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ARTIFICIAL INTELLIGENCE FOR DETECTING PUBLIC PROCUREMENT FRAUD THROUGH ESG RISK INDICATORS: A QUALITATIVE SECONDARY STUDY OF SDG 16

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ABSTRACT

Public procurement absorbs 12.7% of GDP across OECD countries (OECD, 2025), and bribery to win public contracts featured in 57% of concluded foreign-bribery cases in the OECD's 2014 analysis. This study asks whether AI-enabled screening that incorporates environmental, social and governance (ESG) indicators can deliver accountable procurement-integrity gains, and under what conditions. It uses a qualitative, theory-informed secondary comparative design: three core cases (Brazil, Ukraine, Italy), two supplier-side illustrations (Odebrecht, Grenfell Tower) and two algorithmic-accountability comparators (the Netherlands, Australia), assessed against a five-level evidence hierarchy running from operational scale to verified outcomes. Governance and procedural indicators are operational; no reviewed case demonstrates validated environmental or social integration. Reported benefits mostly measure exposure, activity or self-reported savings; low selectivity, signal decay and weak follow-through limit effect; and automated enforcement without due process has caused severe harm elsewhere. The paper contributes the ESG-Integrity Analytics Framework (EIAF), five testable propositions and a replicable evidence-grading protocol, and concludes that AI's contribution to SDG 16.5, 16.6 and 16.10 is conditional on validation, institutional follow-through and accountability.

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Introduction

Public procurement represented 12.7% of GDP across OECD countries in 2023 (OECD, 2025) and is a principal arena of corruption. In the OECD's 2014 analysis of 427 concluded foreign-bribery cases, 57% involved bribes to obtain public contracts and about three-quarters used intermediaries. A 2013 study by PwC and Ecorys for the European Commission estimated direct corruption costs of €1.4–2.2 billion in 2010 across five sectors in eight member states, yet such figures extrapolate from detected cases and share the measurement problem of all hidden-crime statistics (Fazekas et al., 2016; Fazekas and Kocsis, 2020). The Odebrecht resolution shows the pattern: US prosecutors documented roughly US$788 million in bribes across more than 100 projects in twelve countries, paid through shell companies and off-book accounts, generating about US$3.3 billion in profit and a US$3.5 billion global settlement with Braskem in 2016. Concealed ownership and intermediaries, not visibly irregular tenders, enabled the scheme.

AI, machine learning, natural language processing (NLP) and network analytics can screen large datasets and link records that manual audit misses. Yet alert counts and contract value reviewed are not confirmed fraud or prevented loss. The decisive questions are whether alerts are selective, reach investigators in time, and lead to proportionate remedies.

ESG broadens the evidence base. Governance (G) signals such as ownership links, conflicts of interest and suspicious amendments are visible in procurement records; environmental (E) signals (waste violations, false carbon claims, material substitution) and social (S) signals (wage violations, unsafe work, concealed subcontracting) usually sit in fragmented regulatory and inspection data. Neither an ESG breach nor an unusual tender pattern proves fraud. Work on AI-enabled ESG and forensic analytics concentrates on corporate finance and reporting (Aladwey, 2026; Hossain, 2026; Nazarova and Prorok, 2026; Rahmadina et al., 2025), and AI–ESG reviews are largely conceptual syntheses with limited outcome evidence (Khamisu et al., 2026; Meti and Rane, 2026; Panda, 2026; Ramanjaneyulu and Mondal, 2025). The gap is whether verified E and S indicators add validated value beyond established governance red flags in public procurement.

The study asks: (RQ1) which ESG-related indicators may signal procurement-integrity risk; (RQ2) how AI-supported analysis can convert them into accountable audit priorities; and (RQ3) which technical, legal and institutional conditions constrain effectiveness. It contributes a theory-derived framework with testable propositions, a transparent evidence-grading protocol that separates activity from outcomes, and a comparative critical evaluation focused on SDG Targets 16.5, 16.6 and 16.10 (United Nations, 2015).

Theoretical and conceptual framework

Red-flag research and its limits

Procurement-risk research uses single bidding, restricted procedures, short advertising periods, repeated awards and contract amendments (Fazekas et al., 2016; Fazekas and Kocsis, 2020). These traces are ambiguous (a single bid may reflect a specialist market); labels derive from enforcement and so inherit its biases; and accuracy can mask poor precision when confirmed fraud is rare. Decarolis and Giorgiantonio (2022) validate Italian red flags against external measures but show that conspicuous indicators lose power as bidders adapt. Neither stream explains why valid alerts fail to produce action, which requires organisational and institutional theory.

Theoretical lenses

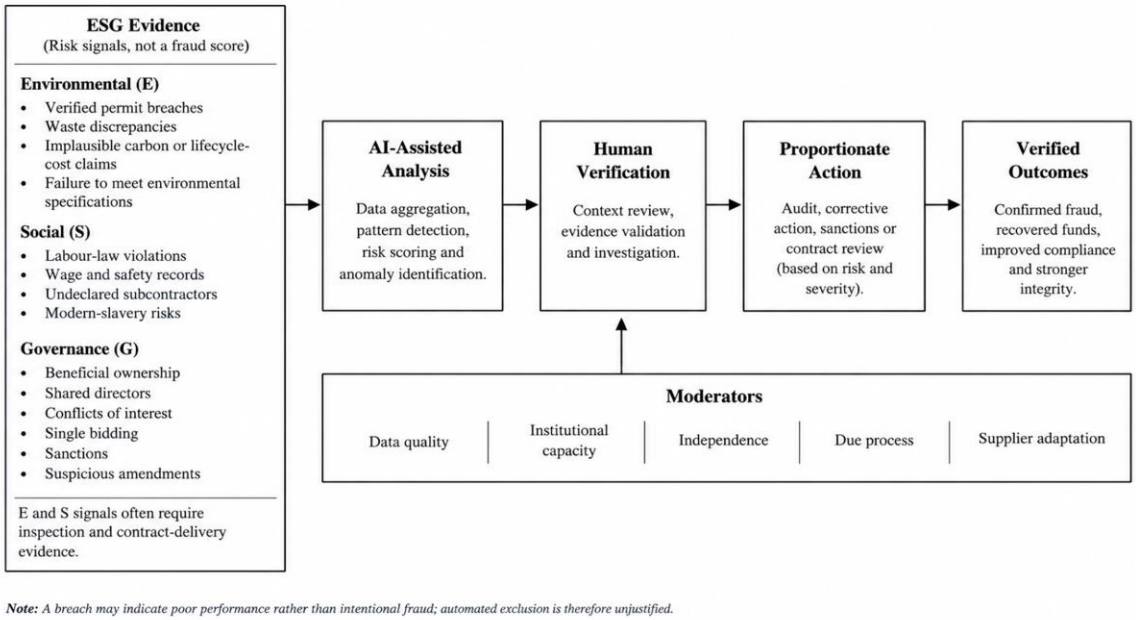
Four lenses are combined. Principal–agent theory explains how delegated authority and information asymmetry let officials and suppliers exploit procurement; AI is a monitoring technology that narrows the asymmetry only where indicators are valid proxies. Collective-action and institutional-power theory explains why valid alerts may be ignored: where corruption is systemic, actors expect rules to be bypassed (Persson et al., 2013); extractive institutions shield incumbents (Acemoglu and Robinson, 2012); and political selection of leaders for loyalty rather than competence erodes agency and state-owned-enterprise capacity (Tipurić, 2025; Tipurić and Cindrić, 2026). Sociotechnical and neo-institutional theory holds that technology's effects depend on enactment in routines (Orlikowski, 1992), that organisations may adopt tools symbolically while decoupling them from practice (Meyer and Rowan, 1977; DiMaggio and Powell, 1983), and that niche innovations do not automatically reconfigure regimes (Geels, 2002). Micro-level mechanisms include groupthink (Janis, 1972), weak psychological safety to challenge alerts (Edmondson, 1999), functional stupidity (Alvesson and Spicer, 2016), overconfident self-assessment (Kruger and Dunning, 1999) and field-specific habitus (Bourdieu, 1990). Finally, accountability theory requires information, justification and consequences (Bovens, 2007), operationalised for algorithms as end-to-end internal audit (Raji et al., 2020). For ESG, the triple-bottom-line view (Elkington, 1997) justifies treating environmental and social performance as integrity-relevant, but disclosure can be performative, so operational claims need evidence beyond reporting (Asif et al., 2023; EEA, 2024).

The ESG-Integrity Analytics Framework (EIAF)

The EIAF (Figure 1) treats ESG as a taxonomy of risk signals, not a fraud score. Evidence moves through AI-assisted analysis and human verification to proportionate action and independently verified outcomes, moderated by data quality, institutional capacity, independence, due process and supplier adaptation. It draws on procurement-risk measurement, AI-governance and ESG-integration scholarship (Asif et al., 2023; Batool et al., 2025; Raji et al., 2020; Ramanjaneyulu and

Mondal, 2025). Table 1 converts the lenses into propositions; the E and S extensions remain hypotheses.

Figure 1. ESG-Integrity Analytics Framework (EIAF)



Source: authors' conceptual synthesis. A breach may indicate poor performance rather than intentional fraud; automated exclusion is unjustified.

Table 1. Theory-derived propositions

Proposition	Theoretical basis	Claim tested
P1 Validity	Principal–agent; red-flag research	Indicators add integrity value only if validated against independent outcomes.
P2 Decay	Strategic adaptation	Visible indicators lose power unless models are revised and tested out of sample.
P3 Embedding	Collective action; neo-institutional theory	Alerts yield outcomes only where capacity, independence and enforcement exist; otherwise adoption is symbolic.
P4 Due process	Accountability theory	Automated action without human review, reasons and appeal produces false-positive harm and loses legitimacy.

P5 Evidentiary asymmetry	Triple bottom line; greenwashing	G indicators are more operational than E/S; E/S add value only when independently verified.

Methodology

Research design

The study adopts a critical-realist, abductive stance: it seeks the mechanisms explaining why AI screening does or does not yield integrity outcomes, moving iteratively between the propositions in Table 1 and the documentary evidence. A qualitative secondary design suits a concealed phenomenon: investigative files are inaccessible, and the empirical question concerns how institutions measure and report their own performance. The unit of analysis is the institutional system (indicators plus response pathway), not the algorithm. Comparative case logic aims at analytic generalisation to propositions, not statistical representativeness. Following Snyder (2019), the work is a targeted critical synthesis informed by systematic-review principles, not a PRISMA review; no screening totals are claimed.

Case selection

Core cases were selected theoretically on two dimensions, operational deployment and independent validation: Brazil's Alice (high deployment, little independent validation), Ukraine's Prozorro (open data and rule-based indicators, contested selectivity) and Italian public-works research (strong validation, no deployment). Two supplier-side illustrations test the signal logic: Odebrecht (governance-type concealment) and Grenfell Tower (performance-claim manipulation, an E/S-type signal). Two comparators from algorithmic public administration outside procurement, the Netherlands and Australia, inform only P4 and are analogies, not evidence of procurement performance. The UK Procurement Act 2023 and the EU Corporate Sustainability Due Diligence Directive (CSDDD) are treated as enabling contexts.

Corpus and verification

Four source tiers were used: (A) institutional and official documents (CGU, World Bank, European Commission, Transparency International Ukraine, OECD, United Nations, court rulings, inquiry reports and prosecution records); (B) peer-reviewed empirical studies; (C) theoretical works; and (D) 2025–2026 AI–ESG reviews, used to frame the field but not as performance evidence. Search concepts combined AI, machine learning, NLP, procurement fraud, bid-rigging, ESG indicators, beneficial ownership, shell companies, SDG 16 and algorithmic accountability. Sources were included if they addressed procurement analytics, public-sector integrity, supplier-level ESG evidence or algorithmic accountability; promotional claims and purely technical work without a governance link were excluded as effectiveness evidence. Each document was appraised for authority, independence (self-reported or external), methodological transparency and recency.

Headline figures were cross-checked against secondary reports in October 2026; conflicting figures are reported side by side with source and date, not reconciled. No database-level search log exists, so the corpus is purposive and claims are scoped accordingly.

Evidence hierarchy and analysis

Claims were graded on a five-level hierarchy (Table 2) and credited at the highest level their source supports; self-reported institutional figures are capped at Level 3 without independent corroboration.

Table 2. Evidence hierarchy

Level	Evidence type	Typical indicator
L1 Exposure	Processes screened; contract value reviewed	Value of audited purchases
L2 Process output	Alerts raised; audits opened	Audit counts
L3 Administrative action	Suspensions, cancellations, claimed savings	Self-reported benefits
L4 Independent validation	Indicator performance against external outcomes, out of sample	Precision; predictive tests
L5 Verified outcome	Confirmed irregularity, recovery or reduced recurrence, with counterfactual	Audited recoveries

Documents were coded in a matrix on six dimensions: purpose and inputs; indicators and automation; institutional owner and response pathway; reported outputs; ESG coverage; and accountability safeguards and limitations. Deductive codes derived from P1–P5; inductive codes (ambiguous metrics, alert fatigue, delayed intervention, ESG data gaps, symbolic compliance, adaptation) were added. Negative-case analysis sought evidence disconfirming each proposition, which was then judged supported, partly supported or untested.

Trustworthiness

Credibility rests on triangulating official, independent and peer-reviewed sources; dependability on the documented protocol and grading rules; confirmability on separating reported from inferred claims; and transferability on explicit contextual limits. Reflexively, the analysis is deliberately sceptical of unvalidated benefit claims; negative-case analysis counterbalances that stance. Because cases differ in legal setting and metrics, they are compared analytically, not ranked (Bovens, 2007; Raji et al., 2020).

Findings and critical evaluation

Brazil: operational scale is not causal proof

CGU's Alice screens procurement notices through automated audit trails and text analysis, sending alerts on directed specifications, overpricing and unnecessary purchases to human auditors. CGU (n.d.) reports more than 190,000 processes analysed in 2023, with preventive suspension or cancellation of purchases worth over R$2.08 billion, and for 2024 more than 161,000 processes, 212 audits of purchases worth R$30.57 billion and R$1.25 billion in financial benefits. CGU's own journal describes 37 audit trails cross-referencing 46 government databases. These figures evidence scale and a screening-to-audit pathway (Levels 1–3), not fraud: R$30.57 billion is the value of purchases audited, not proven loss. Interim CGU communications for 2024 reported 118,069 processes, 206 audits over R$25.57 billion and R$257.25 million in savings from concluded audits. The nearly five-fold gap with the later benefit figure is unexplained in the sources reviewed, illustrating P1's concern that benefit metrics lack stable definitions, counterfactuals and published precision. By simple arithmetic, 212 audits from 161,000 processes is a conversion of about 0.13%: a narrow funnel that could reflect high selectivity or capacity rationing, and without precision data the two cannot be distinguished. Alice's declared risk categories also target tender-level irregularities; an Odebrecht-type architecture (shell companies, intermediaries, off-book payments) would largely lie outside them, an inference from published descriptions, not a documented evaluation.

Ukraine: open data cannot compensate for weak selectivity

Prozorro combines electronic procurement data, automatic risk indicators, State Audit Service monitoring and civil-society scrutiny. The World Bank (2024) found that indicators often flagged non-risky transactions, weakening prioritisation; the European Commission (2025) identified continuing control and enforcement weaknesses. Transparency International Ukraine (2026) reported that 2,913 of 10,828 monitoring cases in 2025 (26.9%) rested on automatic indicators and questioned case materiality and proportionate remedies. Roughly three-quarters of monitored cases therefore originated elsewhere, suggesting indicators were not the main detection channel. Low selectivity breeds alert fatigue, and late or weakly enforced review lets accurate alerts fail to prevent harm (P1, P3). Open data enables scrutiny but not action, and no systematic E or S integration was found.

Italy: validation matters, and indicators decay

Decarolis and Giorgiantonio (2022) apply LASSO, ridge regression and random forests to Italian roadwork tenders, testing features against measures linked to investigations and judicial risk. This is the only Level 4 evidence in the corpus. It shows that some tender features carry risk information but that conspicuous red flags lose predictive power once suppliers learn what attracts scrutiny

(P2). Proxies are context-specific and not proven fraud, so transfer requires local validation (Fazekas and Kocsis, 2020).

Supplier-side illustrations

Odebrecht shows why G signals matter: ownership opacity, intermediaries and off-book payments sustained a fifteen-year scheme (2001–2016) whose contracts returned roughly 4.2 times the bribes paid in profit. Grenfell Tower shows why E/S signals cannot be read from disclosures: the 2024 inquiry concluded that three manufacturers (Arconic, Celotex and Kingspan) engaged in "systematic dishonesty", manipulating tests and misrepresenting data to mislead the market, among multiple failures contributing to 72 deaths; the companies deny responsibility for the deaths. A text-mining system would have read polished product claims, and only independent test, certification and complaint records could contradict them. Both cases support P5.

Failure-mode comparators

Two non-procurement cases show the cost of false positives. In the Netherlands, The Hague District Court ruled in 2020 that the SyRI fraud-risk system violated the right to private life, and algorithmic risk profiling in childcare benefits wrongly accused an estimated 26,000 parents of fraud, contributing to the government's resignation in January 2021. In Australia, Robodebt used automated income averaging to raise debts of roughly A$1.7–1.8 billion against more than 400,000 people between 2015 and 2019; a 2023 Royal Commission called it a costly failure of public administration. Both paired automated accusation with limited explanation or recourse, and in Robodebt legal warnings were disregarded, consistent with groupthink and weak psychological safety (Janis, 1972; Edmondson, 1999). In procurement the harmed parties are legitimate suppliers, particularly small firms, but the mechanism transfers (Raji et al., 2020; Lemajic and Durnik, 2026).

Comparative analysis

Table 3. Cross-case comparison

Case	Deployment	Best evidence	ESG coverage	Main constraint	Tests
Brazil (Alice)	National, operational	L3 (self-reported)	G/procedural	Unstable benefit metrics; no precision data	P1, P3
Ukraine (Prozorro)	National, open data	L2	G/procedural	Low selectivity; enforcement gaps	P1, P3
Italy (research)	Research only	L4	G/procedural	Signal decay; context-specific proxies	P1, P2
Netherlands, Australia	Operational, non-procurement	Documented harm	None	Weak review and appeal	P4

Odebrecht, Grenfell	Illustrative	Official findings	G; E/S-type	Concealment; falsified claims	P5

Across cases, the strongest mechanism is AI-assisted prioritisation followed by human investigation, not autonomous judgement. Only Italy reaches Level 4 and no case reaches Level 5. P1 is partly supported (one validated study; operating systems report self-assessed benefits); P2 is supported but rests on one study; P3 is supported by Ukraine and, by inference, Brazil, though attribution is impossible; P4 is supported by the comparators but untested in procurement; P5 is supported because no case demonstrates validated E or S integration. Enabling regimes may improve data availability but do not evidence deployed AI-ESG detection. The AI–ESG literature identifies data integration and governance as conditions (Abaker et al., 2026; Ofosu-Ampong et al., 2026) and multi-stakeholder ESG governance as an anti-corruption route (Tun, 2026, preprint), without fraud-detection performance data. Hossain's (2026) hybrid blockchain–machine-learning–ESG framework is likewise proposed, not validated, and blockchain cannot make false inputs true.

Critical appraisal of the evidence base

Four weaknesses recur. First, metric conflation: exposure (value reviewed), activity (alerts) and claimed savings are reported as if they were outcomes. Second, enforcement bias: validation labels derive from investigations and prosecutions, which capture detected, not total, corruption; the OECD's 2014 figures likewise cover only concluded cases. Third, reporting asymmetry: operational systems publish favourable aggregates while independent evaluations are rare. Fourth, the AI–ESG literature is dominated by reviews, conceptual frameworks and corporate-finance settings, with little procurement-specific evidence despite calls to govern AI for ESG and SDG outcomes in the Global South (Ofosu-Ampong et al., 2026; Khamisu et al., 2026). A validation–deployment gap follows: the settings that deploy AI at scale lack independent validation, while the setting with validation lacks deployment.

Discussion and implications

Answering the research questions

RQ1: governance indicators (single bidding, ownership links, conflicts, amendments, price anomalies) are operational; E and S indicators are plausible but unvalidated. RQ2: AI converts indicators into accountable priorities only through human verification, recorded reasons and proportionate action. RQ3: effectiveness is constrained by indicator validity, selectivity, signal decay, institutional follow-through and due process.

Theoretical implications

Three refinements follow. First, the binding constraint is conversion, not detection: valid alerts need capacity, independence and enforcement (P3), consistent with institutional decoupling. Second, verification asymmetry implies sequencing: G indicators first, E and S only through independently verified data. Third, two biases require testing: NLP may reward polished reports and disadvantage smaller suppliers with fewer reporting resources (digital greenwashing), and historical enforcement bias may focus scrutiny on small suppliers while influential firms escape.

Recommendations

Authorities should publish separate measures of activity and outcomes (alerts, audit-conversion rates, confirmed irregularities, false positives, review times, remedies and benefit-calculation methods; Rahmadina et al., 2025) and test indicators out of sample against audit or judicial outcomes (Decarolis and Giorgiantonio, 2022). Where lawful, high-priority alerts should reach reviewers before award. ESG integration should begin with a few legally defined indicators linked to ownership registries, environmental permits, labour-inspection data and contract-acceptance records, tested separately and jointly; risk scores should trigger investigation, not automatic debarment. Safeguards include human review before consequential action, recorded reasons, data provenance, versioned models, subgroup testing, appeal routes, whistleblower protection, trained auditors and independent oversight (Raji et al., 2020; Batool et al., 2025). Simpler methods may be more proportionate than computationally intensive ones.

Implications for SDG 16

AI-supported screening may contribute to Target 16.5 by prioritising investigations, 16.6 by strengthening accountable institutions and 16.10 by supporting access to procurement information, but only if shown through better investigations, fair competition, timely remedies and reduced recurrence. Vinuesa et al. (2020) estimate that AI may enable 134 of the 169 SDG targets while inhibiting 59, which fits this evidence: transparency without enforcement exposes problems without resolving them, and automated scrutiny without due process weakens legitimacy.

Limitations and future research

This design identifies mechanisms and evidence gaps but cannot establish that AI caused fraud reductions. Coding was not subject to inter-coder testing; official figures are self-reported and sometimes revised; non-English primary documents were accessed unevenly; the comparators are analogies; and the E and S extensions remain conceptual. Future research should test the EIAF across sectors and jurisdictions, compare models with and without verified E/S data, and report precision, false-positive burdens, subgroup effects, cost-effectiveness and credible counterfactuals; audit methods for AI in ESG reporting (Nazarova and Prorok, 2026) offer a starting point.

Conclusion

AI can widen procurement screening and reveal patterns manual review misses, but the evidence does not show that technology by itself detects or prevents fraud. Brazil demonstrates operational scale and reported benefits, not validated impact; Ukraine shows how weak selectivity and enforcement blunt performance; Italy shows both the value of external validation and the decay of visible indicators; Odebrecht and Grenfell show why governance and verified E/S evidence differ in tractability; and the Dutch and Australian cases show the price of unaccountable automation. The EIAF links verified ESG evidence to AI-assisted analysis, human verification, proportionate action and independently assessed outcomes. For SDG 16, success should be judged by fairer, more transparent and accountable procurement, not by technological sophistication or alert volume.

References

Abaker, A., ElGili, M., & Arees, B. (2026). Emerging Technologies as Enablers of Sustainable Management: A Comprehensive Framework—The Role of Saudi Arabia's Vision 2030. Sustainability, 18(7), 3168.

Acemoglu, D., & Robinson, J. A. (2012). Why Nations Fail: The Origins of Power, Prosperity, and Poverty. Crown Publishing Group.

Aladwey, L. (2026). Artificial intelligence and unethical financial practices: Examining the mediating role of environmental, social, and governance (ESG) performance in the Saudi financial sector. Borsa Istanbul Review, 26(2), Article 100784. https://doi.org/10.1016/j.bir.2026.100784

Alvesson, M., & Spicer, A. (2016). The Stupidity Paradox: The Power and Pitfalls of Functional Stupidity at Work. Profile Books.

Asif, M., Searcy, C., & Castka, P. (2023). ESG and Industry 5.0: The role of technologies in enhancing ESG disclosure. Technological Forecasting and Social Change, 195, 122806.

Batool, A., Zowghi, D., & Bano, M. (2025). AI governance: A systematic literature review. AI and Ethics, 5(3), 3265–3279.

Bourdieu, P. (1990). The Logic of Practice. Stanford University Press.

Bovens, M. (2007). Analysing and assessing accountability: A conceptual framework. European Law Journal, 13(4), 447–468.

Comptroller General of Brazil (CGU). (n.d.). Alice: Analisador de Licitações, Contratos e Editais.

Decarolis, F., & Giorgiantonio, C. (2022). Corruption red flags in public procurement: New evidence from Italian calls for tenders. EPJ Data Science, 11, Article 16.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. American Sociological Review, 48(2), 147–160.

Edmondson, A. (1999). Psychological safety and learning behavior in work teams. Administrative Science Quarterly, 44(2), 350–383.

Elkington, J. (1997). Cannibals with Forks: The Triple Bottom Line of 21st Century Business. New Society Publishers.

European Commission. (2025). Ukraine Report 2025.

European Environment Agency (EEA). (2024). Europe's Circular Economy in Facts and Figures. EEA Report.

Fazekas, M., & Kocsis, G. (2020). Uncovering high-level corruption: Cross-national objective corruption risk indicators using public procurement data. British Journal of Political Science, 50(1), 155–164.

Fazekas, M., Tóth, I. J., & King, L. P. (2016). An objective corruption risk index using public procurement data. European Journal on Criminal Policy and Research, 22(3), 369–397.

Geels, F. W. (2002). Technological transitions as evolutionary reconfiguration processes: A multi-level perspective and a case-study. Research Policy, 31(8), 1257–1274.

Hossain, M. Z. (2026). AI-driven forensic accounting: A hybrid fraud detection framework integrating blockchain, machine learning, and ESG risk indicators. Journal of Artificial Intelligence and Technological Development, 2(1), 19–33. https://doi.org/10.59324/jaitd.2026.2(1).03

Janis, I. L. (1972). Victims of Groupthink: A Psychological Study of Foreign-Policy Decisions and Fiascoes. Houghton Mifflin.

Khamisu, M. S., Khandelwal, N., & Paluri, R. A. (2026). Research Progress on Artificial Intelligence in Environmental Social and Governance (ESG). Discover Sustainability, Article in Press.

Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments. Journal of Personality and Social Psychology, 77(6), 1121–1134.

Lemajic, M., & Durnik, M. (2026). The Algorithmic Gap: Ensuring SDG 16 Compliance in Public Sector Decision-Making. In D. Tipurić, L. Cindrić, & L. Obuljen (Eds.), Challenges of Corporate Governance in State-Owned Enterprises: Between Accountability, Efficiency, and Social Value (pp. 107–116). CIRU & University of Dubrovnik.

Meti, A., & Rane, N. L. (2026). Enhancing ESG performance and business sustainability through artificial intelligence: A review. International Journal of Applied Resilience and Sustainability, 2(1), 122–146.

Meyer, J. W., & Rowan, B. (1977). Institutionalized organizations: Formal structure as myth and ceremony. American Journal of Sociology, 83(2), 340–363.

Nazarova, K. O., & Prorok, A. V. (2026). The use of artificial intelligence in the audit of financial and ESG reporting of a public company in the context of European integration. Economics, Management and Administration, (3(117)), 132–137. https://doi.org/10.26642/ema-2026-3(117)-132-137

OECD. (2025). Government at a Glance 2025: Size of public procurement.

Ofosu-Ampong, K., Oppong, M., Ninson, G., & Ofori, W. O. (2026). Governing AI for ESG and SDG Outcomes in the Global South: A Systematic Review. Digital Society, 5, 51.

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. Organization Science, 3(3), 398–427.

Panda, S. (2026). Artificial intelligence, corporate information governance, and Environmental, Social, and Governance (ESG) performance: A systematic review. International Journal of Applied Resilience and Sustainability, 2(2), 842–868. https://doi.org/10.70593/deepsci.0202035

Persson, A., Rothstein, B., & Teorell, J. (2013). Why anticorruption reforms fail—systemic corruption as a collective action problem. Governance, 26(3), 449–471.

Rahmadina, S., Irawan, B., Indarto, K., Angreni, D. K. D., Fatmala, A. N. P., Suryawati, D., & Zulkifli, Z. (2025). Advancing financial risk management: Transparent frameworks for enhancing fraud detection efficiency. E3S Web of Conferences, 657, Article 04003. https://doi.org/10.1051/e3sconf/202565704003

Raji, I. D., Smart, A., White, R. N., et al. (2020). Closing the AI accountability gap: Defining an end-to-end framework for internal algorithmic auditing. Proceedings of the 2020 ACM Conference on Fairness, Accountability, and Transparency, 33–44.

Ramanjaneyulu, G., & Mondal, T. (2025). AI for environmental, social and governance (ESG) integration in strategic management: A PRISMA systematic review. International Journal of Environmental Sciences, 11, 22s.

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. Journal of Business Research, 104, 333–339.

Tipurić, D. (2025). Morocracy. Ekonomski Pregled, 76(6), 482–502.

Tipurić, D., & Cindrić, L. (2026). Political Selection and Morocracy: Implications for Board Competence and Dynamics in State-Owned Enterprises. In Book of Proceedings of the 14th OFEL Conference 2026 (pp. 10–19). CIRU.

Transparency International Ukraine. (2026). Analysis of the Roadmap for Strengthening Public Procurement Oversight for 2025–2027.

Tun, P. (2026). Multi-stakeholder collaboration and ESG-governance to combat corporate corruption and achieve SDG 16: A case study of the United Nations Global Compact Network India's ACCA project [Preprint]. ResearchGate. https://doi.org/10.13140/RG.2.2.36675.87842

United Nations. (2015). Transforming Our World: The 2030 Agenda for Sustainable Development. UN Publishing.

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., et al. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. Nature Communications, 11(1), 233.

World Bank. (2024). Growth Foundations Development Policy Operation: Public procurement risk indicators and procurement integrity.