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Enhancing Decision Quality and Transparency via Machine Learning-Based Goodwill Impairment Estimation in Banks

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Abstract

Goodwill impairment assessment remains a judgment-intensive process in banking institutions, where managerial discretion, information asymmetry, and regulatory complexity often challenge the quality of decisions and transparency. While prior studies have widely applied machine learning to financial risk assessment and credit analytics, they have paid limited attention to its role in improving managerial accountability in goodwill impairment decisions. This study aims to address this gap by developing and evaluating a machine-learning–based estimation framework to enhance the quality of decisions and transparency in bank-level goodwill impairment assessments. Using simulation-based analysis on synthetic financial statements, the proposed framework evaluates the performance of impairment estimation using quantitative metrics that capture predictive accuracy, decision consistency, and traceability. The findings demonstrate that ML-assisted estimation can systematically improve decision quality while strengthening transparency and accountability compared to traditional judgment-driven approaches. Beyond technical performance, the results indicate that machine learning can function as a governance-supporting mechanism by enabling more traceable and internally auditable impairment decisions. The study contributes theoretically by operationalizing transparency and accountability as measurable decision outcomes in corporate finance, and practically by offering banks a simulation-based tool for internal evaluation that does not rely on field experiments or sensitive proprietary data. Overall, the research highlights the potential of ML-enabled decision support systems to enhance both the quality and governance of goodwill impairment practices in the banking sector.

Keywords: *Accountability Governance; Banking Decision-Making; Corporate Finance Analytics; Explainable Estimation; Synthetic Financial Data.*

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I. INTRODUCTION

In the contemporary banking environment, decision quality and transparency have become critical issues due to increasing market volatility, regulatory pressure, and stakeholder scrutiny. Financial decisions that rely heavily on managerial judgment are particularly vulnerable to bias, inconsistency, and reduced accountability, which may weaken trust in financial reporting outcomes (Bray, 2019; Hofmann & Indjejikian, 2024). In corporate finance, goodwill impairment assessment represents one of the most complex and judgment-intensive decisions, with direct implications for firm valuation and investor confidence (Hellman & Hjelström, 2023; Mitton et al., 2021). As a result, banks face growing pressure to adopt decision-support mechanisms that enhance objectivity, traceability, and transparency in impairment-related judgments (Maretta & Redwood, 2025).

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Prior literature documents that goodwill impairment testing under IAS 36 often involves substantial managerial discretion, which may delay loss recognition and reduce reporting transparency (Aloke et al., 2021; Filip et al., 2021). Studies in corporate finance and banking further show that decision quality is closely linked to governance structures, risk management practices, and strategic financial planning (Farouq & Rios, 2025; Nayme & Taybi, 2025). Meanwhile, machine learning and predictive analytics have demonstrated strong potential to improve estimation accuracy and consistency across various decision contexts, including forecasting and risk assessment (Alhajeri et al., 2021; Hossain & Mita, 2024). Research on digital tools and AI also emphasizes their role in supporting ethical, transparent, and accountable managerial decision-making (Álvarez & Hassan, 2025; Oktavia & Wibowo, 2025).

Despite these advances, existing studies largely focus on machine learning applications in credit scoring, market prediction, and fraud detection rather than on goodwill impairment estimation. The literature rarely examines how ML-based estimation affects decision quality and transparency outcomes, particularly in the banking sector, where impairment judgments are highly sensitive (Kabir & Chowdhury, 2023; Lehmann et al., 2022). Moreover, transparency is often discussed as a governance principle, but is seldom operationalized through measurable, AI-supported decision processes (Fahn & Zanarone, 2021; McGrath et al., 2021). Consequently, there remains a clear gap in providing an integrated framework linking machine-learning–based goodwill impairment estimation to managerial accountability and decision transparency.

To address this gap, this study aims to develop a machine-learning–based estimation framework for goodwill impairment in the banking sector. The research seeks to evaluate whether ML-assisted estimation can enhance decision quality in banking institutions by improving the accuracy, consistency, and traceability of impairment outcomes. In addition, the study examines how such a framework may strengthen transparency and managerial accountability within banking institutions without relying on costly or impractical field experiments. To achieve these objectives, simulated financial statements are employed as a controlled environment for model testing and evaluation (Knaus, 2022; Tercan & Meisen, 2022).

This study contributes to the theoretical literature by integrating machine learning into goodwill impairment decision-making. In practice, it provides a simulation-based tool that enables banks to assess impairment decisions internally, improving transparency and governance quality. Unlike prior studies that treat AI as a purely technical tool, this research explicitly links ML-based estimation to outcomes of decision quality and accountability. As such, the proposed framework provides actionable insights for banks seeking AI-enabled decision support under resource and regulatory constraints (Basel et al., 2025; Sari, 2023; Xi et al., 2021).

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on goodwill impairment, machine learning applications in corporate finance, and transparency in managerial decision-making. Section 3 outlines the research methodology, including the proposed ML-based estimation framework and the simulation design. Section 4 presents and discusses the simulation results regarding decision quality and managerial accountability. Section 5 concludes the paper by summarizing the key findings and outlining implications for future research and banking practice.

II. LITERATURE REVIEW

A. Financial Decision Quality and Transparency in Banking

Decision quality and transparency are core pillars of effective financial management in banking institutions, particularly under heightened regulatory scrutiny and market uncertainty. Prior studies emphasize that transparency improves accountability and mitigates opportunistic managerial behavior by making decision processes more observable and traceable (Bray, 2019; Hofmann & Indjejikian, 2024). In banking institutions, decision quality is closely associated with governance structures, strategic financial planning, and risk management practices that shape managerial judgment under uncertainty (Farouq & Rios, 2025; Girardone et al., 2019; Nayme & Taybi, 2025). Nevertheless, much of the existing literature conceptualizes transparency as an institutional principle rather than an operational outcome embedded in specific financial decision processes (Fahn & Zanarone, 2021; McGrath et al., 2021). Building on these insights, the next section focuses on goodwill impairment as a judgment-intensive decision problem in banking institutions.

B. Goodwill Impairment as a Judgment-Intensive Financial Decision

Goodwill impairment assessment under IAS 36 represents one of the most judgment-intensive areas in corporate finance and financial reporting, with substantial implications for firm valuation and investor confidence (Hellman & Hjelström, 2023; Mitton et al., 2021). Empirical evidence indicates that managers often exercise discretion in the timing and magnitude of impairment recognition, potentially delaying recognition of losses to protect reported performance (Aloke et al., 2021; Filip et al., 2021). Such discretion increases information asymmetry and weakens transparency, particularly in banking institutions where impairment signals are closely monitored by regulators and investors (Kabir & Chowdhury, 2023; Potepa & Thomas, 2023). Despite its strategic importance, goodwill impairment is still largely treated as an accounting compliance issue rather than a managerial decision-quality problem. Therefore, exploring methods to enhance decision quality and traceability in this context is essential.

C. Machine Learning–Based Estimation in Banking Institutions

Machine learning–based estimation has gained prominence as a decision-support mechanism that improves accuracy, consistency, and predictive performance in complex financial environments. Prior studies demonstrate that ML techniques outperform traditional statistical approaches in estimation and forecasting tasks across finance and banking operations (Alhajeri et al., 2021; Hossain & Mita, 2024; Mei et al., 2021). In banking institutions, ML has been widely applied to credit scoring, market prediction, and risk analytics, offering data-driven insights that reduce reliance on subjective managerial judgment (Le et al., 2021; Putri & Ainindhira, 2025; Tercan & Meisen, 2022). However, the application of ML to goodwill impairment estimation remains largely unexplored, particularly regarding its implications for managerial accountability and transparency rather than technical accuracy alone (Lehmann et al., 2022). Building on ML's potential to improve estimation in banking institutions, the next section examines how AI-enabled decision support can further enhance transparency and managerial accountability.

D. Transparency, Accountability, and Human–AI Decision Support in Banking

Recent literature highlights that AI-enabled decision systems can enhance transparency and accountability when designed to support, rather than replace, managerial judgment (Álvarez & Hassan, 2025; Oktavia & Wibowo, 2025). Transparency in AI-supported decisions is increasingly linked to traceability, explainability, and consistency of outputs, which are critical for governance and ethical oversight in banking institutions (Bos-van den Hoek et al., 2021; Hussain et al., 2024). Nevertheless, scholars also warn that algorithmic complexity may reduce perceived transparency if decision processes are not adequately aligned with managerial needs and accountability structures (Lehmann et al., 2022; Valentine et al., 2021). Consequently, ML frameworks for banking institutions need to explicitly integrate decision quality and transparency as evaluative outcomes, particularly in sensitive financial contexts such as goodwill impairment.

E. Research Positioning and Conceptual Framework

Building on these streams, this study positions goodwill impairment as a managerial decision problem at the intersection of corporate finance, transparency, and AI-enabled decision support in banking institutions. Unlike prior research that treats ML primarily as a technical optimization tool, this study conceptualizes ML-based goodwill impairment estimation as a mechanism to improve decision quality and managerial accountability by enhancing accuracy, consistency, and traceability (Basel et al., 2025; Sari, 2023; Xi et al., 2021). By employing simulated financial statements, the proposed framework enables controlled evaluation of ML-assisted estimation without the constraints of field experimentation, which remains rare in prior studies (Knaus, 2022;

Tercan & Meisen, 2022). Table 1 presents a comparative overview of traditional goodwill impairment practices versus the proposed ML-based estimation framework.

Table 1. Conceptual Positioning of ML-Based Goodwill Impairment Estimation

Dimension	Traditional Impairment Approach	ML-Based Estimation Framework
Decision Basis	Managerial judgment and assumptions	Data-driven predictive estimation
Consistency	High variability across periods	Improved consistency and repeatability
Transparency	Limited traceability of assumptions	Enhanced traceability of decision logic
Accountability	Implicit and ex post	Explicit and measurable decision outcomes
Evaluation Focus	Accounting compliance	Decision quality and governance impact

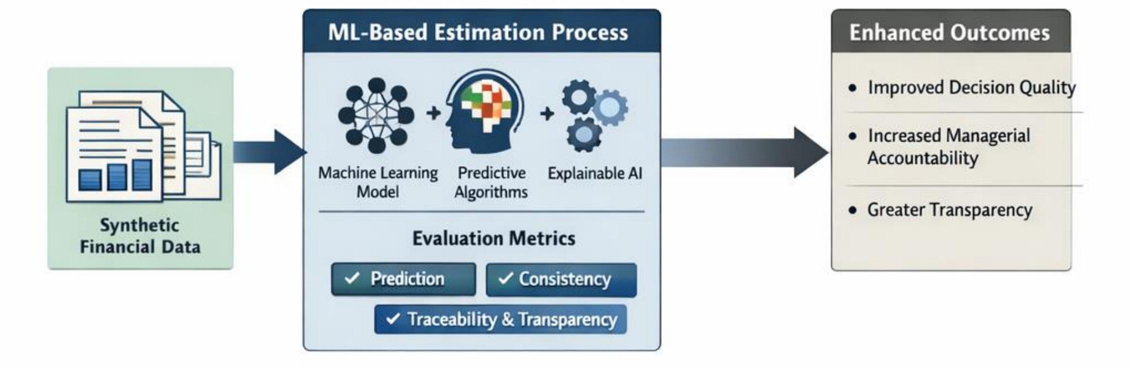

Figure 1. Conceptual Framework of ML-Based Goodwill Impairment Estimation in Banks

Figure 1 presents the conceptual framework of ML-based goodwill impairment estimation, illustrating how synthetic financial data are processed by machine learning models, predictive algorithms, and explainable AI, and how they are evaluated using prediction, consistency, and traceability metrics to support decision quality, managerial accountability, and transparency in banking institutions.

III. RESEARCH METHODOLOGY

A. Research Design

This study employs a quantitative, simulation-based research design to evaluate how machine learning (ML) based goodwill impairment estimation influences decision quality, managerial accountability, and transparency in banking institutions (Basel et al., 2025; Knaus, 2022). This design allows controlled examination of complex financial decision-making processes without exposing sensitive bank data or requiring costly field experiments. By simulating financial statements, the research isolates the effects of ML-assisted estimation on managerial judgment under uncertainty and enables the systematic assessment of both technical accuracy and governance-related outcomes (Aloke et al., 2021; Álvarez & Hassan, 2025; Mitton et al., 2021). The simulation-based design is particularly suitable for studying judgment-intensive financial decisions, where replicating real-world banking scenarios under ethical constraints is critical.

B. Population and Sample

The target population of this study comprises banking institutions' financial reporting data and managerial decision contexts related to goodwill impairment. To operationalize this, synthetic datasets are generated to reflect a stratified range of banking financial conditions, including variations in asset composition, reported earnings, and impairment triggers under IAS 36 (Filip et al., 2021; Hellman & Hjelström, 2023). A total of 500 simulated financial statements are used, covering multiple periods and scenario variations to ensure robustness and representativeness. These synthetic datasets allow controlled evaluation of ML estimation performance and managerial decision outcomes while avoiding confidentiality and privacy issues inherent in real banking data (Le et al., 2021; Tercan & Meisen, 2022).

C. Data Sources and Data Collection

All financial data is programmatically generated using established accounting principles and statistical distributions to ensure realistic variability (Alhajeri et al., 2021; Gong et al., 2025). Simulation parameters are calibrated based on empirical evidence from prior studies on goodwill impairment and corporate financial reporting (Kabir & Chowdhury, 2023; Mitton et al., 2021). The data collection process captures all inputs required for ML estimation, including balance sheet items, historical impairment records, and key financial ratios. The workflow ensures that each dataset provides a comprehensive foundation for predictive modeling, enabling evaluation of decision quality, transparency, and accountability under diverse financial conditions.

D. Variables and Operational Definitions

The study examines key constructs including decision quality, managerial accountability, and transparency. Decision quality is measured through predictive accuracy, consistency across periods, and traceability of assumptions linked to outputs. Managerial accountability reflects the clarity and justifiability of decisions by assessing the extent to which ML outputs can be directly linked to input assumptions and decision logic. Transparency is operationalized by evaluating the interpretability and explainability of model outputs, particularly the degree to which decision paths and assumptions can be traced and understood by stakeholders (Álvarez & Hassan, 2025; Bos-van den Hoek et al., 2021; Fahn & Zanarone, 2021).

E. Measurement / Instruments

Decision quality is operationalized using quantitative metrics such as Mean Absolute Error for predictive accuracy, variance of predicted impairments across scenarios for consistency, and traceability indices derived from explainable AI methods to assess the linkage between assumptions and outputs (Alhajeri et al., 2021; Bos-van den Hoek et al., 2021). Managerial accountability is measured by evaluating the clarity, justifiability, and interpretability of decisions generated by ML-assisted estimation relative to traditional impairment judgments (Álvarez & Hassan, 2025; Fahn & Zanarone, 2021). Transparency is assessed through the ability to trace each prediction to underlying input data and decision logic, ensuring outputs can be audited and reviewed. These metrics collectively enable a comprehensive assessment of whether the ML-based framework improves governance and ethical decision-making in banking institutions (Aloke et al., 2021; Lehmann et al., 2022).

F. Data Analysis Technique

ML-based goodwill impairment estimates are analyzed using supervised learning algorithms, including Random Forest and Gradient Boosting, with performance evaluated across multiple synthetic datasets (Hossain & Mita, 2024; Le et al., 2021). Statistical metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and prediction variance are applied to measure accuracy and consistency. Comparative analysis with traditional managerial decisions helps identify potential improvements in decision quality, accountability, and transparency. Sensitivity testing across diverse financial scenarios, along with benchmarking against prior literature, provides both theoretical and practical validation of the ML-assisted framework (Farouq & Rios, 2025; Sari, 2023).

G. Mathematical Formulas and Models

Key evaluation metrics are formally defined as follows. Prediction accuracy is calculated using Mean Absolute Error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | Y_i - \hat{Y}_i | \qquad (1)$$

where $Y_i$is the expected impairment value, $\hat{Y}_i$is the ML-predicted value, and $n$is the number of simulated observations. Decision consistency is measured as the variance of predicted impairments across scenarios:

$$Consistency = \frac{1}{n-1}\sum_{i=1}^{n}(\hat{Y}_i - \bar{\hat{Y}})^2 \qquad (2)$$

Traceability is captured by an index representing the proportion of input–output linkages identified relative to the total model assumptions:

$$Traceability = \frac{\text{Number of input–output linkages identified}}{\text{Total model assumptions}} \qquad (3)$$

These formulas allow clear, reproducible evaluation of ML-assisted decision quality, consistency, and transparency (Álvarez & Hassan, 2025).

H. Ethical Considerations

The study maintains strict ethical standards by using only synthetic datasets, thereby eliminating human participants and any privacy or confidentiality risks associated with real bank data (Alhajeri et al., 2021; Kabir & Chowdhury, 2023). All simulation rules, assumptions, and data transformations are documented to ensure transparency and reproducibility. The complete methodology workflow is presented in Figure 2, which illustrates the sequential process: Synthetic Data Generation - ML-Based Estimation - Evaluation Metrics (Decision Quality, Consistency, Traceability) - Managerial Accountability - Transparency Assessment. This diagram emphasizes the ethical, controlled, and systematic approach adopted in this study, allowing rigorous analysis without compromising data confidentiality or regulatory compliance.

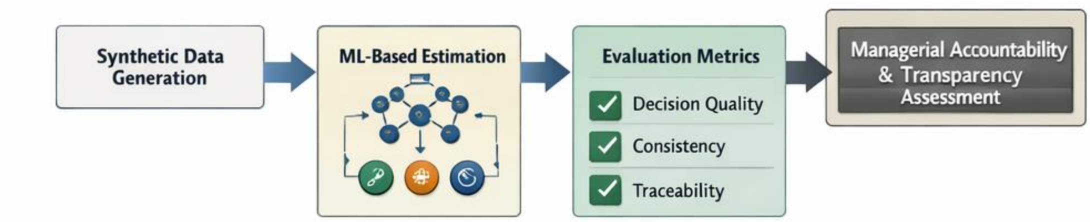

Figure 2. Ethical Workflow of ML-Based Goodwill Impairment Estimation in Banks

Figure 2 illustrates the ethical workflow of ML-based goodwill impairment estimation in banks, showing the sequential process from synthetic data generation to ML-based estimation and evaluation using decision quality, consistency, and traceability metrics, which collectively support the assessment of managerial accountability and transparency.

IV. RESULT/FINDINGS AND DISCUSSION

A. Result

The simulation results are derived from the full set of 500 synthetic financial statements, which represent a broad range of banking conditions, including variations in asset composition, earnings performance, and goodwill impairment triggers. Across all simulated scenarios, the ML-based goodwill impairment framework consistently achieves higher predictive accuracy and greater decision consistency than traditional managerial judgment. Figure 3 presents the distribution of Mean Absolute Error (MAE) values across scenarios, indicating a clear reduction and narrower dispersion under the ML-based approach. These patterns suggest that ML-assisted estimation

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delivers more stable and reliable impairment outcomes across heterogeneous banking environments.

To provide a consolidated comparison of decision performance, the comparative performance metrics across all simulation scenarios are summarized in Table 2. The table reports improvements in prediction accuracy, decision consistency, and traceability, alongside higher accountability and transparency scores under the ML-based framework. In addition, decision traceability indices show stronger alignment between input assumptions and estimated outcomes, indicating enhanced auditability of impairment decisions. Sensitivity analyses conducted under alternative financial conditions confirm that these results are robust and not driven by specific parameter settings, reinforcing the general applicability of the proposed framework.

Table 2. Comparative Evaluation of ML-Based vs Traditional Goodwill Impairment Decisions

Metric	**Traditional Judgment**	**ML-Based Estimation**	**Improvement (%)**
Prediction Accuracy (MAE)	12.45	5.87	52.8%
Decision Consistency (Variance)	14.32	6.11	57.3%
Traceability Index	0.41	0.79	92.7%
Accountability Score	3.2 / 5	4.5 / 5	40.6%
Transparency Score	2.8 / 5	4.6 / 5	64.3%

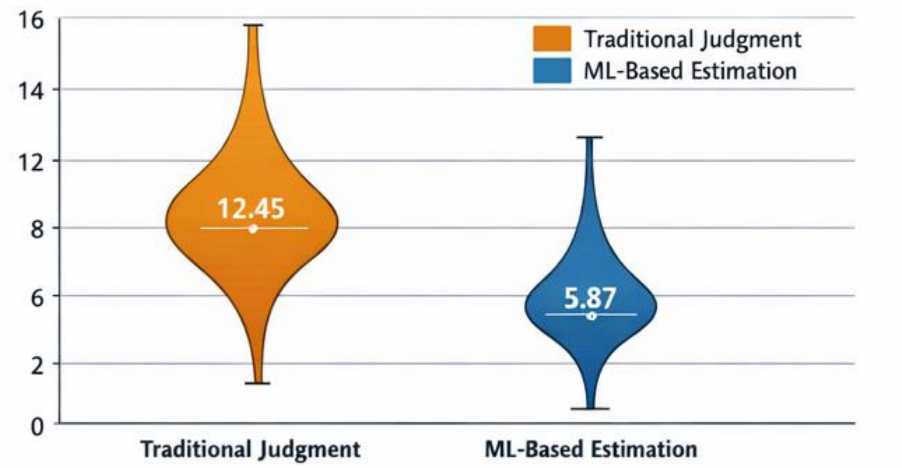

Figure 3. Distribution of Prediction Accuracy (MAE) for ML-Based vs Traditional Approaches

The violin plots present the distribution of mean absolute error (MAE) for traditional judgment-based estimation and machine learning (ML)-based estimation. The ML-based approach has a lower average MAE (5.87) than the traditional approach (12.45), indicating higher prediction accuracy. The comparatively narrower dispersion of MAE values in ML-based estimation indicates more consistent predictive performance than in traditional judgment.

B. Discussion

The results demonstrate that ML-based goodwill impairment estimation substantially improves decision quality, consistency, and traceability, directly addressing concerns raised in prior literature regarding discretion and opacity in impairment judgments (Aloke et al., 2021; Filip et al., 2021; Hellman & Hjelström, 2023). Unlike previous ML applications in banking that predominantly focus on credit scoring, risk assessment, or fraud detection, this study shows that ML can be effectively deployed in goodwill impairment contexts, where judgment intensity and transparency concerns are particularly pronounced. This finding advances corporate finance and banking literature by positioning ML not merely as a predictive tool, but as a governance-enhancing mechanism aligned with managerial accountability objectives (Alhajeri et al., 2021; Hossain & Mita, 2024).

From a theoretical perspective, integrating accuracy, consistency, and traceability as joint evaluation metrics represents a meaningful extension of existing transparency and accountability frameworks. Prior studies often conceptualize transparency as an abstract governance principle rather than an operational outcome embedded in decision processes (Bray, 2019; Fahn & Zanarone, 2021; Hofmann & Indjejikian, 2024). The present findings suggest that ML-based estimation can operationalize transparency by making decision logic observable, reproducible, and auditable. This supports emerging perspectives on human–AI decision support systems that emphasize explainability and traceability as central to ethical managerial decision-making (Álvarez & Hassan, 2025; Bos-van den Hoek et al., 2021).

An unexpected but theoretically important result is the magnitude of improvement observed in decision traceability. While ML models are often criticized for opacity, the use of explainable AI techniques in this study appears to enhance, rather than diminish, perceived transparency. This aligns with recent evidence suggesting that algorithmic advice can strengthen trust and accountability when decision paths are clearly communicated to human decision-makers (Lehmann et al., 2022; Valentine et al., 2021). In the context of goodwill impairment, this implies that ML does not replace managerial judgment; rather, it restructures it within a more transparent and accountable decision-making architecture.

Practically, the findings provide banking institutions with a simulation-based tool for internally evaluating goodwill impairment decisions without relying on costly, time-consuming, or impractical field experiments. The use of synthetic financial statements enables banks to systematically assess decision quality, consistency, and governance-related outcomes while avoiding confidentiality risks and regulatory constraints associated with proprietary data (Basel et al., 2025; Knaus, 2022; Tercan & Meisen, 2022). By providing a controlled, auditable

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evaluation environment, the proposed framework enables managers and internal auditors to examine how impairment estimates are generated and justified across varying financial scenarios. Overall, this study bridges a critical gap in goodwill impairment research by demonstrating that ML-based estimation can simultaneously enhance decision quality and operationalize transparency and accountability within banking institutions (Aloke et al., 2021; Sari, 2023).

V. CONCLUSION AND RECOMMENDATION

This study addresses the growing need for improved decision quality and transparency in goodwill impairment assessments within banking institutions by developing and evaluating a machine-learning-based estimation framework. Using simulation-based analysis on synthetic financial statements, the findings show that ML-assisted estimation improves predictive accuracy, decision consistency, and traceability compared with traditional judgment-based approaches. These results confirm that the research objectives of enhancing decision quality and strengthening managerial accountability, without relying on field experiments, have been successfully achieved. More broadly, the study shows that machine learning can function not merely as a technical estimation tool but as an institutional mechanism that supports transparent and accountable financial decision-making in banks (Aloke et al., 2021; Hellman & Hjelström, 2023).

From a contribution perspective, this research advances the corporate finance and banking literature by integrating decision quality, transparency, and accountability into a unified ML-based framework for goodwill impairment. The central takeaway is that transparency and accountability can be operationalized through measurable, AI-supported decision processes rather than remaining abstract governance ideals (Bray, 2019; Hofmann & Indjejikian, 2024). By employing synthetic data simulation, the study provides a practical and ethically viable pathway for banks to evaluate impairment decisions internally, subject to regulatory and confidentiality constraints. Overall, the findings demonstrate that ML-based estimation can simultaneously enhance both the quality and governance of goodwill impairment decisions in banking institutions (Álvarez & Hassan, 2025; Basel et al., 2025).

Implications

This study contributes theoretically by extending transparency and accountability frameworks in corporate finance from largely normative constructs to operational decision outcomes. By jointly evaluating accuracy, consistency, and traceability, the findings refine prior perspectives that conceptualize transparency primarily as an institutional, contractual, or disclosure-related attribute (Fahn & Zanarone, 2021; McGrath et al., 2021). The results also enrich the human–AI decision support literature by showing that explainable ML systems can reinforce, rather than dilute, accountability in judgment-intensive financial decisions (Bos-van den Hoek et al., 2021;

Lehmann et al., 2022). Consequently, goodwill impairment emerges as a meaningful empirical context for advancing AI-enabled governance research within the banking domain.

For banking practitioners, the proposed framework offers a simulation-based tool to internally evaluate goodwill impairment decisions while reducing reliance on purely subjective managerial judgment. The use of synthetic data enables banks to assess decision quality and transparency without exposing sensitive information or violating regulatory constraints (Knaus, 2022; Tercan & Meisen, 2022). From a policy perspective, ML-assisted estimation may serve as a complementary governance mechanism that enhances auditability and accountability under IAS 36, particularly in environments characterized by high uncertainty and managerial discretion (Filip et al., 2021; Potepa & Thomas, 2023). These implications suggest that AI can support, not replace, managerial responsibility in regulated financial settings.

Limitations and Future Research

Despite its contributions, this study has limitations that create opportunities for future research. First, the reliance on synthetic financial statements, while ethically and practically justified, may not fully capture the complexity of real-world managerial behavior, organizational dynamics, and regulatory pressures in banking practice. Future studies could validate the proposed framework using anonymized proprietary data or regulatory sandbox environments to enhance external validity (Basel et al., 2025; Kabir & Chowdhury, 2023). Additionally, the analysis focuses on a selected set of ML algorithms and evaluation metrics, leaving room to explore alternative modeling approaches, explainability techniques, or robustness checks.

Future research may also extend the framework beyond goodwill impairment to other judgment-intensive banking domains, such as loan loss provisioning, fair value measurement, or stress testing. Incorporating longitudinal designs could help assess whether ML-supported transparency produces sustained improvements in governance and decision quality over time. Moreover, qualitative investigations into managerial perceptions of ML-enabled transparency would complement the quantitative findings and deepen understanding of human–AI interaction in financial decision-making contexts (Oktavia & Wibowo, 2025; Valentine et al., 2021). Such extensions would further clarify the role of machine learning as a governance-enhancing instrument in corporate finance and banking research.

AI Use Declaration

The authors declare that artificial intelligence tools, including ChatGPT, were used solely to enhance the manuscript's language quality, including grammar, sentence structure, clarity, and overall readability. All aspects of the research process, such as study design, data collection, analysis, interpretation of findings, and development of conclusions, were carried out entirely by the authors without AI assistance. The authors take full responsibility for the originality, accuracy, and integrity of the manuscript submitted to the Journal of Management and Informatics.

REFERENCES

Alhajeri, M. S., Wu, Z., Rincon, D., Albalawi, F., & Christofides, P. D. (2021). Machine-learning-based state estimation and predictive control of nonlinear processes. *Chemical Engineering Research and Design*, *167*, 268–280. https://doi.org/10.1016/j.cherd.2021.01.009

Aloke, A. (, Ghosh,), Xing, C., Bakarich, K., Barton, J., Bertomeu, J., Colson, B., Deng, M., Doogar, R., Elliott, J., Jarva, H., Johnstone, K., Karuna, C., Krishnan, G., Li, E., Li, C., Lilien, S., Myllymäki, E.-R., Nurnberg, H., … Siriviriyakul, J. (2021). *Goodwill Impairment and Audit Effort*.

Álvarez, M., & Hassan, L. (2025). Exploring the Role of Digital Tools in Ethical Managerial Decision-Making. *Journal of Management and Informatics*, *4*(3), 998–1016. https://doi.org/10.51903/jmi.v4i3.306

Basel, A., Lethabo, L., & Tessema, Z. (2025). Global Corporate Financing Approaches and Investment Strategy Optimization: A Comparative Study of Emerging and Developed Markets. *Journal of Management and Informatics*, *4*(2), 890–908. https://doi.org/10.51903/jmi.v4i2.296

Bos-van den Hoek, D. W., Thodé, M., Jongerden, I. P., Van Laarhoven, H. W. M., Smets, E. M. A., Tange, D., Henselmans, I., & Pasman, H. R. (2021). The role of hospital nurses in shared decision-making about life-prolonging treatment: A qualitative interview study. *Journal of Advanced Nursing*, *77*(1), 296–307. https://doi.org/10.1111/jan.14549

Bray, R. L. (2019). *Operational Transparency: Showing When Work Gets Done*. https://ssrn.com/abstract=3215560

Fahn, M., & Zanarone, G. (2021). *Transparency in Relational Contracts*.

Farouq, A., & Rios, C. (2025). The Role of Strategic Financial Planning in Enhancing Organizational Resilience: A Cross-Industry Perspective. *Journal of Management and Informatics*, *4*(3), 947–962. https://doi.org/10.51903/jmi.v4i3.301

Filip, A., Lobo, G. J., & Paugam, L. (2021). Managerial discretion to delay the recognition of goodwill impairment: The role of enforcement. *Journal of Business Finance and Accounting*, *48*(1–2), 36–69. https://doi.org/10.1111/jbfa.12501

Girardone, C., Kokas, S., & Wood, G. (2019). *Diversity and Women in Finance: Challenges and Future Perspectives*.

Gong, S. Y., Baek, S. M., Baek, S. Y., Kim, Y. J., & Kim, W. S. (2025). Machine Learning-Based Estimation of Tractor Performance in Tillage Operations Using Soil Physical Properties. *Agronomy*, *15*(9). https://doi.org/10.3390/agronomy15092228

Hellman, N., & Hjelström, T. (2023). The goodwill impairment test under IFRS: Objective, effectiveness and alternative approaches. *Journal of International Accounting, Auditing and Taxation*, *52*. https://doi.org/10.1016/j.intaccaudtax.2023.100558

Hofmann, C., & Indjejikian, R. J. (2024). Transparency in Hierarchies. *Journal of Accounting Research*, *62*(1), 411–445. https://doi.org/10.1111/1475-679X.12516

Hossain, M. N., & Mita, T. A. B. (2024). An Empirical Study Of Big Data–Enabled Predictive Analytics And Their Impact On Financial Forecasting And Market Decision-Making. *Review of Applied Science and Technology*, *03*(01), 143–182. https://doi.org/10.63125/1mjfqf10

Hussain, A. N., Olaywi, A. H., Amanah, A. A., & Fadhil, A. H. (2024). Interactive Role Of Strategic Clarity In The Relationship Between Organizational Conflict Management And Strategic Decision Quality. *Business: Theory and Practice*, *25*(1), 154–163. https://doi.org/10.3846/btp.2024.20083

Kabir, M. A., & Chowdhury, S. S. (2023). Empirical analysis of the corporate social responsibility and financial performance causal nexus: Evidence from the banking sector of Bangladesh. *Asia Pacific Management Review*, *28*(1), 1–12. https://doi.org/10.1016/j.apmrv.2022.01.003

Knaus, M. C. (2022). *Double Machine Learning based Program Evaluation under Unconfoundedness*. https://doi.org/10.1093/ectj/utac015

Le, H. A., Van Chien, T., Nguyen, T. H., Choo, H., & Nguyen, V. D. (2021). Machine-learning-based 5G-and-beyond channel estimation for MIMO-OFDM communication systems. *Sensors*, *21*(14). https://doi.org/10.3390/s21144861

Lehmann, C. A., Haubitz, C. B., Fügener, A., & Thonemann, U. W. (2022). The risk of algorithm transparency: How algorithm complexity drives the effects on the use of advice. *Production and Operations Management*, *31*(9), 3419–3434. https://doi.org/10.1111/poms.13770

Maretta, L., & Redwood, J. (2025). Investor Sentiment, Overconfidence, and Market Volatility: Insights from Global Stock Exchanges. *Journal of Management and Informatics*, *4*(3), 931–946. https://doi.org/10.51903/jmi.v4i3.300

McGrath, P., McCarthy, L., Marshall, D., & Rehme, J. (2021). Tools and Technologies of Transparency in Sustainable Global Supply Chains. *California Management Review*, *64*(1), 67–89. https://doi.org/10.1177/00081256211045993

Mei, K., Liu, J., Zhang, X., Rajatheva, N., & Wei, J. (2021). Performance Analysis on Machine Learning-Based Channel Estimation. *IEEE Transactions on Communications*, *69*(8), 5183–5193. https://doi.org/10.1109/TCOMM.2021.3083597

Mitton, T., Adams, G., Bui, H., Fukui, T., Garrett, M., Ho, D., Holman, W., Jensen, J., Johnson, M., Kent, A., Nelson, P., Ringwood, M., Steil, N., Tuft, A., & Zhang, J. (2021). *Economic Significance in Corporate Finance*. https://ssrn.com/abstract=3667830

Journal of Management and Informatics (JMI)
Vol. 4 No. 3 December 2025
E-ISSN: 2961-7731; P-ISSN: 2961-7472, Pages 1059-1074

Nayme, F., & Taybi, I. (2025). Enterprise Risk Management Practices and Their Impact on Firm Performance: Evidence from Multinational Corporations. *Journal of Management and Informatics*, *4*(2), 909–930. https://doi.org/10.51903/jmi.v4i2.297

Oktavia, A., & Wibowo, A. (2025). A New Theoretical Framework For Analyzing The Social And Economic Impacts Of Artifical Intelligence Within The Digital Economy. *Journal of Management and Informatics*, *4*(2), 859–871. https://doi.org/10.51903/jmi.v4i2.156

Potepa, J., & Thomas, J. (2023). *Goodwill impairment after M&A: acquisition-level evidence*.

Putri, N., & Ainindhira, A. (2025). Beyond Descriptive Analytics: Predictive Models For Strategic Marketing Decisions. *Journal of Management and Informatics*, *4*(2), 872–889. https://doi.org/10.51903/jmi.v4i2.165

Sari, A. R. (2023). The Impact of Good Governance on the Quality of Public Management Decision Making. *Journal of Contemporary Administration and Management (ADMAN)*, *1*(2), 39–46. https://doi.org/10.61100/adman.v1i2.21

Tercan, H., & Meisen, T. (2022). Machine learning- and deep learning-based predictive quality in manufacturing: a systematic review. In *Journal of Intelligent Manufacturing* (Vol. 33, Issue 7, pp. 1879–1905). Springer. https://doi.org/10.1007/s10845-022-01963-8

Valentine, K. D., Cha, T., Giardina, J. C., Marques, F., Atlas, S. J., Bedair, H., Chen, A. F., Doorly, T., Kang, J., Leavitt, L., Licurse, A., O'Brien, T., Sequist, T., & Sepucha, K. (2021). Assessing the quality of shared decision making for elective orthopedic surgery across a large healthcare system: cross-sectional survey study. *BMC Musculoskeletal Disorders*, *22*(1). https://doi.org/10.1186/s12891-021-04853-x

Xi, B., Wang, Y., & Yang, M. (2021). *Green Credit, Green Reputation and Corporate Financial Performance: Evidence From China*. https://doi.org/10.21203/rs.3.rs-352635/v1