 2024), illegal mining (Labbe

2021) and illicit fishing activities (Paolo et al. 2024), among its other uses (see Zinnbauer 2025). For instance, Forest Foresight, developed by WWF-Netherlands with commercial and academic partners, has demonstrated the ability to predict illegal deforestation up to six months in advance with 80% accuracy in pilot projects in Gabon and Borneo (WWF 2022).

AI technologies

Most public policy applications of AI ACTs and academic studies analysed in this Helpdesk Answer targeting corruption risks among public officeholders and firms use ML algorithms (Odilla 2023; Chen 2019; Transparency International Ukraine 2025; Medina-Hernández et al. 2026). In contrast, applications based on satellite imagery typically use deep learning neural networks (CNNs) for image classification (Wacker et al. 2018; Paolo et al. 2024). The former typically favour relatively interpretable models (e.g., random forests and regularised linear/logistic models) that allow feature-level explanations and audit trails, whereas CNN based image classifiers are higher-accuracy but comparatively more opaque.

Some public policy applications combine NLP techniques with ML and deep learning neural networks, for example, for text pattern recognition. An example is Inspector AI in Peru, which uses NLP to process suspicious transaction reports (GIZ 2024; European Parliament 2021; Gerli 2024; Nicaise and Hausenkamph 2025).

Central findings

Evidence from public policy applications of AI ACTs and academic studies show promising results in AI's ability to detect corruption, although some public policy applications are still in their early stages or are currently undergoing further development.

Civic-tech platforms such as Rosie (Brazil) (Odilla 2023; Operação Serenata de Amor n.d.), and DOZORRO (Ukraine) (see Box 4) have helped prevent inefficient spending, blocked corruption-prone contracts before signature and uncovered conflicts of interest among public officials. AI ACTs have also enabled civil servants to detect corruption risks faster by automating processes, such as extracting information from suspicious transaction reports in Peru (GIZ 2024) and automating the process of early detection of illegal deforestation (e.g. WWF 2023; WWF Ecuador 2025). Other deployments, like China's Zero Trust programme, have demonstrated large-scale anomaly detection capacity by cross-referencing extensive government datasets, although this has raised privacy concerns (Odilla 2023; Chen 2019; Transparency International Ukraine 2025).

Academic studies further show AI's potential to detect corruption, for example, by detecting potentially illegal fishing activity by mapping industrial fishing vessels that are not captured by public monitoring systems (Paolo et al. 2024) or by detecting fake suppliers in public contracting (Wacker et al. 2018).

Box 4. Countering public procurement corruption with DOZORRO in Ukraine

DOZORRO is a feedback platform integrated with Ukraine's centralised public procurement database, Prozorro, established in 2016, which uses machine learning to monitor public procurement activities (Strawinska n.d.; Kucherenko 2019). It is an AI-powered system of civic monitoring over public procurement in Ukraine developed by Transparency International Ukraine (2018). Unlike systems that rely on exhaustive lists of corruption risk indicators – an approach vulnerable to gaming of indicators or manipulation by corrupt officials – DOZORRO's software was designed to avoid such predictability (Transparency International Ukraine 2018).

In 2018, 20 experts reviewed approximately 3,500 tenders without access to the amounts or names of procuring entities, simply indicating whether each tender appeared risky. Their assessments were then used to train the AI algorithm (Transparency International Ukraine 2018). Today, the system independently evaluates the likelihood of corruption risks in tenders and forwards high-risk cases to civil society organisations within the DOZORRO network. The model "remembers" correct classifications and "forgets" incorrect ones, enabling continuous refinement over time (Transparency International Ukraine 2018; Aarvik 2019).

DOZORRO has proven effective in preventing inefficient spending and identifying high corruption risk contracts in Ukraine (Open Stories 2021; Transparency International Ukraine 2025a). For instance, in July 2025, the DOZORRO team analysed 165 procurement procedures worth over UAH 10 billion (approx. €207 million) and identified violations in 89 tenders, with inflated pricing the most common issue (Transparency International Ukraine 2025b). Through DOZORRO's requests to procuring entities and its cooperation with law enforcement in the first half of 2025, inefficient spending of UAH 133 million (approx. €2.7 million) was prevented (Transparency International Ukraine 2025b).

Key benefits and challenges

The key benefit of deploying AI technologies for corruption detection is the ability of AI ACTs to detect risky tenders (Transparency International Ukraine 2025), fake bidders (Wacker et al. 2018), suspicious financial transactions that could indicate

money laundering (Gandhi et al. 2024) or conflicts of interest of public officials (Chen 2019; Harutyunyan 2023) before money moves. In addition, these tools can detect environmental challenges such as illegal deforestation (WWF 2023; WWF Ecuador 2025) before environmental degradation occurs, enabling early audits and inspections.

These tools use NLP techniques, ML and deep learning algorithms to sift through and connect heterogenous datasets at a high scale and speed to look for asset declaration discrepancies (Harutyunyan 2023), procurement suppliers' corruption risks (Hlacs and Wells 2025), financial transaction data to identify money laundering patterns (Gandhi et al. 2024) or satellite data to identify potential illegal fishing (Paolo et al. 2024), mining (Labbe 2021) or deforestation (WWF 2023). This can free up human resources to focus on high-risk cases.

Documented impact of these tools includes reduced meal reimbursement spending by approximately 10% after the launch of Rosie in Brazil (Odilla 2023; Operação Serenata de Amor n.d.), twice as many cases referred to prosecutors with Peru's Inspector AI (GIZ 2024) and ranger interventions guided by Forest Foresight risk maps (WWF 2023). This is evidence that AI can translate into concrete enforcement outcomes.

Challenges are, however, significant. As with prevention, data quality remains a central obstacle: incomplete, inconsistent or biased datasets undermine reliability (European Parliament 2021; Gandhi et al. 2024; Paolo et al. 2024; Hlacs and Wells 2025).

Further, the use of high-performance but less-explainable models (e.g. based on neural networks like CNNs) is even more present in detection compared to prevention (see examples below), which carries a risk of public backlash or institutional resistance (Chen 2019). The stakes are also significantly higher in detection: unlike prevention models, which often highlight broad risk patterns or "hotspots," detection tools focus on specific individuals, firms or entities. As a result, errors can have grave consequences: false positives may wrongly implicate officials or companies, damaging reputations, prompting lawsuits or even leading to unjust legal action, while false negatives can allow serious corruption to go undetected. This combination of opacity and high-stakes outcomes makes explainability, transparency and careful human oversight particularly critical at the detection stage.

There are also operational and capacity challenges. The benefits of AI tools depend on embedding them into workflows (case management, audit triggers), sustained funding and skills to retrain/monitor models, plus on-the-ground capacity to act on alerts (e.g., deforestation hotspots) (WWF 2023).

Corrupt actors may also adapt their behaviour once risk indicators become known, requiring regular model retraining against evolving corrupt patterns (see Fazekas et al. 2023).

Finally, some corruption detection tools raised serious privacy concerns, such as SyRi in the Netherlands (Algorithm Watch 2020; Borgesius and van Bekkum 2021) and the Zero Trust programme in China (Chen 2019), due to secrecy of the algorithm used, a lack of transparency on how private data is handled and linkage of vast data sources.

For a list of examples of the application of AI ACTs in corruption detection, see Annex 2.

AI and corruption investigations: Potential, benefits and challenges

Compared to prevention and detection, investigative AI based tools are less common. According to some recent surveys (Ugale and Hall 2024), real-world applications are still limited, particularly in the public sector, and the return on investment remains unclear.

Nonetheless, the potential of AI technologies in corruption investigations is increasingly recognised. For instance, in its 2024 report, the European Public Prosecutor's Office highlights that its digital operations team initiated the Operational Digital Infrastructure Network programme to develop digital tools that would strengthen their investigators' capacities by using artificial intelligence and big data analysis (EPPO 2025). Similarly, the European Investment Bank's investigations division engaged with international investigators in 2024 to explore the use of AI in investigations (EIB 2025).

A recent OECD survey of 59 organisations across 39 countries (Ugale and Hall 2024) found strong interest in generative AI (particularly LLMs) for anti-corruption work. Respondents highlighted their potential to make auditors' and investigators' work more efficient by automating time-consuming tasks and allowing staff to focus on activities requiring human judgement and expertise (Ugale and Hall 2024: 15). Surveyed integrity actors identified the greatest value of LLMs in the areas of investigative and audit processes as relating to evidence gathering and document review (Ugale and Hall 2024: 17). Specifically, LLMs could help investigative work by organising large volumes of text for easy prioritisation and consumption and help in pattern recognition. Indeed, several AI tools have already been deployed in major corruption investigations (see Box 5).

Box 5. AI in corruption investigations: from Operation Car Wash to Rolls Royce bribery cases

In Brazil, the ContÁgil system, a data retrieving and data analysis tool for identifying fiscal fraud and money laundering, developed by the Special Secretariat of Federal Revenue of Brazil (RFB) was used in one of the largest corruption investigations in Brazil, the Operation Car Wash (Lava Jato), to identify complex networks of intermediaries and shell companies and connecting them with politicians and businessmen (Jambeiro Filho 2019; Odilla 2023: 378). It uses data such as asset declarations, ownership registers and tax payments, among other sources (Odilla 2023: 363).

Its resources include an ML environment with supervised learning algorithms and algorithms for clustering, outlier detection, topic discovery and co-reference resolution (Jambeiro Filho 2019). ContÁgil also has a social network analysis tool, which can visualise networks between people and companies based on scanning various data sources (Jambeiro Filho 2019).

The tool increases efficiency dramatically as it reportedly accomplishes in one hour what would take a human inspector a whole week (Jambeiro Filho 2019). The tool however, also exhibited some challenges, such as alert overflow, false positives, slow adaptability to new forms of wrongdoings and limited auditability, among other challenges (Odilla 2023: 372).

In Hong Kong, the Independent Commission Against Corruption (ICAC) unveiled its own AI-powered system to support corruption investigations called Tianma, in August 2026 (Anti-Corruption Portal 2026).

AI has also been used by the Serious Fraud Office (SFO) in the UK. In 2018, the SFO hired an "AI lawyer" tasked with automatically analysing documents (Martin 2018). The SFO previously used similar technology developed by a Canadian firm to spot legally privileged information among 30 million documents during the four-year long Rolls Royce bribery and fraud investigation (Martin 2018; Royas 2017; López Acera 2023). The SFO noted that the technology was 80% cheaper than hiring outside counsel to review documents and identify legally privileged information (Martin 2018).

The OpenText Axcelerate, an AI-driven tool, not only flags legally privileged materials but scans and organises information from various data formats and document types, displaying relevant information for investigation (Martin 2018). However, a recent report highlighted several challenges associated with this and similar tools. In February 2025, SFO noticed that searches did not return expected results as number of documents were omitted due to formatting issues, which required reconfiguration of the software, demonstrating the need for regular maintenance of AI tools (Fisher 2025: 75; Herbert Smith Freehills Kramer n.d.; Ring 2025).

A more serious concern relates to lawyers' recently questioning of SFO's evidence disclosure software, which could undermine historical convictions (Ring 2024). Specifically, SFO is investigating its legacy software tools (its old provider Autonomy Introspect and current Axcelerate system) that were used on dozens of cases to evaluate how it recognised punctuation, and it is reviewing the encoding issue which may have interfered with document searches (Ring 2024). Lawyers have been asking for clarity from prosecutors about how these issues may have affected current and past cases in terms of disclosure (Ring 2024).

While integrity actors considered document analysis and text-based pattern recognition the most valuable uses of LLMs for anti-corruption and anti-fraud investigations, they reported few advanced initiatives (Ugale and Hall 2024: 7). According to the survey, the actors who use LLMs either rely on turnkey foundation models[11] developed by private firms or adapt existing models by fine-tuning them with specific datasets for targeted tasks (Ugale and Hall 2024: 8).

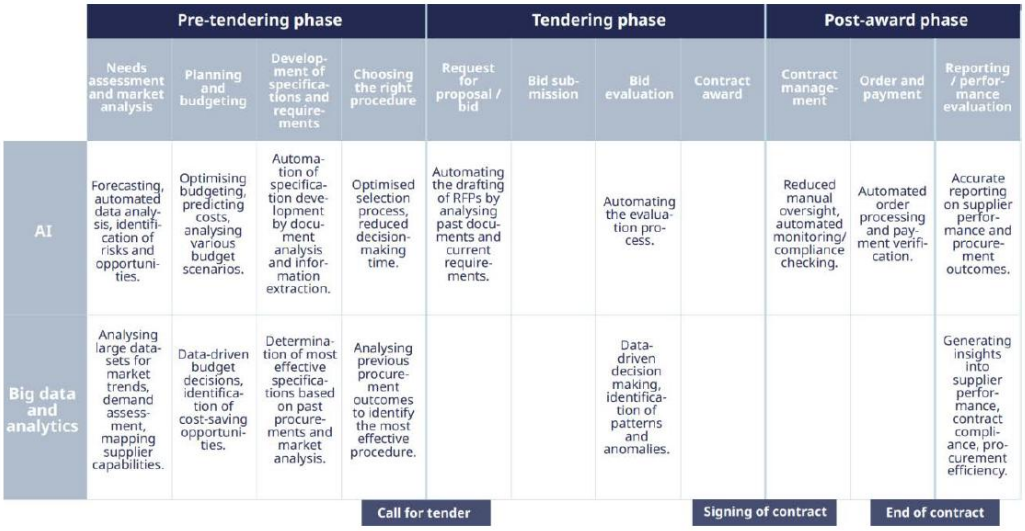
Risk assessments

AI-assisted corruption risk assessment can support prevention, detection and investigation, depending on when risks are identified and how the findings are used. In prevention, tools such as Brazil's Alice flag risks in tender documents so that auditors can intervene before a contract is awarded (Annex 1, Example #5). In detection, Brazil's Rosie flags suspicious reimbursement claims submitted by members of Congress for further scrutiny (Annex 2, Example #1). During an investigation, risk indicators can help investigators decide which leads to pursue. For example, during Operation Car Wash in Brazil, investigators used ContÁgil to trace links between intermediaries, shell companies and public officials during Operation Car Wash (Box 4).

AI-assisted risk assessment is particularly widespread in public procurement, especially in prevention and detection. The OECD (2025: 204) identifies potential and emerging applications throughout the public procurement cycle (Figure 2).

Figure 2: AI potential throughout the public procurement cycle

[11] A model which is available in a ready to use form, without a need for fine tuning (Ugale and Hall 2024: 32).



	Pre-tendering phase				Tendering phase				Post-award phase		
	Needs assessment and market analysis	Planning and budgeting	Development of specifications and requirements	Choosing the right procedure	Request for proposal / bid	Bid submission	Bid evaluation	Contract award	Contract management	Order and payment	Reporting / performance evaluation
AI	Forecasting, automated data analysis, identification of risks and opportunities.	Optimising budgeting, predicting costs, analysing various budget scenarios.	Automation of specification development by document analysis and information extraction.	Optimised selection process, reduced decision-making time.	Automating the drafting of RFPs by analysing past documents and current requirements.		Automating the evaluation process.		Reduced manual oversight, automated monitoring/ compliance checking.	Automated order processing and payment verification.	Accurate reporting on supplier performance and procurement outcomes.
Big data and analytics	Analysing large datasets for market trends, demand assessment, mapping supplier capabilities.	Data-driven budget decisions, identification of cost-saving opportunities.	Determination of most effective specifications based on past procurements and market analysis.	Analysing previous procurement outcomes to identify the most effective procedure.			Data-driven decision making, identification of patterns and anomalies.				Generating insights into supplier performance, contract compliance, procurement efficiency.
				Call for tender				Signing of contract		End of contract	

Note: RFP = Request for Proposal
Source: OECD's illustration based on desk research and (EC, 2020[66]).

Source: OECD (2025: 204).

As examples discussed earlier in this Helpdesk Answer illustrate, machine learning can help oversight bodies identify errors in procurement records and flag patterns that may indicate fraud, collusion among bidders or attempts by contracting authorities to favour a particular bidder (see also OECD 2025: 207).

The cases from Lithuania and Kazakhstan discussed below illustrate how authorities can combine procurement records with other administrative data to prioritise investigations and audits. Beyond procurement, risk assessment can also help authorities screen officials' expense claims, trace links between companies and public officials, and identify corruption reports that warrant follow-up, as the Ethiopian example presented below illustrates.

In Lithuania, the Special Investigation Service (STT) worked with the OECD and the Government Transparency Institute to develop a machine learning tool for risk-based oversight of public spending. The tool combines data from several administrative sources to identify patterns associated with corruption and fraud. It applies a transparent and explainable modelling framework, ultimately aiming at enhancing effectiveness of investigative prioritisation (OECD 2026). The team developed and assessed the tool in several steps:

- Defining key concepts and mapping data sources. The team first defined the fraud and corruption risks it sought to measure, then mapped the administrative data available to assess those risks across the public spending cycle.

- Selecting and linking datasets. After prioritising sources, the team assessed data quality, cleaned the records and linked data from 11 datasets. These covered public procurement, company registration, beneficial ownership, blacklisting, and past criminal and administrative offences.
- Developing indicators and building the model. The team developed risk indicators covering the procurement process, the context of each transaction (such as contract size and the regulatory environment), and beneficial ownership structures. The outcome variable captured documented cases of suspected or proven wrongdoing. They used positive–unlabelled learning because, for cases without documented wrongdoing, it was unclear whether an offence had occurred. Documented cases were also relatively rare, creating a class imbalance. Therefore, a Hellinger Distance Random Forest model was utilised to address these challenges.
- Assessing performance. The model outperformed random selection in identifying documented cases of suspected or proven wrongdoing, suggesting that it could help investigators prioritise cases for review (OECD 2026: 3-8).

In Kazakhstan, Datanomix.pro developed Red Flags Management to help State Audit Institutions prioritise risky procurement transactions. Much procurement information in Kazakhstan is held in unstructured documents, such as technical specifications published as PDFs. The tool uses an LLM to extract specific information from these documents and convert it into structured data for analysis (Open Contracting Partnership 2025). This approach also allows auditors to link procurement information with other sources, such as asset declarations and campaign donation records (Neumann 2026). For each transaction, the tool calculates 43 red flag indicators of procurement risk (Neumann 2026).

The system has two components. The first consists of rule-based algorithms that use corruption risk indicators to determine whether a transaction should be flagged. The second is an LLM that takes unstructured data relevant to procurement audits as input. The LLM extracts specific information and evaluates whether each transaction exhibits any of the red flags. If it identifies a red flag, the system flags the transaction for further review by a government official (Open Contracting Partnership 2025). Further development is planned, but the tool can already detect shell companies, discrepancies between input and output invoices, and instances of overpricing. It can also use government data on family relationships to flag potential cases of nepotism and corruption (Open Contracting Partnership 2025).

In Ethiopia, the National Corruption Reporting System (NCRS) was developed to address barriers that discourage people from reporting corruption, including fear of retaliation, low trust in anti-corruption agencies and limited access to reporting

channels (World Bank no date b). The platform allows citizens and public officials to report suspected corruption anonymously. During the risk assessment step, it uses AI to organise and analyse incoming reports, identify patterns across cases and alert the relevant agencies to allegations that warrant priority investigation. The World Bank (no date b) reports that the system has increased the number and improved the quality of actionable reports. It also reports faster responses and greater public trust in anti-corruption agencies (World Bank no date b).

AI in the appraisal, monitoring and evaluation of national anti-corruption strategies and beyond

There is little published evidence on how public institutions use AI specifically to appraise, monitor or evaluate national anti-corruption strategies. Experience in related fields nevertheless offers valuable lessons. Procurement oversight shows how AI can turn inconsistent administrative records into comparable data. Electoral pledge tracking illustrates how it can help link commitments to emerging evidence. Public policy evaluation offers methods for assessing the evidence behind proposed measures and examining why results vary across institutions. Each addresses a distinct question that those responsible for anti-corruption strategies face: which measures to adopt, how to track their implementation and how to assess their effects.

Ukraine illustrates how digital monitoring can provide a foundation for this work. Its National Agency on Corruption Prevention (NACP) has been utilising AI in monitoring the implementation of the State Anti-Corruption Policy. Its public portal incorporates information about the status and the dynamics of the implementation of anti-corruption strategies by tracking information regarding the percentage of completed activities (NACP 2023). In a separate study, Maletova et al. (2026) prompted six AI systems in Ukrainian and English to propose measures for wartime and post-war reconstruction. The researchers compared the proposals with Ukraine's 2021–2025 Anti-Corruption Strategy and identified possible additions, including more targeted safeguards for defence procurement and humanitarian aid, demonstrating AI systems' capability to identify strategic gaps and propose adaptive frameworks absent from the National Anti-Corruption Strategy for 2021-2025 (Maletova et al. 2026).

While such applications, specifically focused on national anti-corruption strategies, remain limited, LLMs are increasingly being used in related anti-corruption areas to organise information and support analysis to enhance transparency and accountability. These applications suggest clear potential for adapting such tools to track the implementation of anti-corruption commitments.

For example, Brazil's "Medicamentos Transparentes" project uses an LLM-based embedding model to address a longstanding obstacle to monitoring medicine prices: inconsistent descriptions of purchased items in public procurement records (Lisnichuk et al. 2026). The model matched these descriptions to entries in the federal goods and services catalogue based on their semantic similarity, applying a similarity threshold to classify items as medicines. In tests using a manually labelled sample of 1,000 items, it achieved 98% accuracy in identifying medicines and 86% accuracy in assigning the correct catalogue code (Lisnichuk et al. 2026). By making procurement records comparable, this approach facilitates price monitoring and strengthens oversight of potential overpricing and corruption, although these accuracy figures measure classification performance rather than corruption detection. The example suggests promise for using LLMs to support the monitoring and evaluation of national anti-corruption strategies by converting unstructured administrative records into comparable data for tracking relevant indicators, particularly where strategies include procurement-integrity commitments.

Another example involves using AI to monitor government's delivery on electoral pledges, helping voters assess progress. In the UK, the independent fact-checking charity Full Fact developed its Government Tracker using AI, to address a persistent challenge of doing this work manually, considering a sheer amount of information (for example, they identified around 300 tractable pledges only in the Labour manifesto) (JournalismAI no date). Together with Cambridge University, Full Fact developed a two-pronged approach. First, Google Gemini was used to generate questions to help fact-checkers explain each pledge in context. Second, an automated monitoring system using ChatGPT searches trusted sources for relevant updates, constructs timelines of officials' statements and summarises findings for review, to track pledge updates (JournalismAI no date). Human oversight remains central as fact-checkers review all AI outputs prior to publication (JournalismAI no date). Although the model accuracy has improved from 50% to 80%, there is still a lot of space for improvement (JournalismAI no date). This approach suggests that LLMs could support monitoring of national anti-corruption strategies by linking commitments to emerging evidence (i.e. tracking the implementation of pledges included in these strategies) and organising updates for expert review, while leaving judgments about substantive implementation to human assessors.

Another useful application of AI with lessons for national anti-corruption strategies extends to its role in public policy evaluation.[12] In this context, AI can be used to help

[12] As the OECD (2025b: 225) notes, there are inherent risks to using AI in public policy evaluation, many of which are similar to the general challenges discussed earlier in this Helpdesk Answer, such as training algorithms with skewed or incomplete data, automation bias (over-reliance on automation which can reduce the role of human judgement and potentially oversimplify complex social and economic assumptions) and the lack of transparency of certain AI tools.

evaluators process a large amount of content, which can be useful to design and implement evaluations (OECD 2025b: 221). Specifically, AI tools can help in processing large volumes of texts to gauge public sentiment, synthesise literature, policy reports and legal documents, and condense lengthy materials into usable documents for policymakers (van de Laar 2026). The OECD identifies several ways in which AI can support policy evaluation that could also inform the evaluation of national anti-corruption strategies, although these applications extend beyond anti-corruption and include methods other than LLMs (OECD 2025b: 221-225):

- Supporting evaluation design and implementation. AI can assist with searching and screening literature, extracting information and synthesising findings from previous studies. These capabilities can broaden the evidence base and reduce the time required to prepare evaluations. For national anti-corruption strategies, they could help evaluators assess existing evidence on proposed interventions and inform the design of evaluations.

- Supporting analytics. AI can analyse large volumes of reports, interviews and administrative records to identify recurring themes, stakeholder perspectives and patterns associated with programme success or failure, using tools like NLP-enabled text mining (OECD 2025b: 222). The OECD report gives an example of the World Bank using unsupervised machine learning to analyse 392 project reports in 92 aid-recipient countries to identify novel factors affecting project success and failures (see Franzen et al. 2022). The OECD also discusses its potential to support causal inference within appropriate evaluation designs. Applied to anti-corruption strategies, these methods could help identify implementation barriers and examine differences in results across institutions or interventions, although identifying patterns alone does not establish causal effects.

- Supporting management and communication. AI can assist with scheduling, allocating resources and drafting terms of reference, while LLMs can summarise evaluation reports, translate findings and support searches across evaluation repositories. These functions could help coordinate evaluations of anti-corruption strategies, make findings more accessible to policymakers and the public, and facilitate learning from previous assessments.

In addition, AI has begun to play a growing role in project evaluations in the field of development assistance. External evaluators of development interventions have reportedly employed AI tools for tasks such as desk reviews, qualitative data coding, and drafting evaluation reports. More recently, however, discussions have emerged around the possibility of conducting evaluations entirely in-house through AI-enabled processes (Sagmeister, 2026). Such an approach could generate significant time and cost savings in a sector facing ongoing budget constraints. It may also

enable programme staff to engage more directly with the evaluation process, developing a deeper understanding of the underlying evidence and interacting with AI systems to explore findings, test assumptions, and ask detailed questions about the data and results (Sagmeister, 2026).

One evaluation team for UNFPA's humanitarian action work used the platform NotebookLM at the data analysis phase, after removing personal identifiers from key informant interviews and focus group transcripts. The tool identified recurring themes, patterns, and emergent evidence across the transcript database (UNFPA 2026). It also scanned and extracted relevant passages from the 1,500 documents that were provided as the evidence base. It finally assisted in cross-country comparisons and flagged points of convergence and divergence between data sources (UNFPA 2026). This ultimately cut the time needed to conduct the evaluation and saved approximately US $12,000 on the evaluation (UNFPA 2026).

Existing initiatives and potential synergies

Audit institutions, procurement authorities and anti-corruption agencies are increasingly incorporating AI into established oversight procedures as part of broader efforts to modernise public administration.

Public audits illustrate several ways in which these technologies can complement existing instruments. Auditors use machine learning to select transactions for testing, classify reports and identify emerging risks. They also use gen AI to retrieve information from previous cases and relevant regulations.

Beyond audit, procurement and integrity authorities are linking these tools to ownership registers, whistleblowing channels and investigative files.

Across these initiatives, an important distinction is how the AI generated results inform the human-led oversight process: a risk score can inform the selection of a transaction for audit, a registry match can prompt a conflict-of-interest check, and a document search can help an investigator follow up on a lead (see Heyaca and Pallotta 2026).

Audit institutions

Between March and July 2025, the OECD surveyed 15 audit institutions across 14 countries and the EU. Of these, 87% reported that they had integrated at least one AI tool into a workflow (Heyaca and Pallotta 2026: 11). The extent of adoption varied considerably. Some institutions reported a single application, such as summarising documents, while others had introduced several tools across different audit functions. Many individual projects were still at the pilot stage. The study identifies several applications relevant to anti-corruption and integrity work (Heyaca and Pallotta 2026: 11).

Anomaly detection

First, audit institutions use AI for anomaly detection, to assess risk and select transactions or entities for closer scrutiny. Supervised and unsupervised machine learning can complement conventional audit sampling by screening a larger population of transactions and identifying entries that auditors have reason to

examine. Techniques include random forests and autoencoders, depending on the data available and the patterns auditors want to identify (Heyaca and Pallotta 2026). Costa Rica's Comptroller General, for example, applies machine learning to records from the national e-procurement system to identify unusual purchasing patterns. In the UK, the National Audit Office uses anomaly detection tool in financial audits to identify high-risk transactions, relying on a blend of analytical indicators and unsupervised machine learning techniques to assign risks scores (Heyaca and Pallotta 2026).

Singapore's Auditor-General's Office takes a similar approach in its audits of government financial statements. They use an unsupervised technique called Isolation Forest to detect anomalies more effectively than traditional approaches as they can avoid pitfalls of rule-based methods that can overlook unusual transactions that exhibit only minor deviations from the expected norms (Heyaca and Pallotta 2026: 16; see also Ministry of Finance of Singapore 2025). Visualisations then help auditors understand why an entry stands out and decide whether it warrants investigation. The approach reportedly provides a more precise identification of risk areas (see Annex 2, Example #14).

Account classification

Second, audit and oversight bodies use AI to classify the accounts they received for review (Heyaca and Pallotta 2026). In 2018, Brazil's federal government developed Malha Fina de Convênios to assist with oversight of discretionary federal transfers to subnational governments. The system draws on transfer agreements recorded in Transferegov.br and uses a supervised random forest model trained on previous audit decisions (Fajardo and Neiva 2026). It assigns each set of accounts a score indicating the likelihood of approval or rejection, allowing reviewers to prioritise cases that require more detailed examination (Fajardo and Neiva 2026). Its benefit is in using supervised learning to adapt to complex audit scenarios in order to automate routine audits and predict outcomes based on historical data (Fajardo and Neiva 2026). Using 46,432 audit reports, Fajardo and Neiva (2026) found that a model trained on data from multiple agencies performed better than agency-specific models. This finding points to a practical benefit of cooperation across institutions: agencies reviewing similar transfers can draw on a wider range of past decisions than any one agency holds.

A related initiative shows how this approach can become part of routine oversight. Brazil's National Cinema Agency (ANCINE) and the Office of the Comptroller General (CGU) developed a version of Malha Fina to review accounts for publicly funded audiovisual projects (ANCINE 2026). It combines a predictive model with automated checks, the financial value at stake and individual examination of selected

cases. The OECD reported that the initiative increased the agency's capacity to review accounts and reduced operating costs (Heyaca and Pallotta 2026: 17). In October 2026, ANCINE formally adopted the approach as a permanent part of its review procedures. The agency reported that it had completed approximately 6,100 reviews between 2024 and 2026, clearing around 90% of its historical backlog. It estimated that the change in review procedures had avoided more than BRL 1.5 billion in administrative costs over that period (ANCINE 2026).

In the private sector, the consultancy KPMG assessed an AI-supported audit and reported that AI asked "better questions" about a company's finances than its own accountants and provided better analytical depth(Kissin 2026). However, the UK accounting regulator, the Financial Reporting Council – while noting "clear time-saving opportunities" with AI audits – warned that AI could pose a threat to auditor's integrity and independence if they used insights from AI agents to advise their clients (Kissin 2026).

Red flagging

Third, predictive and preventive models can give auditors early warning of emerging risks. These applications extend the approaches discussed in the risk assessment section by bringing information to auditors at a point when they can still intervene. In Italy, for example, models draw on data from the National Anti-Corruption Authority and other procurement databases to help prioritise oversight of maintenance and infrastructure projects (Heyaca and Pallotta 2026). Nonetheless, the examples documented by the OECD provide more evidence about the ability to prioritise reviews or carry them out more quickly than about whether the resulting interventions prevent corruption (Heyaca and Pallotta 2026).

Knowledge management

Fourth, AI can help auditors search and use the knowledge their institutions already hold. Audit work often requires staff to consult earlier cases, legislation, technical standards and records supplied by the bodies they audit. Semantic search can retrieve relevant material even when a document uses different wording from the auditor's query. They typically rely on semantic search engines, Retrieval-Augmented Generation (RAG) pipelines, vector databases, and domain-adapted LLMs (Heyaca and Pallotta 2026: 20). Brazil's Federal Court of Accounts (TCU), for example, introduced ChatTCU in 2023. Integrated with the court's internal systems, the assistant helps staff consult case files, summarise documents and find regulatory or administrative guidance. The court uses a controlled environment hosted on Microsoft Azure to restrict access to sensitive information. This arrangement gives

auditors a way to use generative AI with material held by the court while retaining institutional controls over that material (Ugale and Hall 2024, OECD 2025b).

Public procurement authorities and integrity agencies

Public procurement authorities are also combining AI with established integrity controls. ChileCompra, Chile's central purchasing body, operates Mercado Público, the platform through which public entities procure goods and services. Its work illustrates two distinct uses of procurement policy. The first concerns how public bodies purchase AI. Through the Ethical Algorithms initiative, ChileCompra worked with Universidad Adolfo Ibáñez and BID Lab to introduce standard bidding templates for AI and data science projects. These allow contracting authorities to specify requirements relating to transparency, privacy, non-discrimination and explainability when commissioning a system (OECD 2025b).

The second use concerns how ChileCompra monitors procurement itself. Its Public Contracting Observatory uses tools including LLMs to examine procurement data for possible irregularities and support compliance checks (OECD 2025b). The wider monitoring system cross-references beneficial ownership information with records of public officials and government contractors. These links can reveal, for example, whether a public official has an interest in a supplier, giving the Observatory a reason to examine the contract more closely. Automated checks, predictive models and natural language processing form part of a process that also draws on human review and whistleblower reports (Neuman 2026). Bringing these sources together allows officials to examine both the relationships visible in administrative records and concerns raised by people familiar with a procurement procedure (Neumann 2026). In Hungary, the Integrity Authority has developed AI tools to support procurement monitoring and investigations. Its annual report describes how it began developing relevant information systems by mapping available data and investigative processes, planning how to bring the data together and identifying the software it needed (Hungarian Integrity Authority 2026). Its in-house team began work on two components: an automated forecasting system and an LLM-assisted search tool to help staff analyse material from ongoing investigations. The intended design combines rules developed by experts, network analysis and machine learning (Hungarian Integrity Authority 2026). One aim is to monitor EU-funded procurement procedures from the point of publication, allowing investigators to examine relationships among entities (Hungarian Integrity Authority 2026).

In June 2026, Ferenc Biró, head of the Authority, told the Financial Times that it had integrated AI and machine learning into a system capable of monitoring economic

transactions in real time (Dunai 2026). He made these remarks in the context of efforts to trace public funds that may have been improperly awarded to members of former prime minister Viktor Orbán's circle. Biró put the amount potentially involved at around €160 billion (Dunai 2026). That figure was his estimate of the scale of the alleged awards. The Authority's annual report provides a more specific account of the technology's intended contribution: helping investigators search case materials, analyse connections and identify procurement procedures that merit scrutiny (Hungarian Integrity Authority 2026).

The initiatives discussed above also differ in how institutions obtained the expertise needed to develop AI tools. Drawing on desk research and interviews with public officials, activists, developers and journalists in Brazil, Estonia, Germany, Italy and Venezuela, Gerli and Odilla (2026) identify three approaches. Organisations can develop tools in-house, obtain an existing solution from an external provider or develop a tool jointly with partners. The authors find that the choice depends in part on the funding available, the urgency for innovative solutions and the AI expertise an organisation can draw on (Gerli and Odilla 2026).

Two cases discussed in this section illustrate this distinction. Hungary's Integrity Authority built an in-house team to design tools around its investigative procedures (Hungarian Integrity Authority 2025). In Brazil, ANCINE worked with the Office of the Comptroller General to adapt predictive screening to the review of publicly funded audiovisual projects, combining the agency's knowledge of the accounts under review with the Comptroller General's experience in risk-based oversight (ANCINE 2026).

Broader challenges and implications of AI in anti-corruption efforts

Addressing risks of potentially harmful uses of AI systems

As highlighted in previous sections, including the Zero Trust programme in China, many AI ACTs involve centralised government control over sensitive data. This raises significant risks of surveillance, political capture and consolidation of power by political officeholders and tech companies at the expense of public interest (Köbis et al. 2022b; Köbis 2023). Similar concerns have been raised about the consolidation of power in the hands of small number of highly influential tech companies developing AI systems, who "are likely to steer the technology in a direction that serves their narrow economic interests rather than the public interest" (von Thun 2023).

In such contexts, AI systems may even be deliberately abused by power holders for private gain at the expense of the public interest through the intentional design of AI systems for corrupt purposes, manipulation of training data or corrupt application of otherwise legitimate tools (Köbis et al. 2022b: 7). Transparency International (2025: 3) has sought to draw attention to these risks through its advancement of the concept of "corrupt uses of AI", defined as the abuse of AI systems by entrusted powerholders for private gain. Commercial vendors can also exacerbate these risks by promoting opaque, top-down solutions that create vendor lock-in,[13] inefficiencies or undue influence (Köbis et al. 2022a).

A first line of defence lies in ensuring algorithmic transparency[14] and accountability, recognising that algorithmic systems are far from being neutral forms of technology (Zerilli et al. 2019; Jenkins 2021). Kossow et al. (2021: 11) highlight two key goals of algorithmic transparency and accountability: understanding how an algorithmic system generally functions and clarifying how it reaches individual outcomes. To this

[13] Referring to a situation in which a customer is dependent on a single vendor for a product or service, making it difficult and costly to switch to an alternative provider due to proprietary technologies.
[14] As Kossow et al. (2021: 11) note, there is no precise definition of what constitutes algorithmic transparency as these systems can come with different degrees of transparency depending on their technical properties and governance processes.

end, the Association for Computing Machinery (2017: 2) proposes seven key principles for algorithmic transparency and accountability:

1. "Awareness: owners, designers, builders, users, and other stakeholders of analytic systems should be aware of the possible biases involved in their design, implementation, and use and the potential harm that biases can cause to individuals and society.
2. Access and redress: regulators should encourage the adoption of mechanisms that enable questioning and redress for individuals and groups that are adversely affected by algorithmically informed decisions.
3. Accountability: institutions should be held responsible for decisions made by the algorithms that they use, even if it is not feasible to explain in detail how the algorithms produce their results.
4. Explanation: systems and institutions that use algorithmic decision-making are encouraged to produce explanations regarding both the procedures followed by the algorithm and the specific decisions that are made. This is particularly important in public policy contexts.
5. Data provenance: a description of the way in which the training data was collected should be maintained by the builders of the algorithms, accompanied by an exploration of the potential biases induced by the human or algorithmic data gathering process. Public scrutiny of the data provides maximum opportunity for corrections. However, concerns over privacy, protecting trade secrets, or revelation of analytics that might allow malicious actors to game the system can justify restricting access to qualified and authorised individuals.
6. Auditability: models, algorithms, data, and decisions should be recorded so that they can be audited in cases where harm is suspected.
7. Validation and testing: institutions should use rigorous methods to validate their models and document those methods and results. In particular, they should routinely perform tests to assess and determine whether the model generates discriminatory harm. Institutions are encouraged to make the results of such tests public."

Complementing these principles, emerging integrity frameworks for public administration emphasise that (see Jenkins 2021; Kossow et al. 2021):

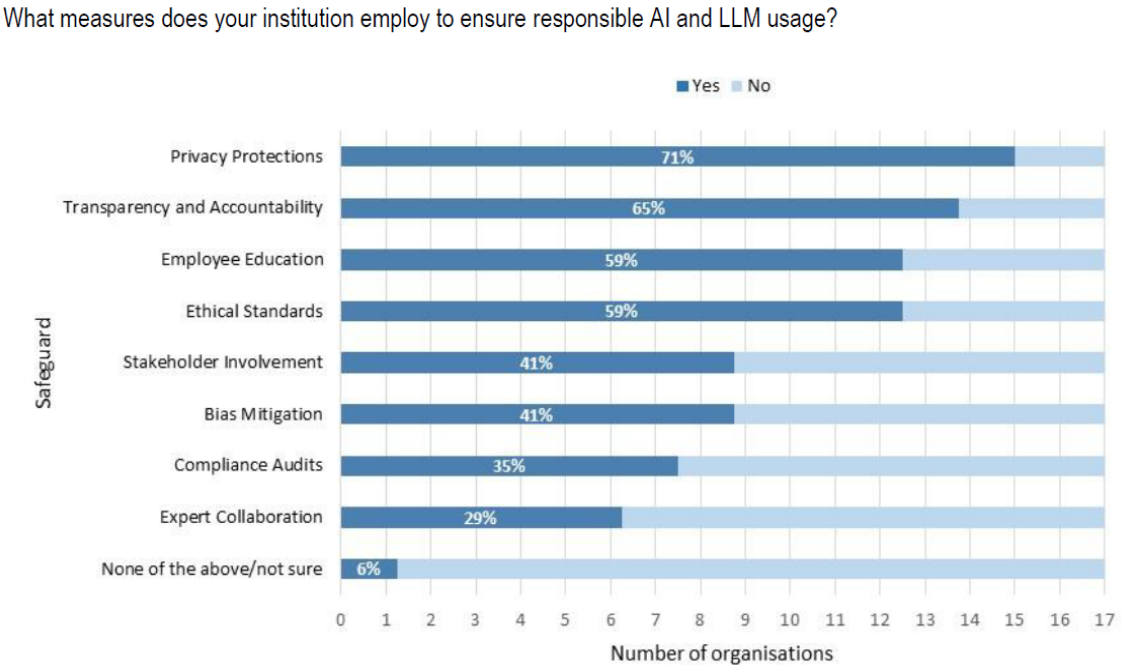
- people have to be informed when they interact with or are subject to an AI system
- individuals affected by an AI decision must be helped to understand its outcome

- those who are affected by an AI system decision should be able to challenge the outcome

Köbis et al. (2022b) further stress the importance of data and code transparency, routine model audits, ethics training for data scientists and strengthened whistleblowing mechanisms to minimise the risk that AI tools are misused or even used themselves to perpetrate corrupt acts.

There is some limited emerging evidence of responsible AI practices beginning to be deployed in certain countries. An OECD survey of integrity actors (such as anti-corruption agencies, supreme audit institutions and internal audit bodies) on their use of gen AI found that most of the institutions surveyed already employ privacy protections, transparency and accountability measures and employee education as central safeguards for ethical use of AI tools and LLMs (Ugale and Hall 2024: 35) (see Figure 3).

Figure 3. Reported safeguards for ensuring responsible use of AI and LLMs.



Note: Possible responses included the following: 1) Ethical Standards: Implementation of ethical guidelines and policies; 2) Transparency and Accountability: Ensuring open AI decision making and maintaining accountability; 3) Bias Mitigation: Actively addressing biases to promote fairness; 4) Privacy Protections: Adhering to privacy and data protection standards; 5) Compliance Audits: Conducting regular ethical and legal compliance assessments; 6) Stakeholder Involvement: Engaging with stakeholders for input and addressing concerns; 7) Employee Education: Offering training and awareness programmes on responsible AI; 8) Expert Collaboration: Working with external experts for ethical and legal guidance; 9) None of the above/not sure; 10) Other. None of the respondents selected other.
Source: OECD questionnaire

Source: Ugale and Hall 2024: 35.

As Gerli (2024) notes, there is currently a broad scholarly consensus that AI should complement existing anti-corruption efforts rather than replace them, and that the overall ecosystem in which AI-driven solutions are designed, developed and implemented is critical for its success, as will be discussed in the following section (Etzioni and Etzioni 2017; Köbis et al. 2022a).

Addressing institutional and regulatory gaps

Without a broader institutional framework, it is difficult to ensure that AI systems for anti-corruption are procured, designed and used in a responsible manner (Gerli 2024). Over the past five years in particular, new standards and pieces of legislation specifically addressing AI have emerged (see Box 6).

Box 6. Standards and principles for the development and deployment of AI systems in public administration

There is a growing body of international standards aimed at ensuring the responsible use of AI in public administration, with a focus on accountability and public integrity (Ubaldi and Zapata 2024; OECD 2025). In parallel, an increasing number of countries is adopting national level regulations and principles (Ugale and Hall 2024; Maslej et al. 2025; UK Government 2025). These frameworks seek to mitigate risks of bias, opacity, misuse and lack of accountability by embedding transparency, human oversight, explainability and rights protection into AI systems (OECD 2019).

The OECD Principles on Artificial intelligence (2019, updated in May 2024) were the first intergovernmental standards on AI, setting out five core principles for policy makers and AI actors: 1) inclusive growth, sustainable development and well-being; 2) human rights and democratic values, including fairness and privacy; 3) transparency and explainability; 4) robustness, security and safety; and 5) accountability. For example, the transparency and explainability principles require AI actors to provide meaningful information about AI systems – their data sources, logic, and limitations – so that those affected can understand and challenge automated decisions (OECD 2019). Accountability further requires traceability of datasets, processes and decisions (OECD 2019).

The EU AI Act (2024) is the world's first comprehensive framework for AI regulation (European Parliament 2023; Elbashir 2024). It establishes obligations for AI systems based on risk levels, distinguishing between four risk levels (Ubaldi and Zapata 2024: 16):

- unacceptable risk: prohibited uses (e.g. predictive policing, social scoring or assessing the risk of an individual committing criminal offences)

- high-risk: uses with significant potential harm to health, safety, democracy (e.g. most public sector applications), which therefore require establishing a risk management system, data governance, compliance documentation and fundamental rights impact assessments, among other requirements)
- limited risk: applications such as chatbots and deep fakes, where transparency obligations require informing users that they are interacting with AI
- minimal risk: systems which require code of conduct, such as video games.

These measures prioritise transparency obligations to ensure AI systems' accountability and explainability (Elbashir 2024). Implementation of the EU AI Act was simplified through the legislative proposal called AI Omnibus, which was adopted in November 2025 and entered into force in July 2026 (EC 2026). The amendment postponed the application of the main requirements for high-risk AI systems. For systems in specified high-risk areas, including biometrics, critical infrastructure, education, employment, migration, asylum and border control, these requirements will apply from 2 December 2027. For high-risk AI systems covered by the Act's product-safety provisions, including certain systems integrated into products such as toys, the requirements will apply from 2 August 2028 (EC 2026).

At the national level, several initiatives complement these frameworks. In 2025, the UK government published its artificial intelligence playbook, which sets out ten principles for safe, responsible and effective use of AI in government organisations. In January 2024, the Netherlands became one of the first countries to publish a strategy specifically focused on gen AI, outlining a vision for using gen AI in the public sector (Ugale and Hall 2024: 14). These principles include developing and applying gen AI in a safe way, developing and applying it equitably, ensuring that it serves human welfare and safeguards human autonomy, and that it contributes to sustainability and prosperity (Ugale and Hall 2024: 14).

Other countries have advanced oversight mechanisms for the deployment and use of AI systems in the public sector: Norway's office of the auditor general began auditing central government AI use in 2023; France published a guide on algorithmic transparency; Ireland issued guidelines for AI in the public service; and the Netherlands developed governance guidance for responsible AI applications (Ubaldi and Zapata 2024: 15, 19).

Procurement of AI systems also requires clear standards. A recent Transparency International (2025: 10) paper addresses corrupt uses of AI and recommends that:

- authorities should publish plans for establishing or procuring AI systems in advance, with information on the purpose of those systems
- contracting authorities should require suppliers to demonstrate transparency (e.g. by making source code available to independent experts for periodic inspections)

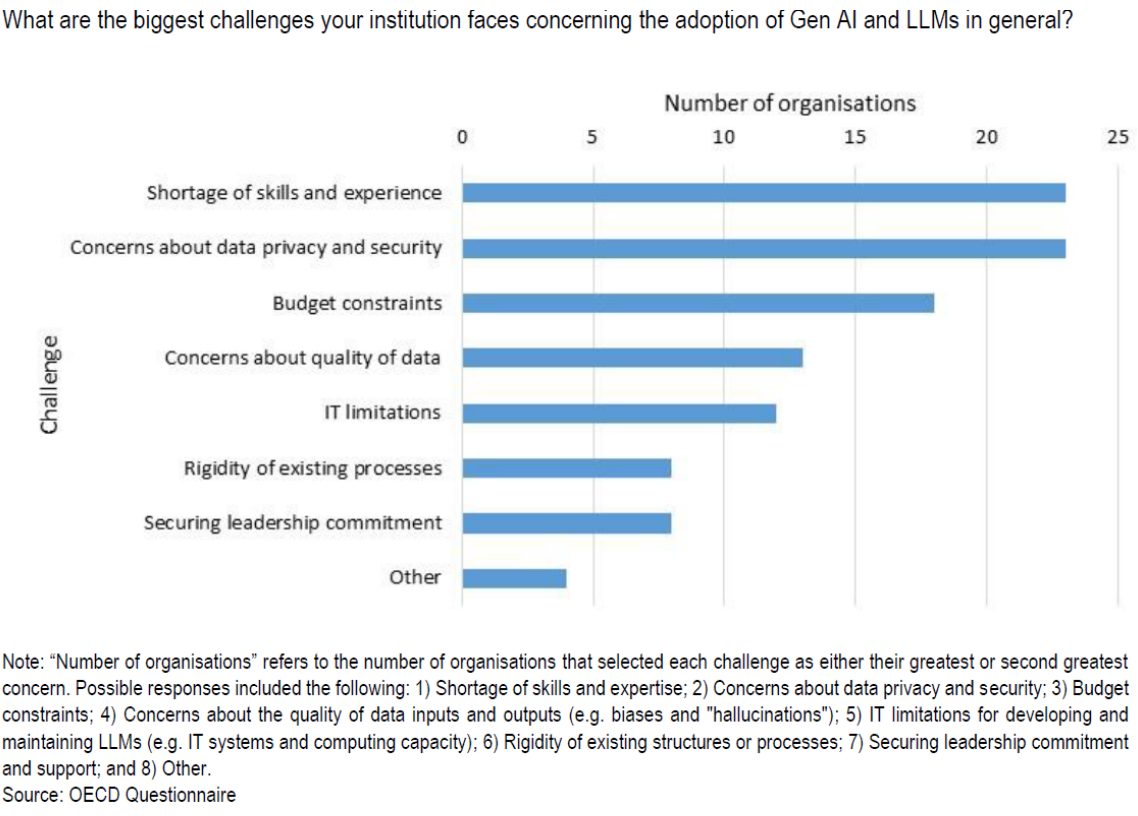
- contracting authorities should have in place impact assessments and audit systems to reduce risks of misusing AI systems for private gain

Capacity building challenges and lessons

Alongside ensuring transparent and accountable deployment of AI in the anti-corruption field and developing the necessary regulatory and institutional frameworks, it is equally important to address capacity building challenges (OECD 2025).

A recent OECD survey of integrity actors found that a shortage of skills and experience ranked as the most pressing concern in implementing gen AI and LLMs, followed by concerns over data privacy and budget constraints (Figure 4).

Figure 4. Key perceived challenges for the adoption of gen AI and LLMs in the public sector.



Note: "Number of organisations" refers to the number of organisations that selected each challenge as either their greatest or second greatest concern. Possible responses included the following: 1) Shortage of skills and expertise; 2) Concerns about data privacy and security; 3) Budget constraints; 4) Concerns about the quality of data inputs and outputs (e.g. biases and "hallucinations"); 5) IT limitations for developing and maintaining LLMs (e.g. IT systems and computing capacity); 6) Rigidity of existing structures or processes; 7) Securing leadership commitment and support; and 8) Other.
Source: OECD Questionnaire

Source: Ugale and Hall 2024: 26.

A 2026 World Bank survey provides further insight into how capacity building challenges vary across economies. The Artificial Intelligence and Data for Better Governance survey, conducted among public servants between December 2025 and May 2026, covered 60 economies across all regions and examined differences across

income levels (Lundy et al. 2026: 19). Data quality and availability emerged as key barriers to AI adoption in government across all income groups. Other barriers, however, varied by income level. Respondents from low-income economies identified the absence of policies, guidelines or standards as a key obstacle, while none from high-income economies cited this as a barrier (Lundy et al. 2026: 20). According to Lundy et al. (2026: 21), this likely reflects the earlier stage of AI development in governments in low-income economies, which mostly rely on off-the-shelf AI tools. In contrast, 65% of respondents from high-income economies cited privacy and ethical concerns as a key barrier, compared with 19% from low-income economies (Lundy et al. 2026: 21). The authors suggest that, having established standards and guidelines, governments in high-income economies face new sets of challenges, such as interoperable data, approaches to protecting privacy and the skills needed to develop AI tools in-house (Lundy et al. 2026: 21).

In relation to this, another pressing challenge is the mismatch between AI tools and institutional capacity, either because agencies lack the people/skills to use them effectively or because the tools themselves fail in ways that carry legal consequences. Brazil's Alice (Annex 1, Example 5) shows the first problem: chronic staff shortages left auditors overloaded with risk-alert emails, unable to triage everything, so potential red flags went unreviewed (Odilla 2023). The example from the UK Serious Fraud Office illustrates the second: AI-assisted disclosure platforms (used to sift tens of millions of documents and identify legally privileged information at far lower cost compared to non-AI alternatives) later omitted material due to formatting/encoding issues, forcing reconfiguration and raising concerns that historical searches – and therefore disclosure in past cases – may have been incomplete (Ring 2024, 2025; Fisher 2025). In investigative settings, such failures can jeopardise prosecutions and undermine trust.

Some of these challenges can be addressed with careful planning from the onset and by learning from experiences of other countries (see Box 7). For instance, the findings of a recent OECD survey of using gen AI and LLMs in the public sector for anti-corruption and integrity suggest several ways of piloting and scaling gen AI initiatives (Ugale and Hall 2024: 29):

- start with incorporating gen AI into lower risk areas and processes (e.g. writing document summaries) as such an approach can help with capacity building in areas where mistakes are not that costly
- IT requirements need to be considered for both piloting and scaling AI initiatives, including computational and storage capacities, the availability of high-performance computing power, and data storage and data management capabilities

Further, the initiative with data and AI-driven audits in TdC in Portugal suggests the importance of strengthening data literacy and digital skills of TdC staff to ensure a successful implementation of these audits. This means that users of audit risk models need to undergo continuous training on how to use these tools, understand the outputs and interpret the results, as well as to be aware of any changes (e.g. introduction of new risk indicators) (Hlacs and Wells 2025: 23).

Box 7. GovTech and lessons for responsible AI adoption

Launched in 2019, the World Bank's GovTech initiative takes a whole-of-government approach to modernising the public sector through digital technology (World Bank no date c). It focuses on strengthening core government systems, making public services accessible to all and responsive to citizens' needs and promoting citizen engagement. Stronger systems can help governments raise revenue, identify inefficient spending and allocate resources more effectively. The initiative also seeks to build public trust through greater transparency, better access to justice, more accurate monitoring and timely feedback (World Bank no date c).

GovTech supports the digital foundations for these reforms, including shared infrastructure, digital identification and payments, and open data, alongside the laws and institutions that govern their use. Digitising procurement, public financial management and revenue systems can support anti-corruption efforts by reducing reliance on face-to-face transactions, limiting opportunities for abuse of discretion, creating audit trails and making it easier to publish data.

A World Bank study produced under the initiative examines how public institutions in different countries put internationally recognised principles for responsible AI into practice. Its lessons are also relevant to anti-corruption institutions adopting AI (World Bank 2026: 49-51):

- Make oversight visible and credible. Start by publishing plain-language descriptions of where and how government agencies use AI. As oversight capacity grows, introduce algorithmic impact assessments, independent audits and registers of government AI systems.
- Coordinate AI adoption across government. A government-wide strategy and action plan can help agencies follow consistent practices and avoid duplicating investments.
- Develop a data strategy in stages. Begin by digitising priority registers and cataloguing existing datasets. Next, develop interoperability standards and publish metadata. Governments with more mature data systems can establish federated data infrastructure or secure data exchange platforms.
- Build computing capacity and test systems for resilience. Cloud-first strategies can give governments access to computing resources that scale with demand.

Regulatory sandboxes can provide a controlled setting for testing AI systems for safety, fairness and resilience. Governments with more advanced infrastructure may also invest in sovereign computing capacity and high-performance data centres.

- Develop staff skills. Equip public officials to commission, use and oversee AI systems safely and effectively.
- Apply investment discipline. Assess the expected costs, benefits and feasibility of AI projects before committing public funds, especially when projects are costly or politically prominent.
- Build public trust through co-creation. Involve citizens and affected groups in designing AI systems so they can raise concerns and shape how the tools are used. This can strengthen the legitimacy of AI adoption and help sustain it over time.

GovTech initiative also supports peer learning through several working groups, including the AI working group, co-chaired by the Republic of Estonia and Nigeria, envisaging a creation of a community of GovTech experts to support governments to develop sound AI policies.

The GovTech initiative also includes a World Bank AI repository, a platform providing examples of real-world applications, helping build a global knowledge base for responsible AI in development.

Annex 1: Examples of AI ACTs in corruption prevention

Example #1: Identifying strategies for limiting competition in public contracting (Katona and Fazekas 2024)

AI technology applied	Machine learning (logistic regression, random forest, XGBoost models) and classical NLP techniques.
Developed by/deployed by	Academics (Katona and Fazekas 2024).
Datasets used	All published government tenders in Hungary between 2011-2020 (approx. 119,000 contracts).
Main objectives	To show the relevance of textual information in bidding conditions, product descriptions and assessment criteria for predicting single-bidding in otherwise competitive markets.
Main benefits	Introducing contract-related textual information improved the model accuracy from 77% to 82% compared to their models containing only structured variables (e.g. no publication of the tender call).
Main challenges	A high rate of missing data, which is likely due to a lot of text being included in the full tender documents, rather than the official tender announcements. The authors used the latter as the first source, which had an irregular structure and contained difficult-to-process formats (i.e. scanned PDFs) (see Katona and Fazekas 2024). The study relies on only one proxy of corruption risk: single-bidding.

Example #2: Identifying politically connected firms (Mazrekaj et al. 2024)

AI technology applied	Machine learning (logistic regression, ridge regression, lasso, random forests and random forests with boosting).
Developed by/deployed by	Academics (Mazrekaj et al. 2024).
Datasets used	The dataset included a population of firms registered in the Czech Republic in 2018 (254,367 firms) filled with information on political donations, donating board members and those running for political office (from domestic sources and Orbis company database).
Main objectives	To show how machine learning techniques can be used to predict political connections.
Main benefits	Machine learning models accurately predict over 85% of politically connected firms based only on firm-level financial and industry indicators, suggesting the potential of ML for public institutions to identify firms whose political connections may represent conflicts of interest (Mazrekaj et al. 2024).
Main challenges	They use easily interpretable machine learning algorithms (i.e. random forests) rather than “black-box” models like neural networks. The trade-off is that the latter have even greater predictive accuracy, at the expense of explainability (Mazrekaj et al. 2024).

Example #3: Identifying public procurement cartels (Fazekas et al. 2023)

AI technology applied	Machine learning (logistic regression, random forests and gradient boosting machines).
Developed by/deployed by	Academics (Fazekas et al. 2023).
Datasets used	Data for 78 cartels in 7 countries between 2004-2021. Public procurement datasets from Bulgaria, France, Hungary, Latvia, Portugal, Spain and Sweden for the 2007-2020 period.
Main objectives	To test the predictive power of machine learning models to detect cartel behaviour in public contracting.
Main benefits	The models demonstrate that no single indicator – or even a small set of indicators – can reliably predict cartel behaviour. Instead, combining multiple indicators yields accuracy rates of 77–91% in predicting cartels across different countries. These models have clear policy relevance: they can support investigations and guide preventive interventions. For instance, given the finding that one-third of procurement markets in the seven selected countries are at high risk of cartelisation, the results could inform the design of preventive policies aimed at removing barriers to competition in these high-risk markets (Fazekas et al. 2023).
Main challenges	There are challenges with data quality of public procurement data (large amount of missing data and of certain fields, such as the losing bidder and bid price information). Learning models require adaptation and improvement with new learning materials (e.g. latest investigative results) (Fazekas et al. 2023: 27) to keep up with cartels changing their behaviour and tactics.

Example #4: Predicting cartel participants in public procurement contracting (Huber and Imhof 2023)

AI technology applied	Deep learning (CNNs) computer vision approach.
Developed by/deployed by	Academics (Huber and Imhof 2023).
Datasets used	Labelled procurement data from Japan and Switzerland with known episodes of cartel activity and competitive periods. These data allow the authors to build many pairwise "bid-image" samples for training and testing the CNN.
Main objectives	Test whether CNNs can reliably flag cartel participants from bidding patterns.
Main benefits	The CNNs on average correctly classify 19 out of 20 firms as cartel members or competitive bidders (Huber and Imhof 2023: 9). CNNs reach a high accuracy of 95% on average for both Japanese and Swiss bid rigging cases.
Main challenges	Variation across simulations, suggesting a need for a substantially larger pool of images for training and testing. Explainability due to the use of black-box models: CNNs are less interpretable, so human audit trails remain important in enforcement. Adaptation risk: publicly known indicators may be gamed; models require periodic retraining as strategies evolve.

Example #5: Alice (Análise de Licitações e Editais, Eng. Analysis of Biddings and Call for Bids) bot in Brazil

AI technology applied	Machine learning (mixed with text preprocessing, data mining and regular expression techniques) (see Odilla 2023: 386).
Developed by/deployed by	Public policy application: the office of the comptroller general and later improved by the federal court of accounts by including ML techniques in the existing regular expressions to conduct data mining on a daily basis (Odilla 2023; OPSI 2024).
Datasets used	The data comes from "tenders published on ComprasNet (public procurement portal), Official Gazette of the Federal Republic of Brazil, sanctions and ownership databases" (Odilla 2023: 363).
Main objectives	Scanning public procurement notices and contracts to spot risks and inconsistencies early, generating email risk alerts and data visualisation on the dashboard before the award of a public contract, so auditors can intervene (Odilla 2023).
Main benefits	The Alice helped suspend or cancel over R$9.7 billion (approx. US$1.75 billion) between 2019 and 2022 (OPSI 2024).
Main challenges	Auditors complained of being overloaded with emails and therefore unable to check every email alert due to staff shortages (Odilla 2023). Although auditable, it is not open to the public (Odilla 2023).

Example #6: Justina del Mar in Peru

AI technology applied	NLP.
Developed by/deployed by	Public policy application: WWF Peru, in collaboration with WWF US, artisanal fishers, shipowners, maritime authorities and subject-matter specialists.
Datasets used	The design of the tool included several phases. First, telephone surveys with artisanal fishers and shipowners to identify existing knowledge gaps in the sector, like reporting mechanisms. Second, the government was consulted about typical request topics from fishers and shipowners. Third, WWF Peru compared this information with their experiences in their work with fishing communities. Finally, this information was then systematised and additional data added from access to information requests and consultations.
Main objectives	To increase fishers' and shipowners' access to accurate, up-to-date regulatory information (WWF 2024). To reduce opportunities for petty corruption such as bribery, extortion or influence peddling in inspections and licensing (WWF 2024). To strengthen transparency and trust between artisanal fishing communities and authorities.
Main benefits	Accessibility: free, 24/7 availability via WhatsApp (WWF 2024). Community engagement: content co-created with target users increases trust and relevance. Ease of updates: regulatory or procedural changes can be quickly integrated into the chatbot's responses.
Main challenges	Dependence on technology access: requires mobile device access, internet connectivity, and WhatsApp literacy.

Example #7: Predicting public corruption in Spanish provinces (López-Iturriaga and Pastor Sanz 2018)

AI technology applied	Deep learning (neural networks: self-organising maps).
Developed by/deployed by	Academics (López-Iturriaga and Pastor Sanz 2018).
Datasets used	Cases of corruption reported by the media or went to the court in Spanish provinces between 2000 and 2012 (a database was gathered by the newspaper outlet El Mundo).
Main objectives	Demonstrating the utility of neural network approach to predict corruption in Spanish provinces based on economic factors.
Main benefits	The authors identified economic and political factors that increase corruption (e.g. taxation of real estate, the same political party remaining in power for a long time). The model could forecast corruption in some provinces up to three years in advance, offering space for preventive and corrective measures.
Main challenges	Data for corruption cases comes from cases reported by the media, introducing bias. Model opacity, due to the use of a black-box model.

Example #8: Predicting corruption related crimes in Italian municipalities (de Blasio et al. 2022)

AI technology applied	Machine learning (classification tree).
Developed by/deployed by	Academics (de Blasio et al. 2022).
Datasets used	Crime data for most Italian municipalities (8,049 out of 8,092) from the Ministry of Interior from which they take white-collar crime data for the period 2008-2014.
Main objectives	To predict white-collar crime rate (identified as crimes committed against public administration and public faith, as defined in the Italian penal code, which include corruption, bribery, embezzlement, abuse of authority and fraud).
Main benefits	Their models correctly classify over 70% of municipalities that experience an increase in corruption crimes.
Main challenges	The risk of bias in the crime data (e.g. possibility that corruption is more likely to be reported in some communities than in others).

Example #9: Early-warning models for predicting malfeasance in public procurement (Gallego et al. 2021)

AI technology applied	Machine learning (lasso and gradient boosting model).
Developed by/deployed by	Academics (Gallego et al. 2021).
Datasets used	Over 2 million public procurement transactions in Colombia between 2011-2015 from the government maintained database (the Sistema Electrónico para la Contratación Pública). They also used a database of vendors who received fines from the office of the comptroller general, those who were fined for breaching contracts, and data on contract amendments.
Main objectives	Testing the power of machine learning models to predict corruption investigations, breaches of contract or implementation inefficiencies related to public procurement contracts in Colombia.
Main benefits	Their models predict contracts that are likely to result in undesirable outcomes early on, which can be used by authorities to select which contracts should be audited. They identified a small number of characteristics of contracts that matter the most out of over 300 different features, including their size, duration and sector. Their models showed that variables related to contracts (their size and duration) were important predictors of malfeasance.
Main challenges	Their measures of malfeasance are prone to the “selective labelling problem” (Gallego et al. 2021: 6). The models require periodic adaptation to prevent corrupt actors from anticipating which traits are more likely to raise an alarm by the early-warning system (Gallego et al. 2021).

Example #10: Identifying collusion in public procurement contracting (García Rodríguez et al. 2022)

AI technology applied	Machine learning (linear models – stochastic gradient descent), ensemble methods (extra trees, random forest, adaBoost and gradient boosting), support vector machines, nearest neighbours (k-neighbours), neural network models (MLP), naïve bayes (Bernoulli naïve Bayes and Gaussian naive Bayes) and Gaussian process.
Developed by/deployed by	Academics (García Rodríguez et al. 2022).
Datasets used	Six public procurement datasets from Brazil (oil infrastructure projects), Italy (road construction), Japan (building construction and civil engineering), Switzerland (road construction, and road construction and civil engineering) and US (school milk market).
Main objectives	To show that machine learning techniques can detect collusion in public procurement contracting.
Main benefits	The study empirically demonstrates that ML tools can be implemented and be useful even when only few pieces of information are available from a large number of auctions, such as bid values and the winning bidder from each auction in their research. The analysis found that three models (extra trees, random forest and adaBoost) performed best overall. When complete information about auctions was available, these models correctly identified cartel behaviour in 81% to 95% of cases, with their accuracy holding up consistently across most datasets (with the exception of the US case).
Main challenges	Explainability issue, related to the use of some black-box models. Requirement for a large amount of reliable historical data, which may be challenging due to issues data availability.

Example #11: Predicting municipal level corruption (Gallego et al. 2022)

AI technology applied	Machine learning (random forests, gradient boosting machine, lasso) and deep learning (neural networks).
Developed by/deployed by	Academics (Gallego et al. 2022).
Datasets used	Disciplinary prosecutions conducted by the Colombian office of the inspector general in charge of monitoring the behaviour of public officials in the 2008-2011 and 2012-2015 mayoral periods.
Main objectives	To show whether machine learning can predict municipal level corruption, proxied by politicians' (i.e. mayors) misconduct in Colombia.
Main benefits	Based on 147 municipality level predictors grouped into ten categories (e.g. financial sector, conflict, human capital, local politics, public sector), their models show which categories of factors are best predictors of politicians' misconduct, including financial variables, local demographics, local politics and human capital variables, offering promise for identifying municipalities for prioritised audit (Gallego et al. 2022).
Main challenges	"Selective labelling problem", in other words the fact that the decision about who and when to prosecute is not random, and it can be politicised, and consequently is not free from bias (Gallego et al. 2022).

Example #12: Global Health Atlas (Transparency International Global Health 2025)

AI technology applied	Gen AI (LLMs).
Developed by/deployed by	Public policy application: Transparency International Global Health (2025).
Datasets used	A raw dataset had several hundred thousand news articles from around the globe about corruption manifestations in healthcare, with the data from Newscatcher. This was then filtered down to approximately 26,000.
Main objectives	To show the scale and complexity of integrity issues in health around the globe and counter corruption within health systems around the world (Transparency International Global Health 2025; n.d.).
Main benefits	Using AI to systematically identify and categorise public reporting of health-related corruption (Transparency International Global Health 2025) based on geographical location, integrity area (e.g. misappropriation), health area (e.g. medicines) and date range (Transparency International Global Health n.d.). The system identifies articles relevant to corruption, classifies the specific type of corruption (e.g., bribery) and extracts key metadata like location and date, creating the world's largest repository of evidence on health corruption.
Main challenges	The data only includes cases reported by the media, introducing risks of bias. The data is also affected by factors like freedom of the press, and saturation of internet news, among other challenges.

Example #13 Analysing lobbying records (Transparency International UK)

AI technology applied	Gen AI (LLMs), machine learning and NLP techniques.
Developed by/deployed by	Public policy application: Transparency International UK (n.d.).
Datasets used	Data sources include UK government transparency disclosures and the Scottish statutory lobbying register (Transparency International UK n.d.).[15] There were more than 140,000 lobbying records.
Main objectives	To automatically categorise lobbying meetings by analysing the meeting descriptions, hosts and lobbyists (Transparency International UK n.d.).
Main benefits	Using AI to categorise lobbying meetings into (currently) four categories: health, housing, defence and climate (Transparency International UK n.d.).
Main challenges	Occasional misclassification of a lobbying meeting.

[15] A paper based on the analysis of this data: Whiffen 2025.

Example #14 ALMA (Algorithm for Timber Legality in the Amazon, Peru)

AI technology applied	Machine learning (binary classification with Random Forest), integrated into a robust Drupal-based platform with Flask/Python services. It includes dynamic analytical dashboards, interactive risk maps, and auditable records.
Developed by/deployed by	Developed by the Environmental Governance Program of Proética (Peruvian chapter of Transparency International), with the support of the Environmental Investigation Agency (EIA). The platform features a reinforced architecture and advanced security measures for institutions and authorised users.
Datasets used	Data from the SIGO-sfc system of OSINFOR (field inspections), Forest Transport Guides (GTF), and access-to-information requests. These inputs feed the risk models and analytical dashboards.
Main objectives	- Analyse the information contained in GTFs to project the risk of illegality in timber products. - Provide interactive and objective tools for authorities, justice operators, buyers, the press, academia, and civil society to assess risks in the forest traceability chain. - Strengthen forest governance and support evidence-based decision-making to reduce illegal timber trade.
Main benefits	- Free and open access for multiple stakeholders. - Increased transparency in the forest sector. - Early identification of high-risk operations, enabling additional field verifications. - Technical credibility grounded in historical evidence and actual inspections. - Technological innovation applied to fighting corruption and environmental crimes. - Secure and scalable platform with role-based access. - Exportable and auditable records that reinforce institutional traceability.
Main challenges	- Continuous maintenance and updates required. - Dependence on the quality and completeness of input data. - Risk of users placing excessive trust in risk scores without conducting additional verifications through official sources.

Example #15 The DREAM AI (AI assistant for Public Investment Management (PIM) Reform in Ukraine)

AI technology applied	GenAI (LLMs) (locally hosted language models use retrieval-augmented generation (RAG) to provide guidance grounded in verified laws, manuals and guidelines)
Developed by/deployed by	Public policy application: The DREAM Project office, backed by Open Contracting Partnership, and together with uStudio as IT and AI innovation partner, GCIEP and PwC (supported by FCDO) (Nestulia 2026).
Datasets used	Verified laws, manuals and guidelines on public investment management and project preparation. DREAM also connects various state-owned and external registers, supporting over 12,900 public investment projects across 18 sectors.
Main objectives	- Help officials understand and apply public investment management rules. - Provide accessible guidance on project preparation and appraisal. - Reduce officials' workload and improve consistency in decision-making. - Planned for 2027: identify missing information and inconsistencies in project proposals to strengthen quality assurance. - Planned for 2028-2029: support investment modelling and comparison of alternative investment options.
Main benefits	- Easier access to guidance: translates complex requirements into practical explanations tailored to officials' roles, sectors and locations. - Potential time savings: helps officials navigate rules and prepare projects, reducing reliance on manual searches. - More consistent decisions: provides a shared, verified knowledge base for applying public investment rules. - Traceability: links answers to approved sources, with timestamps and human validation.
Main challenges	- Continuous maintenance and updates required (keeping laws, manuals and guidelines verified and up to date). - Limited evidence of impact: initial user feedback is positive, but effects on efficiency, project quality and corruption remain to be seen, as the project is in its early stages.

Example #16 Corruption Radar in Ukraine

AI technology applied	GenAI (LLMs) and NLP.
Developed by/deployed by	Public policy application: Better Regulation Delivery Office (BRDO), a Ukrainian think tank focusing on better regulation.
Datasets used	Data from the Unified State Register of Court Rulings, which is published by the State Judicial Administration as open data (BRDO 2025).
Main objectives	- To provide easier access to corruption-related court verdicts. - To provide a realistic overview of the situation with prosecuting corruption, amid a discourse that "corruption is thriving" in the country (BRDO 2025). - To be additional tool of public oversight.
Main benefits	- Improving public access to corruption-related court information, making lower-profile cases easier to monitor. - Increasing the visibility of routinely published judicial decisions, thereby strengthening public monitoring of corruption cases (World Bank no date).
Main challenges	- AI-generated summaries of court rulings may contain inaccuracies.

Example #17 The VigIA system in Colombia for flagging high-risk public contracts before violations occur (Salazar et al. 2024)

AI technology applied	Machine learning (random forests, logistic regression).
Developed by/deployed by	Academics (Salazar et al. 2024).
Datasets used	The case of the city of Bogota and the data from the contracting platform SECOP II, complemented by the record of sanctions imposed by the overseeing agency. The final dataset consisted of 87,027 contracts and 47 variables.
Main objectives	- To flag high corruption risk contracts before violations occur. - To predict whether a contract is likely to present inefficiencies, measured as cost overruns or delivery delays. - Provide interpretable results using regularly updated open data.
Main benefits	- Reliance on explainable models. - The random forest model for cost overruns achieved 87.47% accuracy and an AUC[16] of 0.943. The delivery-delay model achieved an AUC of 0.936. - Helping oversight agencies to prioritise investigations.
Main challenges	- Relying only on explainable models has implications for accuracy. - Cost overruns and delays can arise from multiple causes, so their relevance to corruption requires further assessment.

[16] AUC means “Area Under the Curve” - it shows how well a model separates the two outcomes, such as projects that overrun costs and projects that don’t, across every possible decision threshold.

Annex 2: Examples of AI ACTs in corruption detection

Example #1: Rosie in Brazil

AI technology applied	Machine learning: "a Python-programmed application that first applies hypothesis and test-driven development processes and then unsupervised learning algorithms to estimate a 'probability of corruption' based on standard deviations for each reimbursement receipt submitted by MPs" (Odilla 2023: 384).
Developed by/deployed by	Public policy application: Open Knowledge Brazil, as part of the civic-tech initiative Operação Serenata de Amor.
Datasets used	Public data on congressional spending and attendance, ownership registers and private data on Google, Foursquare and Yelp.
Main objectives	To detect and flag suspicious reimbursement claims by members of Brazil's congress. To publicly share suspicious cases to promote accountability. To empower citizens with easier access to structured transparency data via Jarbas, which is a platform that puts together data previously scattered across various government datasets, and which can be easily navigated (Cordova and Gonçalves 2019).
Main benefits	Automatically tweets suspicious cases, encouraging public scrutiny. Behavioural impact (reduced meal reimbursement spending by app. 10% after launch). Civic empowerment (enables citizens and journalists to verify and challenge expenses). Rosie identified 8,276 suspicious transactions and 735 different congresspeople involved in these suspicious transactions (Operação Serenata de Amor n.d.).
Main challenges	Fewer engagements on X than expected by creators (Odilla 2023: 379). A broader challenge of sustainability of accountability projects based on bottom-up initiatives (Odilla et al. 2022).

Example #2: Asset declaration system in Armenia

AI technology applied	Machine learning.
Developed by/deployed by	Public policy application: Armenia's corruption prevention commission.
Datasets used	Officials' asset declarations and other state databases.
Main objectives	To enable greater scrutiny of public officials and enhance accountability by making asset declaration information more accessible to state institutions and the general public (Harutyunyan 2023).
Main benefits	Streamlining data entry and collection. Automatically integrating data from other state agencies. Automated verification function comparing submitted data in new declarations with previously submitted declarations and other state databases. Identified discrepancies are marked as a red flag, triggering a comprehensive analysis of the official's assets. The public application programming interface (API) enables interested third parties to use their own software tools to sift through data on the public website. Initially, the algorithms for flagging corruption risks were based on a static set of corruption risk indicators, but plans are that after the initial trial period they will activate an ML component that would enable the system to learn from the data it processes, helping to identify novel corruptive and deceptive practices (Harutyunyan 2023: 4).
Main challenges	The algorithmic tool that is being developed to flag corruption risks is kept private, citing compliance with the EU's General Data Protection Regulation (GDPR) (Harutyunyan 2023: 5). The (current) reliance on static corruption risk indicators.

Example #3 DOZORRO (Transparency International Ukraine)

AI technology applied	Machine learning.
Developed by/deployed by	Public policy application: Transparency International Ukraine).
Datasets used	A database of public procurement tenders from Prozorro, an e-procurement system launched in 2016 (Transparency International Ukraine n.d.).
Main objectives	To detect and flag tenders with a high likelihood of corruption risk. To support CSOs in the DOZORRO network by prioritising which tenders to investigate.
Main benefits	Avoids static risk-indicator lists, reducing the chance officials can "game" the system. Identifies suspicious tenders before the contract execution. Proven to help prevent inefficient spending and uncover high-risk contracts (Transparency International Ukraine 2025).
Main challenges	Sustainability of bottom-up, CSO-led initiative.

Example #4: Zero Trust Programme in China

AI technology applied	Machine learning.
Developed by/deployed by	Public policy application (Chinese Academy of Sciences and the Chinese Communist Party's internal disciplinary bodies).
Datasets used	Over 150 central and local government databases, covering bank account records, property registries, corporate ownership records, land acquisitions and others (Chen 2019).
Main objectives	To detect irregular financial movements by civil servants. To identify conflicts of interest (e.g., relatives bidding for contracts). To calculate and score the probability of corrupt activity. To alert authorities for investigation if assigned scores exceed set thresholds.
Main benefits	High detection capacity: identified around 8,700 officials engaged in misconduct in pilot jurisdictions. Broad coverage of data: enabled cross-sector risk detection that traditional audits might miss.
Main challenges	Opacity: black-box decision-making, with limited ability to explain AI conclusions. Surveillance and privacy concerns: extensive surveillance of officials' financial and personal relationships. Political sensitivity: resistance from senior bureaucrats led to discontinuation in many areas.

Example #5: Identifying money laundering patterns (Gandhi et al. 2024)

AI technology applied	Machine learning (random forests, elastic net, lasso, gradient boosting, linear regression, logistic regression, k-nearest neighbours) and deep learning (MLP, CNN).
Developed by/deployed by	Academics (Gandhi et al. 2024).
Datasets used	Financial transaction data from the US Treasury's Financial Crimes Enforcement Network (FinCEN), with each record documenting a specific suspicious activity, covering the period 2014-2023 (some of the variables include the state that reported suspicious activity, year of reporting, industry sector, description of suspicious activity, etc.) (Gandhi et al. 2024: 11).
Main objectives	Testing the ability of ML models to predict variables from the financial transaction dataset.
Main benefits	ML models performed well in predicting financial transaction variables (state and year) and classifying credit and debit card activities. Random forest classifier had 99.9% accuracy in state prediction.
Main challenges	A major challenge in integrating ML models into AML (anti-money laundering) systems is the quality and availability of data, as financial transaction data can suffer from incompleteness, inaccuracies and bias (stemming from underreporting of suspicious activities, changes in reporting regulations and variations in data collection practices) (Gandhi et al. 2024: 24). Regulatory barriers and data privacy concerns may limit the access to financial transaction data (Gandhi et al. 2024: 24).

Example #6: Inspector AI (Evaluating suspicion transaction reports in Peru)

AI technology applied	NLP techniques using neural networks (text pattern recognition, reading free-text fields, applying filtering/scoring) (GIZ 2024; OAS 2023).
Developed by/deployed by	Public policy application: National University of Engineering in Lima and Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ).
Datasets used	Suspicious transaction reports.
Main objectives	To shorten the time for processing suspicious transaction reports, enabling the Peruvian financial intelligence unit to focus on analysis, considering that the body receives 23,000 suspicious cases annually, based on the most recent data (GIZ 2024).
Main benefits	The AI-assisted software automatically filters data, such as names, addresses and payment types from the suspicious transaction reports and reads free-text fields which previously could not be logged, running filters to flag high-risk cases. Concealed money laundering in relation to drug trafficking or corruption can be identified faster and charges brought faster (GIZ 2024). Since the software was introduced, the number of suspicious transactions reported to the public prosecutor more than doubled.
Main challenges	Explainability and auditability: the tool uses neural network NLP to structure and score suspicious transaction reports.

Example #7: Forest Foresight (predicting illegal deforestation)

AI technology applied	Machine learning.
Developed by/deployed by	Public policy application: WWF-Netherlands in collaboration with Boston Consulting Group, Deloitte, Amazon Web Systems and several academic institutions).
Datasets used	Historical geospatial data, satellite images (Radar, Sentinel 1) and socioeconomic variables (e.g. population density).
Main objectives	Once trained, it reads real-time satellite images and detects early deforestation predictors like expanding roads, and alerts local authorities (WWF 2023).
Main benefits	The tool, piloted in Gabon and Borneo, can predict illegal deforestation up to six months in advance with 80% accuracy (WWF 2022). In Gabon, it helped rangers detect an illegal gold mine, thereby protecting 74 acres of forest (WWF 2023). Key benefits relate to the ability of authorities to react proactively, reducing costs and avoiding irreversible losses (WWF Ecuador 2025).
Main challenges	Capacity building challenges: its effectiveness depends on the infrastructure and enforcement capacity on the ground.

Example #8: Identifying suspicious language patterns in documents

AI technology applied	Machine learning and NLP.
Developed by/deployed by	Public policy application: the European Anti-Fraud Office (OLAF).
Datasets used	Commission and member states' databases and various other sources (e.g. Panama Paper leaks).
Main objectives	Combining keywords that may signal corruption red flags in email exchanges (European Parliament 2021; Gerli 2024; Nicaise and Hausenkamph 2025).
Main benefits	Saves time, enables execution of complex tasks, automates processes.
Main challenges	Data challenges (missing values, lack of interoperability, etc.) (European Parliament 2021). Concerns about data bias (European Parliament 2021).

Example #9: SyRi[17] (system risk indication) in the Netherlands

AI technology applied	Machine learning.
Developed by/deployed by	Public policy application : deployed by the Dutch Ministry of Social Affairs and Employment.
Datasets used	The system relied on vast data sources, including work, fines, penalties, taxes, properties, housing, education, retirement, debts, benefits, allowances, subsidies, permits and exemptions, and others (Algorithm Watch 2020).
Main objectives	It was intended to detect social welfare fraud in the Netherlands by flagging individuals and neighbourhoods at high risk of welfare, tax or benefits fraud by analysing vast cross-referenced personal data, based on which it decided which citizens in the neighbourhood need to be investigated further (Algorithm Watch 2020).
Main benefits	In the first five years, five municipalities requested to analyse a neighbourhood, of which, only two of these projects were executed (Algorithm Watch 2020).
Main challenges	A lack of transparency for citizens about what happens with their data (Algorithm Watch 2020). According to the research of a Dutch newspaper De Volkskrant, none of the algorithmic investigations resulted in detection of new cases of fraud (Algorithm Watch 2020). A lack of algorithmic transparency: the Dutch government refused to provide the details on the models used. In 2020, a Dutch court ordered immediate halt of SyRi due to its violations of the Article 8 of the European Convention on Human Rights, which protects the right to respect for private and family life (Algorithm Watch 2020; Borgesius and van Bekkum 2021).

[17] Although this example refers to fraud, rather than corruption, it offers useful lessons for deploying AI ACTs as it raised significant privacy concerns with data handling, lack of transparency about the algorithm, as well as concerns about discrimination and bias as the tool was primarily used in low-income neighbourhoods (Algorithm Watch 2020).

Example #10: Illicit fishing activities globally (Paolo et al. 2024)[18]

AI technology applied	Deep learning (convolutional neural networks (CNNs)).
Developed by/deployed by	Academics (Paolo et al. 2024).
Datasets used	Satellite imagery between 2017-2021 covering over 15% of the ocean, in which over 75% of industrial activity is concentrated, and vessel GPS data (Paolo et al. 2024: 85).
Main objectives	To map industrial vessel activities and offshore energy infrastructure between 2017 and 2021 (Paolo et al. 2024).
Main benefits	They found that 72-76% of industrial fishing vessels do not appear in public monitoring systems, showing that substantial parts of activity are not publicly tracked (Paolo et al. 2024). Their mapping reveals potential hotspots of illegal fishing activity and can identify industrial fishing vessels encroaching on the artisanal fishing grounds (Paolo et al. 2024: 89). The dataset and technology are freely available.
Main challenges	Their study likely underestimates the concentration of vessels, particularly small vessels, due to data limitations. Risks of misclassification in high-traffic areas, like near cities in wealthy countries, e.g. misclassifying smaller craft as a fishing vessel.

[18] Although this example indicates criminal activity rather than corruption, the technology used has clear relevance for the anti-corruption field, as other cases in this Helpdesk Answer demonstrate the potential of satellite imagery to detect corruption risks.

Example #11: Detecting fake suppliers in public contracting (Wacker et al. 2018)

AI technology applied	Deep learning (convolutional neural networks (CNNs)).
Developed by/deployed by	Academics (Wacker et al. 2018).
Datasets used	A dataset of government suppliers with active contracts in 2016 and 2017 from the Brazilian public purchasing system and data about Brazilian companies from the Brazilian Federal Revenue Office about company addresses. They use Google Street View API to download images of company addresses.
Main objectives	To detect anomalies in government supplier images to identify fake suppliers by automatically distinguishing images of valid supplier locations from arbitrary buildings and landscapes.
Main benefits	High detection performance. By extracting deep features from a collection of Google Street View images using a pretrained convolutional neural network to classify supplier locations, the authors show the application of these features for identifying valid suppliers, regardless of the image perspective (i.e. the angle from which an image of a supplier building was captured) that was collected.
Main challenges	Narrow scope (it only detects whether a supplier building is non-existent based on visuals from Google Street View images). False positive and false negative cases, resulting from its inability to detect if there is a building at a supplier's address, which does not relate to the actual supplier; other kinds of fraud not related to buildings; that the supplier building looks like private residence, etc.

Example #12: DATACROSS I[19] (monitoring corporate ownership anomalies)

AI technology applied	Machine learning (logistic regression, naïve Bayes classifier, decision trees, bagged trees and random forests) and NLP.
Developed by/deployed by	Public policy application: DATACROSS I (2019-2021) was coordinated by Transcrime – Università Cattolica del Sacro Cuore, with the participation of the French anti-corruption agency (AFA), the Spanish police (CNP) and Investigative Reporting Project Italy (IRPI), with Bureau van Dijk as a data partner (Bosisio et al. 2021). The capabilities of the tool were expanded with DATACROSS II (2022-2024) covering 200+ countries and 300+ million firms, with more risk indicators and data sources (Datacross III n.d. a). A new expansion is envisioned in the current DATACROS III project (2024-2026) by integrating advanced AI-driven analytics to detect high-risk entities, while reducing false positives (Datacross III n.d. a). The data is further expanded to new financial and asset related data sources, including beneficial owner registers, company data, real estate data, public procurement data, virtual currencies and transactions, and satellite imagery (Datacross III n.d. b). In terms of AI technologies, the current project relies on ML, NLP based analysis of unstructured information, processing of satellite images and videos, and AI-driven anomaly indicators to detect illicit financial activities (Datacross III n.d. b).
Datasets used	The dataset of Bureau van Dijk - Orbis Europe and other sources (e.g. sanctions data and data on politically exposed persons for eight countries from LexisNexis WorldCompliance) to analyse the ownership structure of 56 million companies in 29 European countries.
Main objectives	Detect anomalies in firms' ownership structure that are indicative of a high risk of collusion, corruption and money laundering corporate ownership across EU countries (DATACROS I Project). Assess the distribution of opaque companies across EU jurisdictions and sectors.
Main benefits	Allows early detection of risk factors within legitimate companies[20] by complementing traditional approaches like searches of sanctions lists with ML algorithms that attribute risk scores to companies (Bosisio et al. 2021). All the considered ML methods showed satisfactory performance. With regards to logistic regression, the algorithms correctly

[19] The table assesses only the DATACROSS I project.

[20] "Legitimate companies" here refer to corporate entities operating in compliance with the law and not established for the purpose of committing or concealing criminal activity.

	predicted 83.3% of sanctions on companies, and 88% of sanctions on owners (Bosisio et al. 2021: 53). The tool complies with personal privacy and law enforcement procedures, as it was designed with the help of legal experts (Bosisio et al. 2021: 9). At the broader level, it enhances police investigations, especially with the cross-border cases, improves the effectiveness of cartel detection by competition authorities and enables investigative journalists, NGOs to monitor opaque interactions between business and politics (Bosisio et al. 2021: 13).
Main challenges	Relies on static risk indicators (developed based on company financial and ownership data). Requires retraining with new learning data to catch up with the emergence of novel illicit schemes.

Example #13: Enhancing public procurement audits in Portugal

AI technology applied	Deep learning.
Developed by/deployed by	Public policy application: the Tribunal de Contas (TdC), the supreme audit institution in Portugal.
Datasets used	Procurement data from various sources, such as the Competition Authority (AdC), the Portuguese transparency portal, and the Institute of Public Procurement, Real Estate and Construction (IMPIC) (Hlacs and Wells 2025: 19). 37 risk indicators related to public procurement were developed, with three approaches: i) rule based (e.g. contract signed before the award decision date); ii) inference based (e.g. ratio of the estimated value and contractual price); and iii) model based (collusion).
Main objectives	Enhancing early detection of public procurement irregularities through advanced data analysis and machine learning (ML) techniques[21] (Hlacs and Wells 2025: 16).
Main benefits	The expected long-term impact includes enhanced identification of risks and unusual transactions, improved early detection of potential irregularities and real-time monitoring, enabled by the application of ML techniques.
Main challenges	The vast majority of indicators are rule and inference based, making the audit risk model predominantly static. The labelled data for training was used from external sources, raising concerns about contextual differences, among other issues. Black-box model used, which is hard to interpret.

[21] As of yet, the audit risk model is not fully integrated within the TdC systems, and it is not a final version of the risk analysis model (Hlacs and Wells 2025: 20).

Example #14: Enhancing audit of government financial statements in Singapore

AI technology applied	Unsupervised machine learning (Isolation Forest).
Developed by/deployed by	Public policy application: Singapore's Auditor-General's Office (AGO).
Datasets used	Accounting data from government financial statements.
Main objectives	- To address weaknesses of the traditional anomaly detection, in which pre-defined rules may overlook unusual transactions that only slightly deviate from the expected norms. - The method involves dividing the accounting data into target groups and enabling each subset to be analysed separately. The model identifies irregular entries within each group, helping prioritise which transactions warrant further scrutiny from auditors (Heyaca and Pallotta 2026).
Main benefits	- The approach offers a more precise way of identifying potential irregularities compared to traditional rule-based methods. - The approach also emphasises interpretability, enabling auditors to understand the nature of entries that were flagged.
Main challenges	- Choosing appropriate comparison groups for journal and payment records, minimising false positives from legitimate but unusual entries and ensuring auditors can understand why a transaction was flagged and assess whether it warrants investigation.

Example #15: Screening of corruption complaints in Thailand (Sereewatthanawut et al. 2026)

AI technology applied	GenAI (LLMs) combined with optical character recognition (OCR), NLP and machine learning. Gemini-1.5-Flash and Gemma-27B use task-specific prompts to summarise and classify complaints, without additional training or fine-tuning.
Developed by/deployed by	Academics (Sereewatthanawut et al. (2026), a research team working with Thailand's National Anti-Corruption Commission (NACC).
Datasets used	Dataset of 160 semi-synthetic complaints, developed to resemble actual NACC submissions and covering ten misconduct categories. The OCR component was refined using 2,892 printed Thai-language documents, with over 14,000 characters across ten fonts, and evaluated on 100 handwritten and scanned samples (Sereewatthanawut et al. 2026).
Main objectives	AI-assisted screening of corruption allegations at Thailand's National Anti-Corruption Commission (NACC) to support subsequent review and investigation and reduce the time and administrative effort required to process complaints.
Main benefits	- In testing, the average processing time fell from approximately 5.6 minutes to 71.47 seconds per complaint, a reported reduction of 78.6%. - Gemini-1.5-Flash achieved 57.5% classification accuracy, while Gemma-27B achieved 52%. - Expert reviewers rated the generated summaries 4.74 out of 5, and the participant survey recorded average satisfaction of 4.2 out of 5.
Main challenges	- Moderate classification accuracy, ambiguity in Thai legal and administrative language, overlapping misconduct categories and uneven representation of categories in the test data. - OCR struggled particularly with handwriting, achieving only 59% word-level accuracy. - Reliance on semi-synthetic complaints limits conclusions about performance on real submissions. - Concerns about algorithmic bias, as historical imbalances in complaint data may influence prioritisation (Sereewatthanawut et al. 2026).

Example #16: Detecting corruption and fraud in public contracting in Mexico (Medina-Hernández et al. 2026)

AI technology applied	Machine learning (positive-unlabelled (PU) learning algorithms) and network analysis.
Developed by/deployed by	Academics (Medina-Hernández et al. 2026).
Datasets used	2,301,278 federally funded contracts awarded by the Mexican federal, state and municipal authorities between 2011 and 2022, covering 5,304 public buyers and 259,534 private suppliers, compiled from CompraNet platform. These records were matched with two sanction datasets covering 14,535 companies involved in simulated invoicing or sanctioned procurement misconduct. 1,673 sanctioned companies were matched to the procurement records.
Main objectives	- To support the selection of contracts for audit or investigation. - To identify and rank potentially fraudulent or corrupt procurement contracts by combining established corruption red flags with information about relationships between public buyers and suppliers.
Main benefits	- The best-performing model, Hellinger Distance Stratified Random Forest (HDSRF), captures 32% more known positives on average and performs 2.3 better than random guessing.
Main challenges	- Supplier sanctions provide imperfect contract-level labels, since the study labels all contracts of a sanctioned supplier as positive, irrespective of contract or sanction date. Sanctions may reflect selective enforcement and differences in auditability. - Positive labels are scarce, verified negative cases are unavailable, and contracts are concentrated among a small number of suppliers.

Example #17: AI-driven corruption and fraud detection tool for law enforcement in Lithuania

AI technology applied	Machine learning (positive-unlabelled (PU) learning and Hellinger Distance Random Forest model).
Developed by/deployed by	Public policy application (Special Investigation Service of the Republic of Lithuania (STT) with OECD and the Government Transparency Institute).
Datasets used	The final dataset integrates information from 11 administrative datasets, covering criminal and administrative offences, company and legal entity information, public procurement activities, beneficial ownership details, blacklisting data, and project management for publicly funded initiatives (OECD 2026: 3).
Main objectives	- To strengthen risk-based oversight of public spending by identifying patterns associated with corruption and fraud. - To enhance effectiveness and efficiency of investigative prioritisation.
Main benefits	- The model significantly outperforms random investigation strategies (if authorities would focus on top 25% of contracts ranked by predicted scores, they would capture approximately 60% of the known positive cases). - The model performance is particularly strong at the top of the ranking: within the highest 10% of contracts by predicted risk score, the model predicts five times more known positives than would be expected under random investigation (OECD 2026: 7). - The approach is scalable and compatible with existing institutional infrastructures.
Main challenges	- Transitioning from prototype to deployment requires continuous attention to data governance, technical infrastructure and long-term sustainability, among other considerations.

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U4 is part of the Chr. Michelsen Institute (CMI), an independent development research institute in Norway.

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