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WHO ACTS, AND WHO IS WATCHED? DIFFERENCES BETWEEN TOP-DOWN AND BOTTOM-UP AI ANTI-CORRUPTION TOOL IMPLEMENTATION METHODS

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Abstract. *Recent data shows stagnation in corruption level, eroding public trust in government institutions. AI offers a valuable opportunity to address corruption. This research aims to explore how AI anti-corruption tools differ based on their implementation methods—top-down or bottom-up—and how these methods affect the relationship between society and government. Key tasks include conducting a bibliometric analysis of AI and corruption, comparing top-down and bottom-up implementation approaches, and reviewing real-world practices in the European Union. The research method includes a literature review of existing global studies, supplemented by data from relevant institutions, while the overview of current AI anti-corruption tools primarily relies on publicly available online information. Findings indicate that while top-down method improve efficiency, it may lead to a "corruption trap." Conversely, bottom-up approach empowers citizens but struggle with open data access. The study highlights the need for further empirical research on integrating open data with AI anti-corruption tools and comprehensive evaluations of existing AI anti-corruption applications.*

Keywords: *Artificial Intelligence (AI), anti-corruption, open data, citizens, top-down, bottom-up, EU anti-corruption initiatives, civic engagement.*

Reikšminiai žodžiai: *Dirbtinis intelektas (DI), kovos su korupcija priemonės, atviri duomenys, piliečiai, „iš viršaus į apačią“ ir „iš apačios į viršų“ principai, ES kovos su korupcija iniciatyvos, pilietinis aktyvumas.*

Introduction

Government-society relationships are interactions between state institutions and the citizens they serve. These relationships can foster civic engagement and accountability, or lead to tension and conflict, depending on the level of trust and communication between the government and the public. One of the key reasons that leads to distrust in government is corruption. Corruption is defined as the misuse of public office for private gain (Dulay & Lee, 2024).

It negatively affects a nation's competitiveness by not only decreasing financial investments, economic growth and government expenditures on education and health, but also causing imbalanced expenditures, misguided market incentives and poorly allocated national resources (Huang, 2015).

There are several methods for measuring corruption level in a country or specific region: Corruption Perceptions Index (CPI), Control of Corruption (CC) index, Eurobarometer surveys, European Commission anti-corruption reports and others. For this study, CPI and CC index will serve as examples.

The Corruption Perceptions Index (CPI) from Transparency International association and the Control of Corruption (CC) index from the World Bank both rely on expert assessments and surveys of businesses to evaluate corruption levels in various countries.

Transparency International reports an overall decline in justice over the period from 2012 to 2024, with the Corruption Perceptions Index remaining at the same level in 118 countries, improving in 28, and declining in 34 (Eriksson, 2024).

The Control of Corruption (CC) index provides data on a country-by-country basis rather than as regional averages. For the Baltic countries, data indicate overall improvements from 2014 to 2023; however, the situation has fluctuated in the last three years (World Bank, 2023).

Additionally, internet search data related to corruption can be utilized to supplement the existing information provided by the CPI and CC indexes (Pan et al., 2019).

Google Trends, an internet search tool, shows that interest in the topic of 'corruption' was lower on average in 2020 and 2021 but gained traction in 2022 and 2023. The average search interest in 2024, as well as from January 1 to July 30 has surpassed the levels observed in 2023 (Google Trends, 2025).

Artificial intelligence (AI) presents a promising avenue for combating corruption (Acera, 2023).

The term "artificial intelligence" means a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments (Dalton, 2023). AI algorithms can extract and analyse vast amounts of data, identify patterns, and make informed decisions based on historical insights (Tian et al., 2025).

Data analysed by AI may vary in type. For example, natural language processing (NLP) is a field of Artificial Intelligence and Linguistics, devoted to make computers understand the statements or words written in human languages (Khurana et al., 2022). NLP anti-corruption tools can help monitor suspicious or fraudulent language, analyse social media and public data, monitor official documents and other.

AI whistleblower tools (support individuals report on fraud, unethical behaviour in a secure and confidential environment) employ various analytical approaches tailored to the nature of the data. They can assist in identifying indicators of suspicious behaviour, such as transactions exceeding normal limits, rounded numbers, vague or incomplete details, urgent requests, unusual cash disbursements, or transactions that bypass standard approval processes (Grobart, 2020).

AI network analysis tools examine complex networks, such as social network, supply chain, company's ownership structure and others. In fight against corruption, AI network analysis tools can help predict conflicts of interest in public procurement and cartel behaviours (Gerli, 2024).

Those are few examples how AI anti-corruption tools analyse large volumes of government data, enabling them to identify patterns and anomalies that may indicate fraudulent activities (Thommandru et al., 2024).

Nils Kobis and his research team have identified two approaches of AI solution implementation: top-down and bottom-up. The top-down approach involves public institutions implementing solutions to monitor society, while the bottom-up approach entails society implementing solutions to monitor government actions (Köbis et al., 2021). Society in this context means public – citizens, and government includes all public institutions such as legislative bodies, regulatory agencies, law enforcement agencies and similar.

Building on the points mentioned above, the aim of this research is to synthesize existing studies about AI-based anti-corruption tools, with a specific focus on how their implementation methods (top-down and bottom-up) influence their advantages and disadvantages.

To achieve the aim, the following objectives are defined:

- Conduct bibliometric analysis on AI and Corruption.
- Compare AI anti-corruption tools, highlighting the key differences between top-down and bottom-up implementation methods.

- Assess top-down and bottom-up implementation methods impact on government-society relationships.
- Review real-world practices in European Union where AI anti-corruption tools have been implemented, even if not actively used at this stage.

Methods

The primary research method used is a narrative literature review, which includes studies retrieved from September 2024 to March 2025 from databases such as Scopus (main source for bibliometric analysis), EBSCOhost, Web of Science, and Google Scholar. Search key words were AI, anti-corruption, government (also public institutions, public procurement), AI implementation methods, top-down, bottom-up.

Additionally, bibliometric analysis, using VOSviewer software version 1.6.20, was conducted to provide an overview of current publication trends, identify keyword clusters, and assess the level of research activity surrounding AI-based anti-corruption tools in the governmental sector.

All studies are supplemented with relevant data from OECD, Transparency Internation and others.

The research focusing on studies published in English from around the world, while information on existing AI anti-corruption tools has primarily focused on the EU region. Authors are concentrating on corruption in government institutions or in interactions between the government and citizens. Another limitation is the dependence on publicly available information. Much of the data regarding government AI anti-corruption tools remains inaccessible to the public, especially for those implemented through top-down approaches.

Bibliometric analysis of AI and corruption

There are approximately 624,163 articles, conference papers, books, or book chapters that mention "artificial intelligence" in the title, abstract, or in keywords. Chart 1 showing number of studies within certain period.

Since 2011, there has been a significant increase in the number of studies on artificial intelligence. Most of research has been conducted within the fields of engineering, mathematics, and computer science and then forth category rotates between social science, decision science and overtaken by medicine starting from 2021.

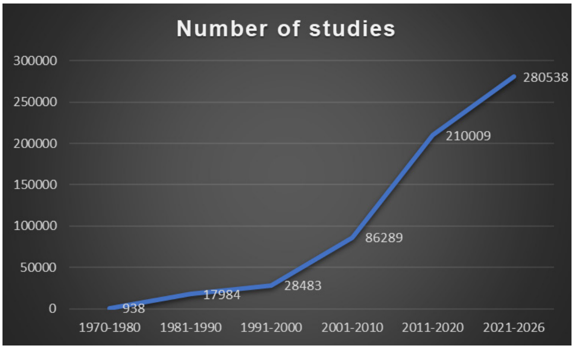

Chart 1. *Number of studies on AI from 1970 to 2026.*
Source: Authors' creation based on Scopus data.

When including the term "corruption" in the search for artificial intelligence studies, there are 274 relevant publications from the period 2021–2026. To obtain a larger sample for bibliometric analysis, the time frame has been extended from 2000 to 2026, resulting in a total of 479 studies. Those studies cover a wide range of topics related to artificial intelligence, including its applications in detecting misinformation, enhancing governance and public administration, addressing ethical and legal challenges, and improving security and transparency through technologies like blockchain. They also explore AI's role in sectors such as healthcare, agriculture, corporate governance, and law enforcement, emphasizing its potential to support sustainable development, fight corruption, and facilitate decision-making processes. Figure 1 summerizes bibliometric analysis on terms occuring at least 10 times.

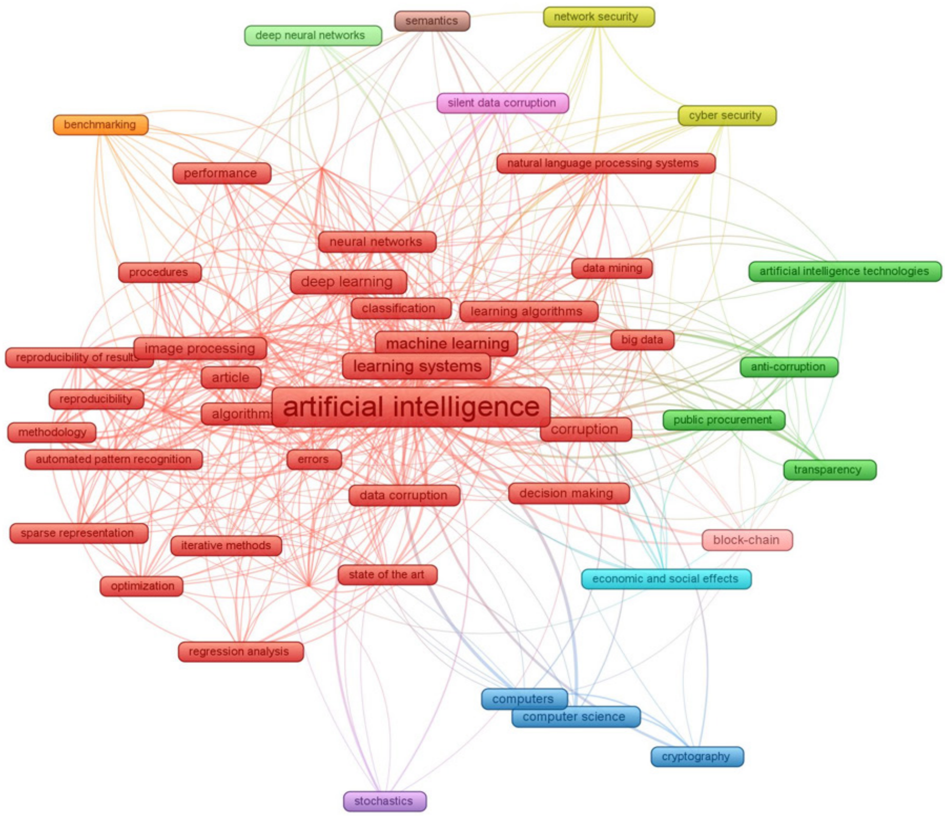

Figure 1. *Bibliometric analysis of citation AI and Corruption.*

Source: Authors' creation based on Scopus data from 2020 - 2026

There are 11 clusters and corruption has connected with two of them. Heavily researched area (cluster 1) includes such terms as algorithms, big data, classification, crime, data corruption, automated pattern recognition, deep learning, errors, humans, imagine processing, machine learning, neural networks, procedures, regression analysis, sparse representation and others (together 34 terms). Those terms can be grouped in four categories AI/ ML techniques, data and data quality, humans and procedures, social issues such as corruption and crime. Therefore, it can be concluded that Cluster 1 primarily focuses on the application of technological methods to address social issues.

Cluster 2 has less connections – 4 items in total: anti-corruption, public procurement, transparency, AI technologies. These studies likely focus on how AI tools can be utilized to promote transparency, enhance public procurement processes, and prevent corrupt practices.

The impact of AI on corruption, particularly in the context of public procurement, is not a widely explored topic - occurred 12 times in the studies.

There are 57 studies when the search terms include "AI," "Corruption," and "Government." The studies highlight the transformative role of digital technologies and AI across various sectors. They emphasize how digital transformation in governance, including e-government and AI-enabled public procurement systems, can enhance transparency and combat corruption. Additionally, AI's application in public administration and safety—such as smart city technologies—contributes to national security through improved cybersecurity and risk management. The research also underscores the importance of institutional measures and government policies, supported by AI and data analytics, in addressing climate change and reducing CO2 emissions. Furthermore, AI and machine learning are increasingly used to combat financial crimes, such as money laundering and fraud, thereby strengthening the integrity of financial and public procurement systems.

Meanwhile, few studies have focused on how AI anti-corruption tools differ based on their implementation strategy - top-down or bottom-up approach. Comparing these approaches may help to identify the most effective strategies for fighting corruption. Understanding their strengths and limitations can guide policymakers and practitioners in designing more effective, sustainable, and inclusive anti-corruption solutions.

Currently there are only three articles in Scopus that include the terms "top-down" or "bottom-up", "AI," and "corruption". To increase the number of studies included, the author expanded the search to the EBSCOhost database, which yielded an additional two studies on this topic. Synonyms were also used, with "centralized approach" replacing "top-down," and "grassroots" or "decentralized approach" replacing "bottom-up." Together with synonyms, there are 11 articles focusing on the top-down approach and 18 articles on the bottom-up approach. Figure 2 and 3 includes illustrations of key terms occurring at least 3 times in mentioned studies.

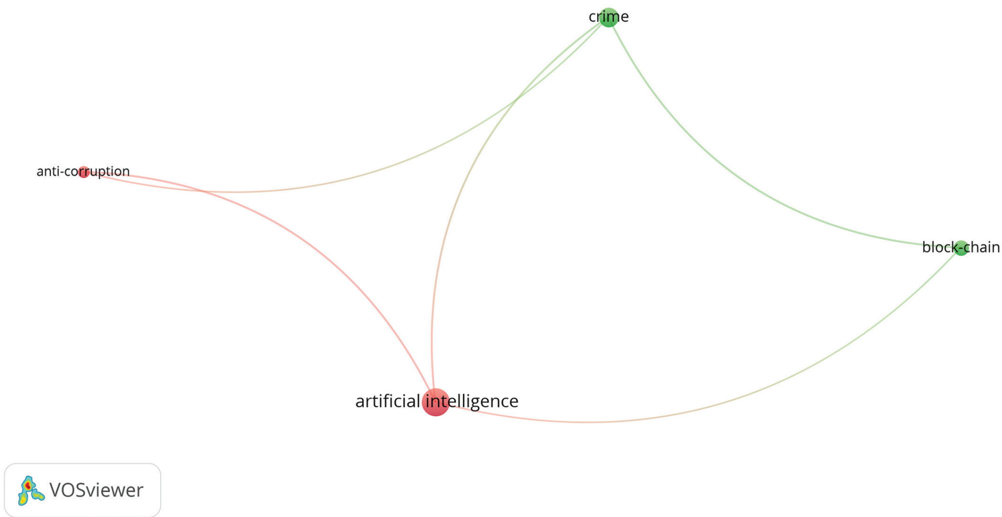

Figure 2. *Bibliometric analysis of citation AI and Corruption and Top down.*

Source: Authors' creation based on Scopus data.

Both approaches emphasize the importance of AI and blockchain technologies in anti-corruption efforts, indicating these are central tools in current research and applications. The top-down approach includes "crime" and "anti-corruption," suggesting a focus on implementing centralized solutions aimed at combating specific issues like crime and corruption.

The bottom-up approach adds "decentralized" and "corruption," highlighting a focus on grassroots or community-driven solutions that leverage decentralized systems, such as blockchain, to promote transparency and integrity.

More typical role for AI anti-corruption tools is to government scrutinizes their citizens (Köbis et al., 2021). Studies focusing on top-down approach analyse different subjects. For example, Villagrasa and Sole examine how the integration of behavioural sciences and artificial intelligence can aid in preventing corruption among public servants, while also highlighting the new risks that such integration may introduce (Villagrasa et al., 2022). Additionally, a research group from Colombia is evaluating the effectiveness of artificial intelligence in combating corruption within public organizations. Their findings suggest that while AI has the potential to significantly enhance anti-corruption efforts, its implementation must be approached ethically, ensuring data privacy and addressing regulatory challenges (Diaz et al., 2024). Older article by Ramio Matas is analyzing risks and opportunities of introducing artificial intelligence and robotics into public administration (Matas, 2018) and Ramirez Perez is writing how AI can predict transparency or indicator of corruption risk (Perez et al., 2023).

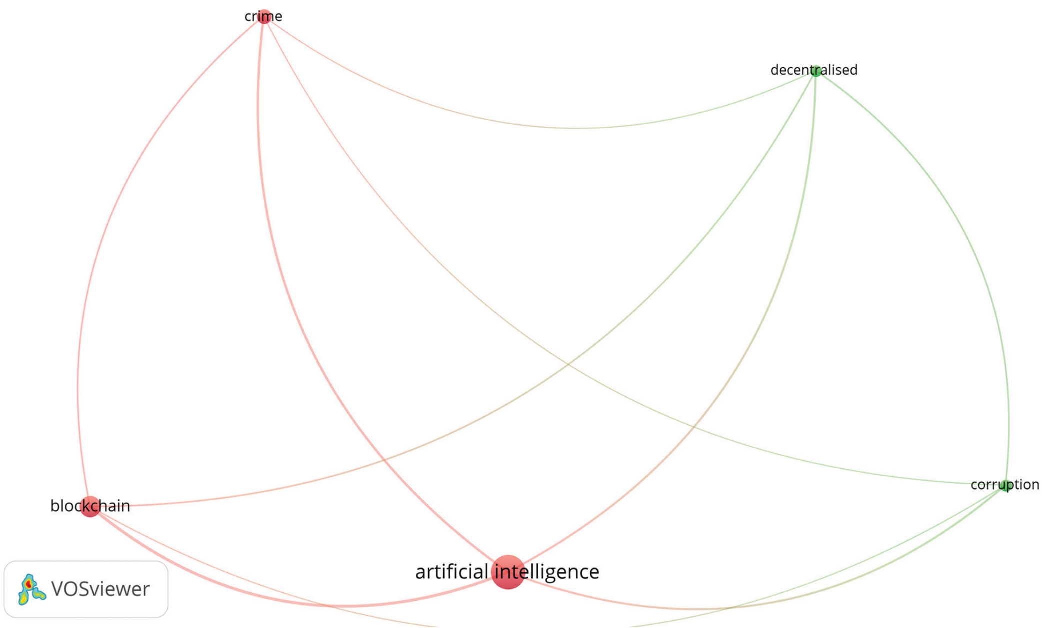

Figure 3. *Bibliometric analysis of citation AI and Corruption and Bottom up.*

Source: Authors' creation based on Scopus data.

Notably Nils Kobis is one of authors who has explored the perspective in which citizens develop AI anti-corruption tools to monitor government actions, representing a bottom-up approach. Together with Starke and Rahwan they have dedicated significant research to comparing these top-down and bottom-up implementation methods (Kobis et al., 2022). Secondly, Freire is one of the few scholars who have not only questioned the impact of bottom-up monitoring on public service performance but have also provided evidence of the negligible effect of a crowdsourcing mobile application that enabled citizens to monitor school construction projects (Freire, 2020). Rather than focusing on AI-driven anti-corruption solutions, Freire has critically examined the principles of bottom-up monitoring.

The third author in this field is Fernanda Odilla, who utilizes data presented by Kobis and Freire to highlight key findings and insights (Odilla, 2023).

Differences between AI tools top-down and bottom-up implementation methods

Further the authors compare the top-down and bottom-up approaches in the table below, illustrating their respective strengths and weaknesses. This comparison aims to provide a clearer understanding of how each approach functions in the context of AI anti-corruption initiatives. The comparison criteria were derived and combined from studies by other authors (such as Kobis, Starke & Rahwan (2021), and Odilla (2023)) and supplemented by the author's own input to summarize the main aspects of the text.

Table 1. *Comparison of AI anti-corruption tools implementation methods*

Comparison Criteria	Top- Down Approach	Bottom- Up Approach
Implementor	Government, public or anti-corruption institutions, criminal investigators (Kobis et al., 2021)	Citizens, Journalists, Bloggers (Kobis et al., 2021)
Monitoring	Government institutions, citizens, private companies (Kobis et al., 2021)	Government institutions, congressman (Kobis et al., 2021)
Data	Internal, External (free availability of data, controlled quality) (Odilla, 2023)	External- open data, data leaks (limited availability) (Odilla, 2023)
Communication	Internal (Odilla, 2023)	External (Odilla, 2023)
Advantages	Improve efficiency, transparency, accountability (Odilla, 2023)	Educated and engaged citizens Improve accountability Collaboration between civil society and public officials Boosts open data programs Ethical behaviour Empowering citizens (Mentioned in all three studies: Kobis et al., 2021 and Forjan et al., 2024, Odilla, 2023)
Disadvantages	"Corruption trap" Citizens may distrust to solutions created behind closed doors (Kobis et al., 2021)	Stream of findings can overwhelm citizens Limited resources (Kobis et al., 2021)
Examples	Mara, Kalsada (Kobis et al., 2021)	Rosie de Serenata, Botivist, Dozorro, ProZorro (Kobis et al., 2021)

Source: Authors based on Kobis et al., (2021), Forjan et al., (2024) and Odilla (2023)

At top-down approach the government and its affiliated institutions will implement AI-powered anti-corruption tools to monitor citizens, private companies (such as during public tenders), and other governmental entities to ensure transparency and accountability in their operations. Citizen groups, journalists, and bloggers seeking materials for articles can act as implementers in a bottom-up approach, monitoring the activities of governmental institutions whose operational data is publicly available.

Data is a first key criterion where significant differences between the two approaches emerge. While public institutions can leverage their internal data, bottom-up initiatives often face challenges in expanding their scope due to their heavy reliance on and limited access to open data (Odilla, 2023). Limited access can even promote unethical behaviour in case of data leakage. (Kobis et al., 2021).

Open data refers to information that anyone is free to use, reuse, distribute, customize, and combine with other datasets. It is typically associated with the public sector and is often provided by the government, commonly referred to as "open government data" (Dang & Vu, 2024).

The quality and accessibility of open government data are essential, as they significantly influence outcomes. Common outputs include updatable dashboards, risk-tracking systems, and instant messaging reports that indicate, for example, the likelihood of risky tenders or suspicious expenditures. Additionally, search engines for network analysis are utilized to illustrate the relationships between individuals and organizations (Odilla, 2023).

High-quality data may reduce errors in conclusions made by AI anti-corruption tools, in addition data availability creates a solid foundation for AI anti-corruption tools, especially for bottom- up approach.

Organizations such as the OECD evaluate countries' open data initiatives based on three key categories: data availability, data accessibility, and government support for data reuse.

The top-performing countries in open data initiatives include Korea, France, Poland, Estonia, Spain, Ireland, Slovenia, Denmark, Sweden, and Lithuania (OECD, 2024). Latvia ranks 27th among OECD countries, particularly struggling in government support for data reuse.

OECD initiatives can promote greater availability of open data for citizens. Whether this will lead to an increase in the development and adoption of bottom-up AI anti-corruption tools remains a subject for further research.

The next comparison criterion is communication. While building trust in AI-centric solutions is a separate topic, this paper focuses on communication related to the findings of AI anti-corruption tools. In the case of a top-down approach, communication tends to be more internal, occurring within the department using the AI anti-corruption tool or among governmental institutions involved in its development or implementation. Consequently, only selective information may be shared with the public.

Odilla is stressing out that top-down efforts are more likely to include using tools to better communicate with civil society, obtaining information and complaints, and scrutinising governmental workers who abuse their position and citizens who attempt to engage in fraud, graft or other spurious transactions involving the government (Odilla, 2023).

In bottom-up approach to addressing corruption cases through AI, mechanisms for checks and balances are lacking, leading to the premature or inaccurate publication of information. This can result in public mistrust and significant damage to reputations (Kobis et al., 2021).

The following comparison examines the advantages and disadvantages experienced by key stakeholders—government and citizens—across both implementation methods. The authors provide a detailed analysis of the strengths and weaknesses associated with each approach, drawing on insights from previous studies referenced in Table 1.

The top-down approach has several advantages for government (together 7 shown in the table 2), with Kobis and his research team identifying its primary benefit is that leveraging the potential of AI can significantly enhance the speed and efficiency of administrative processes within public institutions (Kobis, Starke & Gill, 2022).

However, a significant drawback of the top-down implementation method is the emergence of what is known as the "corruption trap." In this scenario, AI may be exploited for manipulation, resulting from biased input data, faulty algorithms, irresponsible implementation, and misuse for corrupt purposes (Kobis, Starke & Gill, 2022).

One key benefit of the bottom-up approach is the empowerment of citizens, which promotes both individual and community actions. It also results in a more engaged and informed populace regarding state affairs. This approach offers multiple advantages for both citizens and the government, including fostering open communication between the public and governmental institutions, encouraging collaboration, and creating an environment that supports open data initiatives.

Primary challenge of the bottom-up strategy is the availability and quality of data (as mentioned already at the beginning of this chapter). Additionally, there is a significant lack of diverse resources and skills, including technical expertise and sufficient human resources. Furthermore, the presence of excessive or misleading information can overwhelm citizens, leading to mistrust in AI-ACT tools.

Table 2. *Analysis of advantages and disadvantages depending by implementation approach*

Advantages	Disadvantages	Affected party	Evaluation basis
Government-led tools ensure official backing and resources	Citizens may distrust government-created solutions if developed behind closed doors	Government (advantage), Citizens (disadvantage)	Trust and legitimacy of the tool's origin
Government workers or outsourced experts ensure professional development	Citizen-developed tools may face resource constraints	Government (advantage), Citizens (disadvantage)	Quality and sustainability of development
Controlled quality of data (internal) ensures reliability	Open data and leaks may have limited availability or quality issues	Government (advantage), Citizens (disadvantage)	Data quality, availability, and openness
Internal communication hides AI errors, protecting reputation	External communication exposes AI errors, which may affect public trust	Government (advantage), Citizens (disadvantage)	Transparency vs. risk of reputational damage
Improves efficiency, transparency, accountability (government)	"Corruption trap" risk (government)	Government (advantage and risk)	Operational effectiveness and ethical risks
Educates and engages citizens (bottom-up)	Limited resources and potential distrust (citizens)	Citizens (advantage and risk)	Civic engagement and resource availability
Empowering citizens (bottom-up)		Citizens (advantage) Government (disadvantage)	Civic engagement
Collaboration between civil society and officials (bottom-up)		Citizens and Government (advantage)	Cooperation and social capital
Boosts open data programs (bottom-up)		Citizens and Government (advantage)	Data openness and accessibility

Source: Authors created

Existing AI anti-corruption tools in European Union

Information in scientific databases as Scopus, EBSCOhost, Web of Science, and Google Scholar shows that there have been conducted studies on existing AI anti-corruption tools in Brazil (Odilla, 2024 and Mencke, Gomes & Xavier, 2024), Columbia (Diaz, Pabon & Ceballos, 2024), South Africa (Chetty et al., 2024). Data regarding the situation in EU countries is lacking.

Additionally, the information available in existing materials misleading or difficult to corroborate with evidence from public sources. For instance, Acera mentions AI anti-corruption tools such as Lince and Saler, where Lince monitors employee sick leaves to detect fraud related to absenteeism, while Saler enhances transparency in public contracts by improving customer engagement and providing insights into market trends (Acera, 2023). According to information from internet resources Lince is ChatGPT version for queries in Spanish created by start-up Clipbrain.

Google search engine provides information under search words "Saler anti-corruption", which is the computer system, which homepage is not active and last information update was on 2021 (European Commission, n.d.).

It is important to consider that some AI tools serve diverse roles and can promote anti-corruption indirectly. For instance, the primary function of the AI agent Burokratt in Estonia is to simplify communication between the state and citizens, enhance the accessibility of public services, and ensure privacy when processing personal data (Witismann, 2023). While these objectives are not explicitly focused on anti-corruption, increased transparency and closer collaboration with public institutions can help reduce corruption.

The authors with support of ChatGPT and Google search have summarized publicly available information on existing anti-corruption tools (agents) in EU. Key words used to find information were AI anti-corruption tools, AI anti-corruption, AI anti-corruption agents.

Table 3. *Overview of existing AI anti-corruption tools in European Union*

Name	Region or country, year	Functionality	Implementation approach	Reference
Datacros I and II	EU (OLAF, tests started in France), I phase in 2019	Detects anomalies in firms' ownership structures	Top-down	Hertie School, n.d. Transcrime, n.d..
Digiwhist (opentender.eu)	Consortium from 6 EU universities, 2018	Improving transparency and accountability in public procurement processes	Top-down	DigiWhist, n.d.
Ravn	UK, 2010 (previous EU participant)	Summarize documents quickly and accurately.	Used as top-down (created by private company, but used by governmental insitutions)	Acera A., 2023. Wallqvist P., 2018.
Falcon (isnot solely an AI project, but significantly relies on AI technologies).	EU, 2023 (Europe Horizon project)	Developing new, data-driven indicators and tools that can provide a comprehensive understanding of corruption dynamics. Analysing large data sets.	Mixed, can be used by government or civil society organizations, for example, advocacy groups.	Falcon Horizon, n.d..
Arachne (incorporate elements of AI)	EU, 2022	Risk scoring tool to help detect most risky projects, contractors and beneficiaries in EU funded projects.	Top-down	European Commission, n.d..

Source: Authors

Implementation approach was selected depending on who was developer of the system, who will be monitored and who will use the system on daily basis. According to the data presented in the table, many tools are utilized in a top-down manner. Authors found information on one tool, which was implemented from the bottom up is known as "The Red Flags," which was used in Hungary. This tool automatically checked procurement documents and filtered out high-risk procurements, which were subsequently published. However, it is important to note that "The Red Flags" has not been active since 2023 (Red Flags, accessed 2025).

Majority of AI initiatives are sponsored and organized by EU and its related institutions (Europe Horizon, OLAF), which reflects a growing recognition of the role that AI can play in enhancing transparency, accountability, and integrity within the EU, as well as the need for continuous adaptation and innovation in the fight against corruption.

Conclusions

The main research findings indicate:

1. The body of research on artificial intelligence has grown substantially since 2011, with a diverse range of studies exploring AI's applications across fields such as engineering, social sciences, and medicine; however, the specific intersection of AI and corruption remains relatively underexplored, particularly regarding the comparative effectiveness of top-down versus bottom-up implementation approaches, highlighting a critical gap that future research must address to optimize AI's role in enhancing transparency, governance, and anti-corruption efforts.
2. The main differences between top-down and bottom-up implementation methods lie in their focus and approach to data and communication. The top-down approach is driven by government and public institutions, leveraging internal data to enhance efficiency and accountability. The bottom-up approach leveraging external (government open data) promoting citizen involvement and fostering transparency but faces challenges related to data access and the overwhelming nature of information for citizens.
3. Each implementation method has distinct implications for government-society relationships. The top-down approach can enhance cooperation between the government and citizens while demonstrating the efficiency and accountability of public institutions, whereas the bottom-up approach empowers citizens by placing them in the driver's seat and providing them with the opportunity to hold the government accountable for its actions.
4. The effectiveness of AI anti-corruption tools is heavily dependent on the quality and accessibility of data. Open data initiatives are essential for bottom-up approaches, as they enable citizens to engage meaningfully in monitoring government actions.
5. Existing AI anti-corruption tools within the European Union are predominantly implemented through top-down approaches led by government and related institutions, with limited publicly available and verifiable information on their deployment and effectiveness; while some tools indirectly support anti-corruption by enhancing transparency and citizen engagement, there is a notable scarcity of active bottom-up initiatives.

Future studies will continue to analyse the relationship between open data and AI anti-corruption tools. Additionally, there will be further examination of existing tools, which will include conducting interviews with anti-corruption agencies and other relevant stakeholders.

Data Availability Statement

The data used to support the findings of this research are available from the corresponding authors upon request.

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KAS VEIKIA, O KAS STEBIMAS? SKIRTUMAI TARP „IŠ VIRŠAUS Į APAČIĄ" IR „IŠ APAČIOS Į VIRŠŲ" DIRBTINIO INTELEKTO KOVOS SU KORUPCIJA PRIEMONIŲ ĮGYVENDINIMO METODŲ

Anotacija. *Šiame tyrime nagrinėjama besikeičianti dirbtinio intelekto (DI) vaidmuo kovojant su korupcija, daugiausia dėmesio skiriant vyriausybinių institucijų ir piliečių santykiams. Korupcija menkina pasitikėjimą vyriausybe ir daro neigiamą poveikį ekonomikos augimui bei išteklių paskirstymui. Korupcijos lygis matuojamas įvairiais metodais, pavyzdžiui, korupcijos suvokimo indeksu (CPI) ir korupcijos kontrolės indeksu (CC), kurie rodo, kad nuo 2012 iki 2024 m. pasaulinis korupcijos suvokimas nesikeitė. Tyrime išskiriami du pagrindiniai AI įgyvendinimo metodai: „iš viršaus į apačią", kurį taiko vyriausybinės institucijos, naudodamos vidinius duomenis visuomenei stebėti, ir „iš apačios į viršų", kurį taiko piliečiai, naudodami atvirus duomenis vyriausybės veiksmams stebėti. Kiekvienas metodas turi savitų privalumų ir iššūkių, ypač susijusių su prieiga prie duomenų, komunikacija ir pasitikėjimu. Bibliometrinė analizė rodo, kad vis daugiau tyrimų skiriama AI ir korupcijai, tačiau lyginamieji tyrimai apie įgyvendinimo strategijas tebėra riboti. Europos Sąjungoje dauguma AI kovos su korupcija priemonių yra iš viršaus į apačią iniciatyvos, kurias remia vyriausybinės institucijos, o aktyvių iš apačios į viršų priemonių yra nedaug. Tyrimas pabrėžia, kad reikia tolesnių empirinių tyrimų, kuriuose būtų nagrinėjama atvirų duomenų integracija su AI pagrįstomis kovos su korupcija priemonėmis, taip pat išsamaus esamų AI kovos su korupcija iniciatyvų Europos Sąjungoje vertinimo.*

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