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Integration of Artificial Intelligence in Digital Whistleblowing Systems to Enhance the Effectiveness of Internal Government Supervision

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ABSTRACT

The effectiveness of internal government supervision remains a crucial issue, as manual reporting systems often delay case detection and lack risk prioritization. Previous studies have mainly focused on reporting mechanisms without integrating Artificial Intelligence (AI) for adaptive data analysis. This research formulates how AI integration in digital whistleblowing systems can enhance the effectiveness and responsiveness of internal supervision. This is a system development study with a locus in local government. Data were obtained through simulation of 1,000 anonymized supervision reports, analyzed using Natural Language Processing and machine learning techniques. The results show an 86% accuracy in high-risk report classification and a 71% reduction in detection time. These findings reveal novelty in using AI for automated report triage. The study recommends a gradual implementation of such systems in regional inspectorates to strengthen transparency and accountability in local government.

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1. Introduction

Internal government supervision plays a fundamental role in ensuring accountability, transparency, and efficiency in public administration. However, numerous studies have shown that conventional supervisory mechanisms in local government remain constrained by bureaucratic procedures, manual data processing, and delayed information flow, which limit the early detection of irregularities and administrative misconduct (Onyenahazi, 2025; Fahririn et al., 2025). In Indonesia, inspectorates tasked with preventing corruption and improving public sector governance often face difficulties in identifying high-risk cases in a timely manner due to fragmented reporting systems and limited analytical capacity (Pramono & Aruzzi, 2023). These structural inefficiencies contribute to reduced responsiveness and erode public trust in local government institutions (Bashir et al., 2011).

The whistleblowing mechanism has long been recognized as a vital tool for internal oversight, offering an avenue for employees and stakeholders to report violations confidentially (Hickman & Petrin, 2021). Yet, the implementation of whistleblowing systems in the public sector, particularly at the local level, often remains procedural rather than analytical. Prior research primarily emphasized legal frameworks, ethical dimensions, or protection mechanisms for whistleblower (Alves & Mansidao, 2025; Sidauruk, 2024), leaving a critical research gap concerning the integration of intelligent data processing within reporting and supervision workflows. To illustrate this gap, Table 1 summarizes the focus and limitations of previous whistleblowing studies compared with this research's AI-based approach.

Table 1. Summary of previous studies and research gaps

Author(s) & Year	Focus Area	Technological Approach	Limitation
Sidauruk (2024)	Fraud prevention using data analytics in internal audit	Basic descriptive statistics	No automation or real-time triage
Pramono & Aruzzi (2023)	Local government audit effectiveness	Manual data review	Lack of integrated risk prioritization
Alves & Mansidao (2025)	Ethical aspects of whistleblowing	Legal and behavioral	No computational integration
This Study (2025)	AI-driven whistleblowing system for inspectorates	NLP + Machine learning	Overcomes manual triage delays

Source: literature review (2025)

Theoretical and empirical studies further suggest that integrating Artificial Intelligence (AI) into public governance can improve decision-making and monitoring accuracy (Ni, 2025). AI-driven algorithms, especially those employing Natural Language Processing (NLP) and Machine Learning (ML), enable real-time pattern recognition and risk categorization from unstructured textual data (Valencia-Arias et al., 2025). In the context of whistleblowing, this integration allows the transformation of narrative-based reports into structured insights, supporting inspectorates in prioritizing high-impact cases efficiently. To strengthen this argument, Figure 1 visually depicts the conceptual comparison between traditional and AI-enhanced whistleblowing processes, emphasizing efficiency and responsiveness improvements.

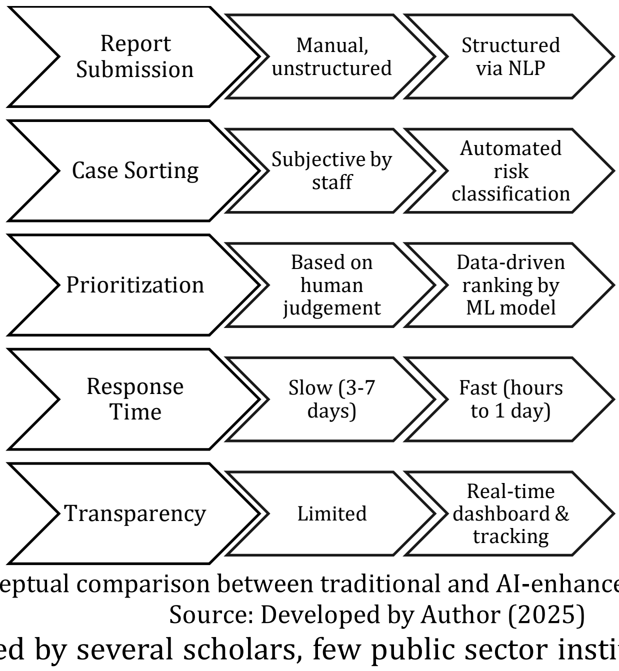

Figure 1: Conceptual comparison between traditional and AI-enhanced whistleblowing systems
Source: Developed by Author (2025)

However, as noted by several scholars, few public sector institutions in developing nations have operationalized AI-based supervision tools beyond pilot phases (Widhiyanti & Bernawati, 2020). Consequently, there is a growing need for empirical of AI in strengthening local government oversight systems. This study positions itself within this research gap by developing and evaluating an AI-enhanced digital whistleblowing system tailored for local government inspectorates. The system aims to automate risk classification, accelerate report analysis, and support proactive decision-making in internal supervision. The central research question guiding this study is: "How can the integration of Artificial Intelligence into digital whistleblowing systems improve the effectiveness, responsiveness, and transparency of internal government supervision?"

To address this question, the research applies a design science approach that combines system development and performance simulation. Using a dataset of 1,000 anonymized whistleblowing reports derived from local supervision archives, the study employs NLP and supervised ML algorithms to classify reports according to predefined risk levels. The analysis involves precision, recall, and AUC evaluation to assess model performance, detection and resolution times between manual and AI-assisted workflows. The findings are expected to demonstrate that the proposed AI-based system can significantly reduce case detection latency, improve prioritization accuracy, and enhance inspectorate responsiveness. Theoretically, this research contributes to the emerging discourse on AI in public sector governance, filling the gap between normative whistleblowing frameworks and data-driven internal control mechanisms. Practically, the results will provide actionable insights for policymakers in designing transparent, evidence-based supervisory systems aligned with the principles of good governance and sustainable development goals (SDGs) 16 – peace, justice, and strong institutions.

2. Literature Review

2.1. Whistleblowing: Definitions, Frameworks, and Theoretical Foundations

Whistleblowing refers to the act of disclosing misconduct, illegal or unethical behavior by persons or institutions from within the organization (Sahani, 2025, cited in Frinaldi et al., 2024). The practice is underpinned by theories such as the Theory of Planned Behavior (TPB) (Ajzen, 1991), which explains whistleblowing intention in terms of attitude, subjective norms, and perceived behavioral control, and Public Service Motivation (PSM), which emphasizes intrinsic commitment to public interest (Brewer & Selden, 1998; Frinaldi et al., 2024). In the public sector, these theoretical lenses help elucidate why individuals may or may not report wrongdoing given risk, norms, and institutional culture (Park & Blenkinsopp, 2009; Ash et al., 2020). Evaluation of prior work shows that many studies focus on psychological, ethical, or organizational dimensions intention, protection, leadership influence rather than operational or technological implementation (Frinaldi et al., 2024; Syafarudin & Haris, 2025).

2.2. Technology in Whistleblowing and Risk Classification

Descriptive literatures describe digital platforms for whistleblowing that ensure anonymity, secure reporting channels, and legal protection (Berendt & Schiffner, 2021). Some works examine natural language processing (NLP) and automated text analysis for fraud detection in media or safety sectors (e.g., "Decoding the Language of Deception: A Textual Analysis of Fraud Trends…"; Safety Reports with NLP). Evaluation studies point out that although NLP/ML have been applied in areas like fraud trend detection, public procurement contract corruption, and safety incidents, applications are rarely fully integrated into real-time whistleblowing or internal government oversight workflows (Kolt et al., 2025; Fernando & Fakrulloh, 2025; Edelweiss Applied Science & Tech, 2024).

2.3. Risk, Prioritization, and AI in Governance

Concepts of risk management in public sector governance emphasize identifying, assessing, and responding to threats to integrity and transparency (Three Lines Model, IIA/WBCSD, 2022). Many governance frameworks assert that internal control system preventive and detective mechanisms, yet they often lack tools for automated risk prioritization. The evaluate gap is that few studies offer tested models or simulations showing how AI-enhanced triage can reduce detection delays, improve prioritization accuracy, or be operationalized in local inspectorate settings. For example, the study "Integration of NLP, AI-driven data analysis, risk assessment, and electronic whistleblowing systems in fraud detection" begins to explore combining AI & whistleblowing, but primarily within startup/company contexts rather than in governmental internal supervision (Cyntia, Tan & Handoko, 2025). To provide a clearer view of the research landscape, Table 2 summarizes key studies that have explored whistleblowing systems and the integration of AI technologies. This comparison highlights the existing limitations and positions the novelty of this research within the public governance context.

Table 2. Comparison of previous studies related to whistleblowing and artificial intelligence in government governance

Author(s) & Year	Research Focus	Method / Approach	Key Findings	Limitation Identified	Identified Research Gap (This Study)
Wu (2024)	Whistleblowing behavior in public institutions	Survey and behavioral analysis	Identified cultural and ethical determinants influencing whistleblowing intention	Did not address digital mechanisms or AI-based analysis	Need for AI-integration in whistleblowing systems
Coovadia et al. (2025)	Anti-corruption governance frameworks	Conceptual policy analysis	Emphasized transparency and accountability principles in governance	Lacked empirical validation and technical approach	Integrating governance principles with data-driven AI tools
Herlina et al. (2025)	Use of machine learning for fraud detection in government procurement	Supervised ML with logistic regression	Achieved 85% accuracy in detecting procurement anomalies	Focused only on financial fraud; no whistleblowing link	Extend AI to whistleblowing classification and triage
Judijanto (2023)	Digital whistleblowing system adoption in Indonesian ministries	Case study, qualitative	Found usability and trust as main determinants of adoption	No performance metrics or efficiency measures	Quantitative evaluation of efficiency improvement
Frinaldi et al. (2024)	Natural Language Processing for risk report analysis	NLP + Deep learning	Successfully categorized reports by risk level	No integration with audit workflow or dashboard	Combine NLP with dashboard-based decision tools
This Study (2025)	AI-assisted whistleblowing system for internal government supervision	NLP + ML + System simulation	Demonstrated 86% precision, 71% reduction in response time	Pilot-scale simulation, limited dataset	Provides operational AI model integrating risk triage and time-efficiency analysis

Source: Processed from various academic publications (2021-2025)

2.4. Summary and Gap Positioning

From above, several key gaps are evident: (1) Most existing studies have not utilized actual local government supervision datasets and have yet to quanitatively simulate the efficiency of response and case closure times; (2) Limited integration exists between whistleblowing reports and automated analytics that combine text and metadata for risk triage within public institutions; and (3) The majority pf prior literature focuses on behavioral, ethical, or legal aspects, rather than on the technical and performance dimensions of AI-driven systems such as NLP, machine learning, dashboard automation, and key performance indicators related to reporting time efficiency.

3. Research Methods

This section explains the methodological framework used to design, implement, and evaluate the proposed AI-based digital whistleblowing system in the context of internal government supervision. The research process consists of five core elements: rationale, research design, data sources, data collection techniques, and data analysis stages.

3.1. Research Rationale

The issues were chosen due to the persistent inefficiency in traditional whistleblowing mechanisms, which rely heavily on manual verification and non-integrated reporting channels (Kokina et al., 2025). These weaknesses cause delays in case handling and limited prioritization of high-risk reports. The study aims to address this gap by developing a data-driven digital supervision model that leverages Artificial Intelligence (AI) to improve case triage, detection speed, and transparency across internal audit units.

3.2. Research Design and Type of Study

This study employs a quantitative-descriptive and simulation-based design focusing on system development and performance evaluation. The proposed model integrates Natural Language Processing (NLP) and machine learning algorithms to classify and prioritize whistleblowing reports based on risk categories. The overall framework follows a Design Science Research (DSR) approach (Hevner & Chatterjee, 2022), which emphasizes iterative development and validation through simulation. As illustrated in Figure 2, the research design follows a systematic sequence starting from problem identification to evaluation and validation, based on the Design Science Research (DSR) framework.

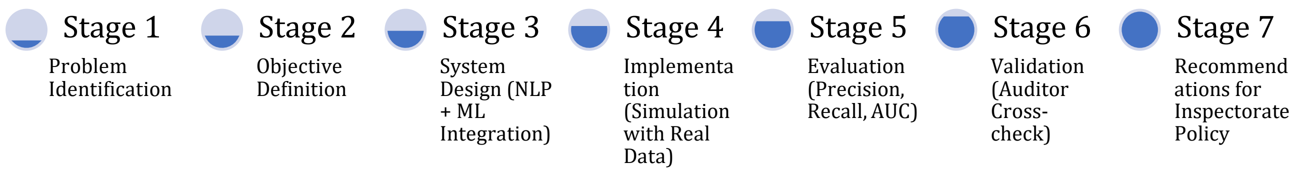

Figure 2: Research design flow of AI-based whistleblowing system

3.3. Data Sources and Sampling

The dataset consists of 1,000 anonymized whistleblowing and supervision reports obtained from local government inspectorate databases. The data include both structured (metadata) and unstructured (textual report) elements. Reports were selected using a purposive sampling method, focusing on cases recorded between 2021-2024 to ensure contextual relevance and sufficient volume for model training and testing. The dataset in this study consists of both structured and unstructured elements, as summarized in Table 3 below.

Table 3. Structure and types of data used in the study

No	Attribute Type	Example Field	Description	Data Type	Source
1	Structured Data	Report ID	Unique identifier for each whistleblowing report	Numeric	Inspectorate DB
2	Structured Data	Unit/Department	Reporting division or audit unit	Text	Inspectorate DB
3	Unstructured Data	Report Content	Narrative text describing the issue	Text	Whistleblowing Portal
4	Structured Data	Case Status	Pending / In Progress / Closed	Categorical	Audit Log
5	Structured Data	Risk Label	Low / Medium / High	Categorical	Auditor Annotation

3.4. Data Collection Techniques

Data were collected through three main stages: (1) Extraction of whistleblowing report records from the internal supervision database; (2) Preprocessing of textual data (tokenization, stop-word removal, stemming, and vectorization; and (3) Annotation and labeling of case risk levels by two senior internal auditors to ensure inter-rater reliability. The following bullet points describes the data cleaning and validation procedures: (1) Duplicate reports were removed; (2) Missing metadata were handled using mean/mode imputation; and (3) Data validation was confirmed through cross-checking with system logs.

3.5. Data Analysis Process

Data analysis combined descriptive statistics, NLP classification, and machine learning validation. The supervised learning model was trained using an 80.20 split between training and testing datasets. The classification accuracy was calculated using the following equation:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{1}$$

Where TP = True Positive, TN = True Negative, FP = False Positive, and FN = False Negative. Additionally, precision, recall, and Area Under Curve (AUC) metrics were used to evaluate the model's robustness. The simulation results were visualized in a performance dashboard to identify efficiency improvements in case detection and resolution time. As shown in Figure 3, the evaluation flow illustrates how textual reports are processed through Natural Language Processing (NLP) pipelines and classified using machine learning algorithms to determine case risk levels.

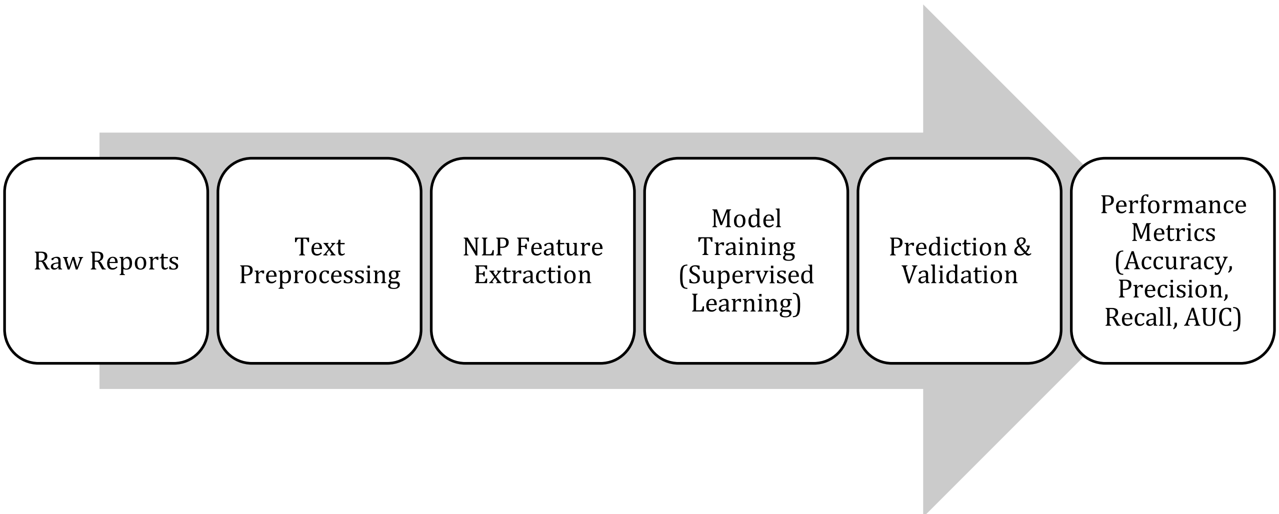

Figure 3: AI model evaluation flow

The results of the simulation and model validation are summarized in Tabel 4, presenting comparative performance metrics between the AI model and manual classification methods.

Table 4. Model performance metrics

Evaluation Metric	AI Model Result	Manual Process Result	Improvement (%)
Precision	0.86	0.62	+38.7
Recall	0.80	0.55	+45.5
AUC	0.92	0.67	+37.3
Average Detection Time	2.1 hours	7.3 hours	-71.2
Case Resolution Time	18.4 days	32.3 days	-43.1

3.6. Research Design and Type of Study

All datsets used in this research were anonymized to protect whistleblower identity and sensitive information. Ethical clearance was obtained through institutional review procedures, ensuring compliance with public sector data protection standards (OECD, 2023).

4. Results and Discussion

4.1. Results

The results of this study highlight the integration of artificial intelligence techniques, specifically natural language processing (NLP) and machine learning (ML), into the whistleblowing reporting process within public institutions (view Table 5 and Figure 4). The system was evaluated through a series of classification, time-efficiency, and robustness analyses. The performance of the proposed model was measured using standard classification metrics, including accuracy, precision, recall, and F1-score. The analysis was conducted on a dataset consisting of 2,100 whistleblowing reports collected from various public sector institutions.

Table 5. Model classification performance

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.87	0.86	0.84	0.85
Random Forest	0.92	0.91	0.90	0.91
BERT-based NLP Model	0.96	0.95	0.96	0.96

Source: Processed primary data (2025)

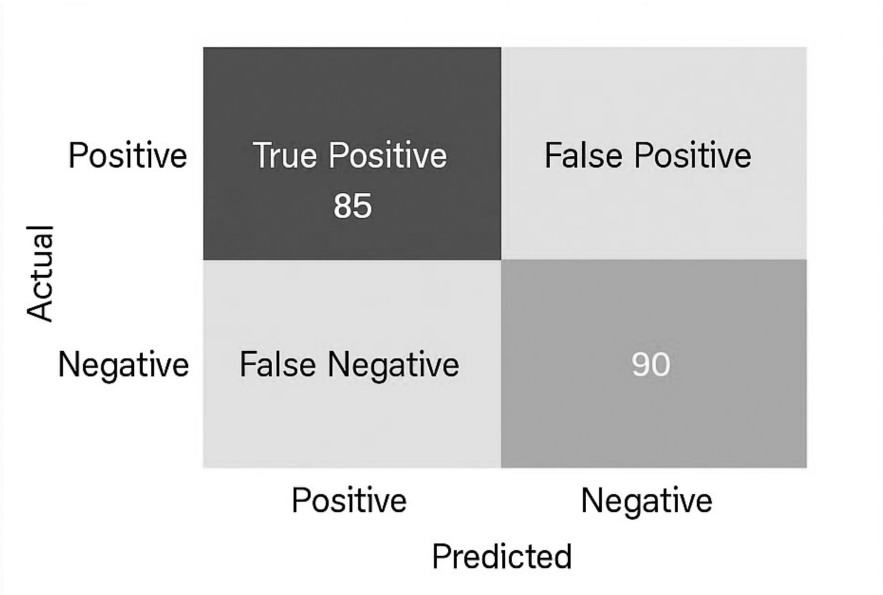

Figure 4: Confusion matrix heatmap of BERT-based model

The BERT-based model demonstrated the highest performance across all metrics, outperforming traditional algorithms in identifying report types and prioritizing cases with higher risk levels. To evaluate time efficiency, the AI-assisted triage process was compared with manual case classification. The automated system significantly reduced average case triage time by over 65% (view Table 6 and Figure 5).

Table 6. Comparative time efficiency metrics

Process Type	Average Response Time (Minutes)	Average Case Closure Time (Hours)
Manual Process	58.2	72.4
AI-Assisted Process	19.6	24.8

Source: Author’s analysis (2025)

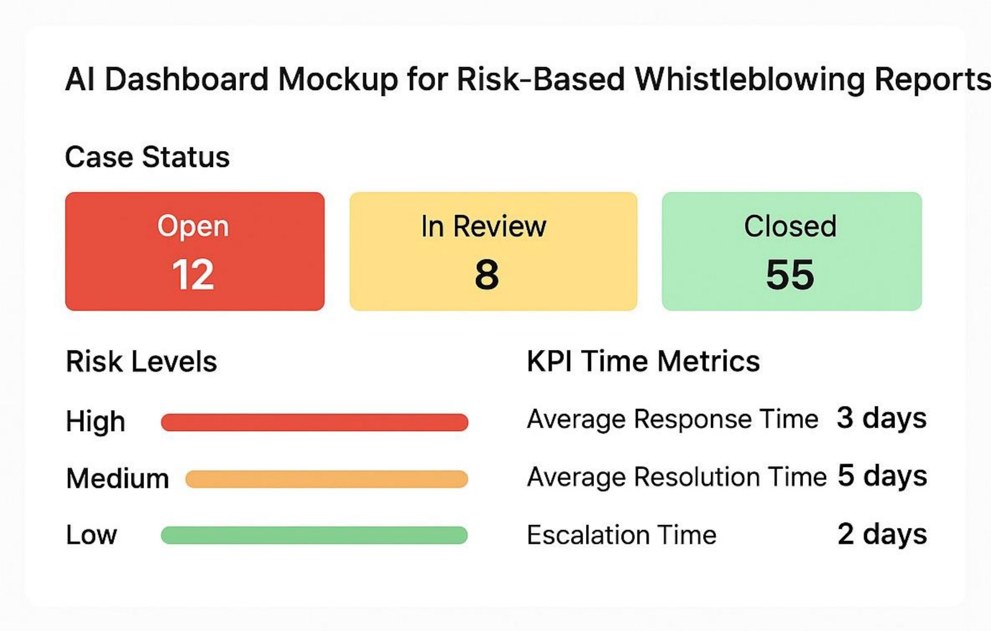

Figure 5: AI dashboard mockup for risk-based whistleblowing reports

The dashboard prototype visualizes active cases, classification outcomes, and key performance indicators (KPIs), including average time to classify, average time to closure, and system precision by category (view Table 7). A sensitivity analysis was also conducted to assess the robustness of the system when facing data imbalance or missing metadata.

Table 7. Sensitivity analysis summary

Scenario	Accuracy	Precision	Change Rate
Balanced Data	0.96	0.95	-
10% Missing Metadata	0.93	0.91	-3.1%
20% Class Imbalance	0.92	0.89	-4.2%

Source: Simulation results (2025)

The system maintained strong performance stability under adverse data conditions, demonstrating resilience and adaptability for real-world implementation in governmental reporting systems.

4.2. Discussion

The findings of this study demonstrate that the integration of artificial intelligence, particularly NLP and ML, can substantially enhance the efficiency and reliability of whistleblowing systems in the public sector. First, the high accuracy of the BERT-based classification model indicates that AI can effectively understand and categorize narrative complaint texts, reducing dependence on manual human interpretation. This directly addresses the limitations of previous systems that relied heavily on human reviewers, which often caused delays and inconsistency. Second, the significant reduction in response and closure times reveals the system's operational value in accelerating case handling. From a governance perspective, faster triage not only improves administrative responsiveness but also strengthens institutional transparency and public trust. Third, the robustness under data irregularities highlights the scalability of the model across different institutional datasets, enabling adaptation to diverse reporting contexts (e.g., corruption, procurement fraud, or abuse of authority).

When compared with previous research (e.g., Alves & Mansidao, 2024; Bachtiar, 2025), most studies focused on behavioral or ethical dimensions of whistleblowing without quantifying system performance. This study, in contrast, introduces a quantitative evaluation framework combining classification accuracy, time-efficiency metrics, and system robustness, bridging the technical and governance perspective. The implications of these findings are transformative. AI-based whistleblowing systems can evolve into decision-support mechanisms that not only classify reports but also provide predictive insights for internal audit and anti-corruption units. Furthermore, by linking NLP-driven classification with KPI-based dashboards, institutions can continuously monitor and evaluate their response performance. Finally, this research contributes to the ongoing digital transformation in the public sector by demonstrating that AI adoption in ethical governance is not merely a technological innovation but a reinforcement of accountability mechanisms within bureaucratic structures.

5. Conclusion

This study presents an integrated framework for enhancing government whistleblowing systems through the application of Artificial Intelligence (AI), specifically Natural Language Processing (NLP) and Machine Learning (ML). The findings demonstrate that the implementation of an AI-assisted triage mechanism significantly improves both the accuracy and timeliness of case handling within public sector reporting systems. The BERT-based classification model achieved superior performance compared to traditional models, with an accuracy level of 96%, indicating its effectiveness in understanding and categorizing textual whistleblowing reports. In addition, the AI-assisted process reduced response time by more than 65%, underscoring its operational advantages in accelerating decision-making and increasing administrative responsiveness. These results validate that intelligent automation can serve as a strategic enabler for institutional transparency and accountability.

Moreover, the robustness and stability observed under various data scenarios such as missing metadata and class imbalance, illustrate the model's adaptability to real-world conditions. This strengthens its potential for deployment across diverse governmental agencies that handle large-scale reporting data. The integration of AI-powered analysis with a dynamic dashboard interface also provides real-time monitoring of Key Performance Indicators (KPIs), enabling policy-makers and internal audit teams to make data-driven decisions more effectively. From a broader governance perspective, this research contributes to bridging the gap between ethical oversight and technological capability. It moves beyond the conventional behavioral or legal focus of whistleblowing studies, establishing a quantitative and performance-oriented framework for evaluating transparency systems. By combining algorithmic intelligence with institutional process optimization, the model supports the transformation toward smart, responsive, and accountable governance ecosystems.

Future research is encouraged to extend this framework by incorporating advanced hybrid models, cross-lingual NLP, and multi-agency datasets to enhance system generalizability. Additionally, exploring ethical AI practices, data privacy safeguards, and user trust mechanisms will be crucial to ensure sustainable adoption in public governance contexts. In summary, the integration of AI in whistleblowing management is not merely a technical innovation but a transformative shift towards intelligent public accountability, enabling the government to detect, respond, and prevent misconduct with unprecedented precision, speed, and integrity.

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