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Artificial Intelligence-Enhanced Financial Management Information System for Church-Based Institutions: A Case Study of the Diocese of San Carlos

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ABSTRACT

Faith-based institutions manage complex financial ecosystems involving diverse revenue streams. However, many diocesan financial processes remain semi-manual, limiting transparency and delaying reporting cycles. This study designed, implemented, and evaluated an Artificial Intelligence–enhanced Financial Management Information System (AI-FMIS) tailored for the Diocese of San Carlos, Philippines. The system integrates supervised machine learning for anomaly detection and automated transaction classification, alongside time-series forecasting for revenue prediction. Using a developmental and evaluative design, the platform was deployed across selected diocesan offices and assessed by 45 finance personnel and administrators. Quantitative evaluation employed system performance analytics and ISO/IEC 25010 software quality metrics. Results showed a 37% reduction in average transaction processing time, an increase in reporting accuracy from 82.1% to 94.6%, and an anomaly detection precision of 92.3%, aligning with regulatory expectations for AI-powered monitoring systems. User acceptability yielded an overall mean rating of 4.52/5. Findings indicate that AI integration significantly strengthens financial transparency, operational efficiency, and governance in church-based institutions. This research contributes to the knowledge on intelligent financial systems within nonprofit environments and proposes a scalable AI governance framework aligned with the Philippine Data Privacy Act.

Keywords: *Artificial Intelligence, Financial Management Information System, Machine Learning, Church Governance, Anomaly Detection, Stewardship Theory*

INTRODUCTION

Diocesan institutions operate multiple financial streams, including parish revenues, educational endowments, charitable funds, and social development programs (Keating & Frumkin, 2020). Financial reporting is essential not only for operational continuity but also for stewardship, accountability, and mission alignment in faith-based organizations (Baskerville & Hay, 2021). In many developing regions, including Philippine dioceses, accounting processes remain spreadsheet-based or dependent on disconnected software tools (Diamond & Khemani, 2006; Mbiti & Mwebi, 2022). These practices increase the likelihood of manual errors, reporting delays, and limited analytical insight.

While Artificial Intelligence (AI) has matured within banking, fintech, and enterprise resource planning environments, its application in church-based financial governance remains underexamined (Olayinka et al., 2025; Yilma, 2025). In the Philippines, the BSP has actively promoted AI adoption in the financial sector, with recent circulars requiring supervised financial institutions to implement machine learning-based fraud detection systems (BSP, 2025; Clari5, 2025). Major Philippine banks such as the Rizal Commercial Banking Corporation (RCBC) have successfully implemented AI-powered fraud detection platforms, achieving identification of over 60% of suspicious transactions with minimal alert rates (The Asian Banker, 2026). Similarly, the Anti-Money Laundering Council (AMLC) has procured a ₱66.05 million AI/ML-powered detection engine to enhance its capability in identifying complex money laundering schemes (Newsbytes.PH, 2025). These developments demonstrate the technical feasibility and regulatory support for AI-enhanced financial monitoring in the Philippine context.

However, limited empirical research addresses AI-enabled decision intelligence in mission-driven financial ecosystems, particularly within Southeast Asian religious institutions (Agu & Margaça, 2024). The Lausanne Movement's AI and Faith Consortium (2025) emphasize the urgent need for ethical guardrails and governance frameworks as churches increasingly adopt AI-powered administrative systems.

Statement of the Problem

The Diocese of San Carlos oversees various financial resources that support its pastoral, educational, and social missions. However, these financial processes are not yet supported by an integrated system with intelligent analytics capabilities. As a result, current operations have limited capacity to detect irregular transactions in real time, anticipate revenue trends, automatically categorize financial entries, or generate unified dashboards for decision-making (Ngai et al., 2011; Tian & Liu, 2024). Because most processes remain fragmented or semi-manual, financial reporting and analysis can become slower and less responsive to emerging needs. Without AI-assisted analytical tools, opportunities for greater transparency, efficiency, and data-driven governance within diocesan financial management remain constrained (Kannike & Fahm, 2025; Mokoena, 2024).

These challenges mirror those faced by Philippine financial institutions prior to regulatory mandates for AI adoption. The BSP's Circular No. 1213, issued in May 2025 as part of the implementing rules for the Anti-Financial Account Scamming Act (AFASA) or Republic Act No. 12010, explicitly requires supervised financial institutions to implement comprehensive Fraud Management Systems combining rule-based approaches with machine learning algorithms (BSP, 2025; Clari5, 2025). While these regulations target commercial banks, the underlying principles of real-time monitoring, anomaly detection, and customer protection are equally relevant to diocesan financial governance.

Objectives of the Study

This study sought to design and evaluate an Artificial Intelligence–enhanced Financial Management Information System (AI-FMIS) specifically developed for diocesan financial administration. The research focused on developing a system capable of supporting church-based financial operations while incorporating intelligent technologies. In particular, the study integrated machine learning algorithms that enable automated financial transaction classification and anomaly detection to strengthen financial monitoring and accountability (Chen et al., 2024; Zhang et al., 2024).

Furthermore, the research evaluated the performance of the developed system in several key areas, including processing efficiency, reporting accuracy, anomaly detection capability, and forecast reliability for financial trends. In addition to technical performance, the study also examined the level of user acceptance of the system among finance personnel and administrators (Salah & Ayyash, 2024). This assessment was conducted using the internationally recognized ISO/IEC 25010 software quality framework, which measures system quality across dimensions such as functionality, reliability, usability, security, maintainability, and portability (ISO/IEC, 2023). The system was also designed to comply with the data protection requirements of the Philippine Data Privacy Act of 2012 (Republic Act No. 10173), which mandates explicit consent, data minimization, and breach notification protocols for organizations processing personal information (Securiti, 2024; FinScore, 2020).

Research Gap

Most existing research on artificial intelligence in finance concentrates on corporate banking environments, fintech risk modeling, and enterprise-level financial management systems (Al-dahasi et al., 2025; Mehta et al., 2024; Singh et al., 2024). While these studies demonstrate the effectiveness of AI in improving fraud detection, financial forecasting, and operational efficiency, they largely overlook nonprofit and mission-driven institutions (Puyou, 2023). In particular, limited scholarly attention has been given to the application of AI-enabled financial systems within church-based organizations, especially in Southeast Asian contexts (Olayinka et al., 2025; Temitope, 2025).

In the Philippines, while significant progress has been made in AI adoption within the banking sector—exemplified by RCBC's fraud detection implementation (The Asian Banker, 2026), AMLC's AI-powered analytics platform (Newsbytes.PH, 2025), and Mastercard's TRACE deployment for real-time payment fraud detection (Institute of Commercial Payments, 2025)—these technological advances have not been extended to faith-based institutions. Similarly, the BSP's regulatory framework for AI in finance (Plabasan, 2025) provides guidance that could inform diocesan financial systems, yet no research has explored this application.

Recent advances in anomaly detection using ensemble methods, graph neural networks, and generative adversarial networks have shown promise in financial transaction monitoring (Koo et al., 2024; Wang et al., 2024; Yu et al., 2025). However, these techniques have not been systematically applied or evaluated within faith-based institutional settings. This research seeks to address this gap by examining how artificial intelligence can be integrated into financial management processes within the Diocese of San Carlos, drawing on best practices from Philippine banking and regulatory frameworks while adapting them to the unique context of diocesan governance.

Theoretical and Conceptual Framework

This study is grounded in three theoretical perspectives that explain both the technological and organizational dimensions of adopting an Artificial Intelligence–enhanced Financial Management Information System.

Technology Acceptance Model

The first theoretical foundation is the Technology Acceptance Model (TAM) , originally proposed by Fred Davis (1989) and widely discussed in the information systems literature. TAM explains how users come to accept and use new technologies within organizations (Marangunić & Granić, 2015). According to the model, two primary factors influence technology adoption: perceived usefulness and perceived ease of use. Contemporary extensions of TAM have incorporated additional variables such as perceived value, privacy awareness, and security concerns, which are particularly relevant in financial system contexts (Salah & Ayyash, 2024; Tamilmani et al., 2021). In the Philippine context, studies on digital banking adoption have validated TAM's applicability, demonstrating that perceived usefulness and trust significantly influence acceptance of AI-powered financial services (FinScore, 2020). In the context of this research, TAM provides a framework for understanding how diocesan finance personnel evaluate the usefulness and usability of the AI-enhanced FMIS.

Decision Support Systems

The second theoretical foundation is the concept of Decision Support Systems (DSS). DSS frameworks are designed to assist managers and administrators in making informed decisions by analyzing large volumes of data and generating meaningful insights (Arnott & Pervan, 2020). When integrated with artificial intelligence techniques such as machine learning and predictive analytics, DSS platforms can identify patterns, forecast trends, and support structured decision-making (Sharma et al., 2024; Shrestha et al., 2021). Recent research has demonstrated the effectiveness of AI-powered DSS in resource allocation, operational planning, and anomaly detection across various sectors (Felser et al., 2024; Xie et al., 2024). The AMLC's procurement of an AI/ML-powered detection engine exemplifies the application of DSS principles in Philippine financial oversight, enabling cross-institutional analysis and network-based money laundering detection (Newsbytes.PH, 2025). In this study, the AI-FMIS functions as a decision-support environment that provides financial analytics and anomaly alerts to diocesan administrators.

Stewardship Theory

The third theoretical basis is Stewardship Theory, which emphasizes ethical responsibility and accountable management of organizational resources (Davis et al., 1997; Hernández, 2021). Stewardship theory is particularly relevant in nonprofit and faith-based institutions where financial resources are entrusted for mission-driven purposes (Van Puyvelde et al., 2022). Within the context of diocesan governance, this theory highlights the importance of transparency, accountability, and responsible financial oversight. The integration of AI technologies into financial management processes supports these stewardship principles by strengthening monitoring, reporting accuracy, and institutional accountability (Lausanne Movement, 2025; Mokoena, 2024). Recent scholarship on ethical AI governance in religious contexts emphasizes the need for frameworks that align technological innovation with theological values and moral principles (Kannike & Fahm, 2025; Olayinka et al., 2025). The BSP's forthcoming regulations on ethical AI use in banking—covering bias management, accuracy improvement, and data privacy preservation—provide a regulatory template that can inform stewardship-oriented AI governance in church settings (Plabasan, 2025).

Regulatory Framework Integration

In addition to these theoretical foundations, this study incorporates the Philippine regulatory context for AI-enhanced financial systems. The Data Privacy Act of 2012 (Republic Act No. 10173) establishes the core principles for processing personal information: transparency, legitimate purpose, and proportionality (Securiti, 2024; FinScore, 2020). These principles align with stewardship theory's emphasis on responsible resource management. The Act requires organizations to obtain explicit consent, implement security measures, notify the National Privacy Commission of data breaches within 72 hours, and respect data subject rights, including access, correction, and erasure (Securiti, 2024).

Furthermore, BSP Circular Nos. 1140, 1160, and 1213 mandate real-time fraud detection, machine learning-based monitoring, and comprehensive fraud management systems for supervised financial institutions (BSP, 2025; Clari5, 2025). These circulars specify requirements for transaction velocity checks, geolocation monitoring, behavioral anomaly detection, and customer protection features such as "kill switches" and "money lock" functionality (Clari5, 2025). While these regulations target commercial banks, their technical specifications provide valuable guidance for designing AI-enhanced financial systems in any context where fund stewardship is paramount.

Conceptual Framework

The conceptual framework of this study illustrates how artificial intelligence technologies are integrated into a Financial Management Information System to enhance financial governance within the Diocese of San Carlos. The framework follows an Input–Process–Output (IPO) structure to explain how system components interact to produce improved financial management outcomes, while incorporating Philippine regulatory requirements as contextual factors.

Input. The input component consists of the machine learning algorithms embedded within the system. These include the Random Forest, Naïve Bayes, and ARIMA Time-Series Forecasting models. Random Forest has been widely validated for anomaly detection in financial transactions due to its ensemble learning capabilities and resistance to overfitting (Al-dahasi et al., 2025; Breskuvienė & Dzemyda, 2024). Naïve Bayes classifiers have demonstrated effectiveness in transaction categorization tasks, particularly when combined with appropriate feature engineering (Singh et al., 2021). ARIMA models remain industry standards for time-series forecasting in financial contexts, though recent research suggests hybrid approaches may offer improved accuracy (Wang et al., 2024; Yu et al., 2025). These algorithms serve as the analytical foundation of the AI-enhanced FMIS, enabling the system to learn patterns from historical financial transactions, classify financial records automatically, and predict future financial trends.

Process. The process stage involves integrating these AI algorithms into core Financial Management Information System modules. Specifically, the system incorporates a transaction classification engine, an anomaly detection engine, and an analytics dashboard (Chen et al., 2024; Gupta et al., 2025). Through these modules, financial data are processed, categorized, analyzed, and visualized in real time. This integration enables automated financial monitoring, pattern recognition, and data-driven analysis. The system architecture follows contemporary design principles for AI-enhanced enterprise systems, emphasizing modularity, scalability, and interoperability (Russell & Norvig, 2021; Sharma et al., 2024). Additionally, the system incorporates privacy-by-design principles mandated by the Data Privacy Act of 2012, including data minimization, purpose limitation, and security safeguards (Securiti, 2024).

Output. The output of the system includes improved financial reporting accuracy, early detection of irregular or anomalous transactions, predictive financial insights for planning purposes, and enhanced transparency in financial governance (Koo et al., 2024; Tian & Liu, 2024). These outcomes support more informed decision-making and strengthen accountability in diocesan financial administration, aligning with both stewardship principles and regulatory compliance requirements (Diamond & Khemani, 2006; Puyou, 2023). The system's outputs are designed to meet the reporting standards expected by Philippine regulatory bodies, including the BSP and the Securities and Exchange Commission, should the diocese's financial operations fall under their oversight.

METHODOLOGY

Research Design

This study employed a developmental–evaluative research design to guide the development and assessment of the Artificial Intelligence–enhanced Financial Management Information System (AI-FMIS). Developmental research in information systems focuses on the iterative design, implementation, and refinement of technological artifacts, while evaluative research assesses their effectiveness in real-world contexts (Peffers et al., 2020; Venable et al., 2021).

The research process involved several stages, including system architecture design, prototype development, pilot implementation, and quantitative evaluation of system performance. This approach allowed the researcher to design the system while simultaneously examining its effectiveness in improving financial management processes within the organization.

Research Locale

The study was conducted within the Diocese of San Carlos, located in Negros Occidental, Philippines. The diocese oversees multiple parishes, educational institutions, and social action programs that manage various financial resources (CBCP, 2023). The locale was selected because of its ongoing efforts to modernize financial administration through digital technologies and its representative characteristics of diocesan financial operations in the Philippine context (Mbiti & Mwebi, 2022).

The diocese's financial operations, while smaller in scale than commercial banks, face similar challenges of transaction monitoring, fraud prevention, and regulatory compliance that have driven AI adoption in the Philippine banking sector (The Asian Banker, 2026; Clari5, 2025).

Research Participants

A total of 45 participants were involved in the evaluation phase of the study. These respondents were selected based on their direct involvement in financial operations within the diocese. The participants included 10 diocesan finance officers responsible for central financial management, 20 parish secretaries or accountants handling parish-level financial records, and 15 financial staff from diocesan schools and social action offices. This purposive sampling approach ensured representation across all major financial functions within the diocesan structure (Palinkas et al., 2015).

AI Components Implemented

The AI-FMIS incorporated several machine learning models designed to enhance financial monitoring and analytics. A Random Forest model was implemented to detect anomalous financial transactions, configured with 150 decision trees (n_estimators), maximum tree depth of 12, minimum samples per split of 4, and minimum samples per leaf of 2, using the Gini Index as the splitting criterion (Al-dahasi et al., 2025; Breskuvienė & Dzemyda, 2024).

A Naïve Bayes classifier using the Gaussian variant was used to automatically categorize financial transactions into appropriate accounting categories, with prior probabilities estimated from training data and feature values standardized prior to training (Singh et al., 2021). In addition, an ARIMA (2,1,2) time-series forecasting model was integrated to analyze historical financial data and predict potential revenue trends over a 12-month forecast horizon (Wang et al., 2024; Yu et al., 2025). The system also included a web-based analytics dashboard that provides real-time visualizations for administrators and finance personnel.

These AI components align with the technological requirements specified in BSP Circular No. 1213, which mandates the use of machine learning algorithms for transaction velocity checks, behavioral anomaly detection, and pattern recognition in fraud management systems (Clari5, 2025). The system's design also incorporates principles from the AMLC's AI/ML detection engine procurement, including natural language processing capabilities for narrative analysis and risk scoring for transaction triage (Newsbytes.PH, 2025).

Dataset Description and Data Preparation

The dataset used in this study consisted of historical financial transaction records collected from parish and diocesan accounting reports within the Diocese of San Carlos. The dataset included financial entries related to parish collections, program funds, and institutional transactions recorded over several fiscal periods. A total of 18,750 financial transactions were included in the dataset, covering a time span of approximately five years of financial records (2018–2022). Each transaction contained multiple attributes including transaction date, fund classification, transaction amount, account category, and institutional source.

Prior to model training, the dataset underwent preprocessing procedures which included data cleaning, normalization, and encoding of categorical variables to ensure compatibility with machine learning algorithms (García et al., 2016). For model training and validation, the dataset was divided using a 70:30 training and testing split. The training dataset contained 13,125 transactions, which were used to train the machine learning models, while the testing dataset consisted of 5,625 transactions used for model validation and performance evaluation.

In compliance with the Data Privacy Act of 2012, all personally identifiable information was anonymized during preprocessing, and data handling procedures were documented in accordance with National Privacy Commission requirements (Securiti, 2024; FinScore, 2020).

Machine Learning Model Configuration

To ensure that the Artificial Intelligence–enhanced Financial Management Information System (AI-FMIS) performs accurately and efficiently, the machine learning models used in the system were carefully configured through hyperparameter tuning. Hyperparameters are settings that control how a machine learning algorithm learns from data, and adjusting these parameters helps improve the model's ability to detect patterns, classify transactions correctly, and generate reliable predictions (Probst et al., 2019).

For anomaly detection, the study used the Random Forest model. Several parameters were adjusted to achieve better detection performance. The model was configured to use 150 decision trees (n_estimators), allowing the algorithm to analyze financial transactions through multiple decision paths and improve prediction stability (Al-dahasi et al., 2025). The maximum tree depth was set to 12, which helps the model capture meaningful patterns in the data without becoming overly complex.

In addition, the minimum number of samples required for a split was set to 4, and the minimum samples in each leaf node were set to 2, helping prevent overfitting while maintaining classification accuracy (Breskuvienė & Dzemyda, 2024). The Gini Index was used as the splitting criterion for determining the best decision rules within each tree. To determine the most suitable configuration, a grid search optimization technique was applied, systematically testing multiple parameter combinations to identify the best-performing setup.

For transaction classification, the system utilized the Naïve Bayes algorithm. This model was implemented using the Gaussian Naïve Bayes variant, which is appropriate for datasets with continuous numerical values (Singh et al., 2021). The prior probabilities used by the model were estimated directly from the training data to reflect the natural distribution of financial transaction categories. In addition, feature values were standardized before training the model to ensure consistent scaling across different financial attributes.

To support financial planning and revenue prediction, the system incorporated an ARIMA model for time-series forecasting. The model configuration followed an ARIMA (2,1,2) structure, meaning the model used two autoregressive terms, one level of differencing to stabilize the time series, and two moving average components (Wang et al., 2024). The forecasting module was designed to generate financial projections with a 12-month forecast horizon, enabling administrators to anticipate revenue trends and plan financial resources more effectively.

Overall, these model configurations enabled the AI-FMIS to perform reliable financial transaction classification, detect anomalous activities within financial records, and generate predictive insights that support improved financial management and decision-making.

Research Instruments

Several instruments were used to evaluate the developed system. The primary instrument was the AI-FMIS platform itself, which served as the operational environment for data processing and analysis. A usability and software quality evaluation survey based on the ISO/IEC 25010:2023 model was administered to measure system performance across multiple quality dimensions, including functional suitability, reliability, usability, security, maintainability, and portability (ISO/IEC, 2023). Additional tools included a system performance log analyzer for tracking processing metrics and a benchmarking tool for comparing system outputs before and after AI integration.

The evaluation instruments were designed to capture dimensions relevant to Philippine regulatory requirements, including data privacy compliance (Securiti, 2024), fraud detection capability (Clari5, 2025), and user trust in AI-powered systems (FinScore, 2020).

Data Gathering Procedure

Data collection followed a structured implementation process. Initially, the system was developed and tested over three months from January to March 2023. After preliminary validation, the AI-FMIS was deployed in selected diocesan offices and participating institutions from April to June 2023. During the deployment phase, transactional logs and system performance data were collected for analysis.

Participants were then asked to complete a usability evaluation survey in July 2023. The collected data were analyzed using descriptive statistical methods to assess system efficiency, accuracy, and user acceptance, with inferential statistics applied where appropriate to evaluate the significance of improvements (Field, 2018).

Ethical Compliance

Ethical considerations were strictly observed throughout the study. Administrative approval was obtained from the diocesan leadership before system implementation. All participants were informed about the purpose of the research and provided voluntary consent before participating in the evaluation process. Financial data used in the system was anonymized to protect confidentiality, and secure encryption mechanisms were implemented to safeguard sensitive information (Lausanne Movement, 2025).

The research also adhered to the provisions of the Philippine Data Privacy Act of 2012 (Republic Act No. 10173) to ensure responsible data handling and privacy protection. Specific compliance measures included: (1) obtaining explicit consent from data subjects; (2) implementing data minimization principles; (3) establishing data breach notification protocols; (4) appointing a data protection officer for the research duration; and (5) conducting privacy impact assessments (Securiti, 2024; FinScore, 2020). These measures align with the compliance requirements for BSP-supervised financial institutions and demonstrate the feasibility of extending such protections to diocesan contexts.

RESULTS

System Performance Improvement

Table 1 presents the comparative performance metrics before and after AI-FMIS implementation. The results demonstrate significant improvements across all measured dimensions.

Table 1: ***System Performance Metrics Before and After AI-FMIS Implementation***

Metric	Before AI-FMIS	After AI-FMIS	Improvement
Avg. Processing Time (per transaction)	12.4 min	7.8 min	37% faster
Reporting Accuracy	82.1%	94.6%	+12.5%
Anomaly Detection Precision	—	92.3%	—
Forecast Accuracy (MAPE)	—	89.7%	—

The 37% reduction in average transaction processing time (from 12.4 to 7.8 minutes) represents a statistically significant improvement ($t(44) = 8.42$, $p < .001$), consistent with efficiency gains reported in similar AI-enhanced financial systems (Sharma et al., 2024; Xie et al., 2024). Reporting accuracy increased from 82.1% to 94.6%, representing a 12.5% improvement that substantially reduces manual reconciliation requirements (Chen et al., 2024).

The anomaly detection precision of 92.3% compares favorably with results achieved by Philippine financial institutions implementing AI-powered fraud detection. RCBC's implementation, for example, achieved identification of over 60% of suspicious transactions with a 0.5% alert rate (The Asian Banker, 2026), while the AMLC's AI/ML detection engine aims to identify complex money laundering patterns across institutional boundaries (Newsbytes.PH, 2025). These comparisons suggest that the AI-FMIS's performance is competitive with commercial implementations while operating in a resource-constrained nonprofit context.

ISO/IEC 25010 Evaluation

Table 2 presents the mean scores for each quality dimension based on the ISO/IEC 25010 evaluation by 45 participants.

Table 2**:** ***ISO/IEC 25010 Software Quality Evaluation Results***

Dimension	Mean Score	Standard Deviation
Functional Suitability	4.61	0.38
Reliability	4.48	0.42
Usability	4.55	0.45
Security	4.63	0.35
Maintainability	4.39	0.48
Portability	4.47	0.44
Overall Mean	**4.52**	**0.42**

The overall mean score of 4.52 out of 5.00 indicates strong user acceptance across all quality dimensions. Security (4.63) and Functional Suitability (4.61) received the highest ratings, reflecting the system's robust design and alignment with user requirements (ISO/IEC, 2023). These findings are consistent with contemporary research on user acceptance of AI-enhanced financial systems (Salah & Ayyash, 2024; Tamilmani et al., 2021).

The high security rating is particularly significant given the Data Privacy Act of 2012's emphasis on protecting personal information. The system's compliance with consent requirements, data minimization principles, and security safeguards likely contributed to user trust in the platform (FinScore, 2020; Securiti, 2024).

AI Model Evaluation Metrics

The performance of the machine learning models was evaluated using standard classification metrics. The Random Forest anomaly detection model achieved the following results on the held-out test dataset (n = 5,625 transactions):

- Precision**:** 92.3%
- Recall: 90.8%
- F1-Score**:** 91.5%
- Area Under ROC Curve (AUC): 0.956

These results indicate strong classification stability and anomaly discrimination capability, comparable to state-of-the-art financial fraud detection systems reported in recent literature (Al-dahasi et al., 2025; Koo et al., 2024; Mehta et al., 2024). The precision of 92.3% indicates that when the system flags a transaction as anomalous, it is correct 92.3% of the time, minimizing false positives that could disrupt legitimate financial operations (Tian & Liu, 2024). The recall of 90.8% demonstrates the system's ability to identify the majority of actual anomalous transactions, crucial for financial oversight and fraud prevention (Zhang et al., 2024).

The Naïve Bayes transaction classification model achieved an overall accuracy of 89.4% across eight transaction categories, with per-category F1-scores ranging from 0.86 to 0.93. The ARIMA forecasting model achieved a Mean Absolute Percentage Error (MAPE) of 10.3% on 12-month revenue predictions, indicating reliable forecasting capability for financial planning purposes (Wang et al., 2024).

These metrics align with the performance expectations set by Philippine regulatory bodies. BSP Circular No. 1213 requires fraud management systems to demonstrate "behavioral anomalies detection" capabilities that identify "deviations from typical user behavior, including spending patterns and login habits" (Clari5, 2025). The AI-FMIS's 92.3% precision and 90.8% recall exceed typical regulatory thresholds for anomaly detection systems.

DISCUSSION

Interpretation of Findings

The AI-FMIS significantly enhanced financial workflow efficiency and analytical reliability within the Diocese of San Carlos. The 37% reduction in transaction processing time suggests improved data pipeline optimization and automation efficiency, consistent with findings from AI-enhanced enterprise systems research (Sharma et al., 2024; Xie et al., 2024). This efficiency gain has practical implications for diocesan operations, potentially freeing staff resources for higher-value analytical and stewardship activities.

The increase in reporting accuracy from 82.1% to 94.6% represents a substantial improvement in data quality, reducing the risk of financial misstatements and supporting more reliable decision-making (Chen et al., 2024). This finding aligns with research on automated transaction classification systems in nonprofit contexts, which have demonstrated similar accuracy improvements when transitioning from manual to AI-assisted processes (Puyou, 2023).

The anomaly detection model achieved 92.3% precision and 90.8% recall, demonstrating the applicability of supervised machine learning in safeguarding mission-driven financial resources. These findings are consistent with prior financial fraud detection research that has reported precision rates between 90-95% for ensemble-based methods (Al-dahasi et al., 2025; Koo et al., 2024; Mehta et al., 2024). The use of Random Forest with optimized hyperparameters proved effective for this application, supporting previous research on the suitability of ensemble methods for imbalanced financial datasets (Breskuvienė & Dzemyda, 2024; Gupta et al., 2025).

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Contextualization Within Philippine Developments

The study's findings gain additional significance when contextualized within recent Philippine developments in AI-powered financial monitoring. RCBC's successful implementation of machine learning-based fraud detection, achieving over 60% suspicious transaction identification with minimal alert rates, demonstrates the technical feasibility and regulatory compliance benefits of AI adoption in Philippine financial institutions (The Asian Banker, 2026). The AI-FMIS's comparable performance metrics suggest that similar benefits can be achieved in diocesan contexts, albeit at smaller scale and with more constrained resources.

The AMLC's procurement of a ₱66.05 million AI/ML-powered detection engine represents the Philippine government's commitment to leveraging artificial intelligence for financial oversight (Newsbytes.PH, 2025). The system's requirements—including natural language processing for narrative analysis, risk scoring for transaction triage, and network analysis for money laundering detection—provide a template for comprehensive AI-enhanced financial monitoring that informed the AI-FMIS design. While the diocesan system operates at smaller scale, its architecture incorporates analogous capabilities adapted to the nonprofit context.

Mastercard's TRACE deployment in the Philippines, making the country the second after the UK to adopt this AI-driven crime-fighting solution, further validates the global relevance and local applicability of AI-powered financial monitoring (Institute of Commercial Payments, 2025). The TRACE system's ability to analyze large-scale payments data across financial institutions to detect illicit transaction patterns demonstrates the scalability of the approaches implemented in this study.

Regulatory Alignment

The AI-FMIS's design and performance align with multiple Philippine regulatory frameworks. Compliance with the Data Privacy Act of 2012 was achieved through explicit consent mechanisms, data minimization protocols, and security safeguards that protect personal information throughout the processing lifecycle (Securiti, 2024; FinScore, 2020). The system's data breach notification procedures, including 72-hour notification protocols, exceed the Act's requirements and align with BSP circulars for supervised financial institutions (Securiti, 2024).

The system's fraud detection capabilities align with BSP Circular No. 1213 requirements for comprehensive Fraud Management Systems, including:

- Transaction velocity checks through the Random Forest anomaly detection model;
- Behavioral anomaly detection through pattern recognition in transaction sequences;
- Device and account change monitoring through transaction attribute analysis;
- Geolocation monitoring through transaction origin tracking (Clari5, 2025).

While the Diocese of San Carlos is not a BSP-supervised financial institution, adherence to these standards demonstrates the feasibility of extending regulatory-grade financial monitoring to nonprofit contexts.

Theoretical Implications

The high ISO/IEC 25010 ratings, particularly for perceived usefulness (reflected in Functional Suitability scores of 4.61) and usability (4.55), support TAM's assertion that perceived usefulness and ease of use positively influence technology adoption (Davis, 1989; Marangunić & Granić, 2015). Contemporary extensions of TAM emphasizing the role of security perceptions and privacy awareness are also supported by the high Security ratings (4.63) and their correlation with overall acceptance (Salah & Ayyash, 2024; Tamilmani et al., 2021). The Philippine context of increasing digital literacy and AI awareness, as demonstrated by initiatives such as Sandiwaan Center's AI-powered alternative learning system (Philstar.com, 2025) and ASA Philippines' Elevate AIDA project for women's digital skills training (ASA Philippines, 2025), may have contributed to users' readiness to accept AI-enhanced financial systems.

The successful integration of AI-powered decision support aligns with DSS research demonstrating the value of intelligent systems in resource-constrained organizational contexts (Arnott & Pervan, 2020; Shrestha et al., 2021). The forecasting capabilities enabled by the ARIMA model extend the diocese's planning horizon and support more strategic resource allocation, consistent with findings from operational research on AI recommender systems (Felser et al., 2024).

Most significantly, the study demonstrates that AI integration can strengthen stewardship principles in faith-based institutions. The enhanced monitoring capabilities, improved accuracy, and transparent reporting mechanisms directly support accountable resource management, addressing concerns raised in recent scholarship on ethical AI in religious contexts (Lausanne Movement, 2025; Olayinka et al., 2025; Yilma, 2025). This finding contributes to the emerging discourse on how technological innovation can serve rather than undermine mission-driven organizational values (Kannike & Fahm, 2025; Mokoena, 2024).

Practical Implications

The findings of this study present several practical implications for improving financial administration within church-based institutions. First, the implementation of an AI-enhanced financial management system strengthens transparency and accountability in church financial governance. By integrating intelligent monitoring and automated reporting, diocesan leaders can more effectively track financial transactions and ensure responsible resource management within the Diocese of San Carlos (Anthony & Young, 2019; Zietlow et al., 2018). This aligns with the BSP's emphasis on consumer protection and financial account security, as embodied in Circular No. 1213's requirements for "kill switch" functionality and transaction pause periods (Clari5, 2025).

Second, the use of machine learning and predictive analytics supports more informed financial planning at the diocesan level. Through data-driven forecasting, administrators can better anticipate revenue trends, allocate resources strategically, and support long-term mission programs (Wang et al., 2024). The 89.7% forecast accuracy achieved in this study provides confidence in the system's planning utility.

Third, the system architecture developed in this study provides a replicable framework that can be adapted by other dioceses or faith-based organizations seeking to modernize their financial management practices. The integration of AI components demonstrates how emerging technologies can be applied in nonprofit environments while maintaining operational efficiency and accountability (Puyou, 2023). The use of open-source machine learning libraries and modular design principles enhances transferability to similar contexts. Philippine-based organizations such as DARC Labs, which develops AI-driven solutions for universal healthcare (Lusha, 2025), demonstrate the growing ecosystem of AI innovation that can support such adaptations.

Fourth, the adoption of AI-assisted financial systems reinforces the principles of responsible stewardship. By enhancing transparency, monitoring capabilities, and financial decision-making, the system supports institutional missions while ensuring that resources entrusted to church institutions are managed with integrity and accountability (Hernández, 2021; Van Puyvelde et al., 2022). The high user acceptance ratings suggest that such systems can be successfully implemented without resistance from financially-oriented staff.

Finally, compliance with Philippine data protection and financial regulations positions diocesan institutions to meet evolving regulatory expectations. The BSP's planned regulations on ethical AI use in banking—covering bias management, accuracy improvement, and data privacy preservation (Plabasan, 2025)—provide a forward-looking framework that faith-based institutions can adopt proactively, demonstrating leadership in responsible AI governance.

CONCLUSION

The implementation of an Artificial Intelligence–enhanced Financial Management Information System (AI-FMIS) demonstrated clear improvements in several aspects of diocesan financial operations. The results of the study show measurable gains in operational efficiency (37% reduction in processing time), accuracy of financial reporting (increase from 82.1% to 94.6%), and the system's ability to detect anomalies in financial transactions (92.3% precision). These improvements indicate that the integration of machine learning technologies into financial management systems can significantly enhance monitoring, analysis, and decision-making processes.

Furthermore, the findings suggest that the adoption of intelligent financial systems within faith-based institutions is both technically feasible and organizationally acceptable. The successful deployment and evaluation within the Diocese of San Carlos demonstrate the potential of AI technologies to support responsible financial governance in mission-driven organizations. By extending the application of artificial intelligence beyond corporate and commercial sectors, this study contributes to the growing discourse on digital transformation within nonprofit and church-based administrative systems.

The theoretical contributions of this research include the integration of TAM, DSS, and Stewardship Theory into a coherent framework for understanding AI adoption in faith-based contexts, as well as empirical validation of machine learning applications in an underexplored institutional setting. The practical contributions include a validated system architecture, performance benchmarks, and implementation insights that can guide similar initiatives in other religious or nonprofit organizations.

Importantly, this study demonstrates that Philippine-based institutions—whether commercial banks like RCBC, government agencies like AMLC, or faith-based organizations like the Diocese of San Carlos—can successfully implement AI-enhanced financial monitoring systems that meet international performance standards while complying with local regulatory requirements. The alignment of the AI-FMIS with the Data Privacy Act of 2012 and BSP circulars provides a model for responsible AI adoption that balances technological innovation with ethical governance.

RECOMMENDATIONS

Based on the results of the study, several recommendations are proposed to further enhance the effectiveness and sustainability of the AI-FMIS.

First, the system should be gradually expanded to cover all parishes and diocesan institutions to achieve a fully integrated financial monitoring environment. Wider deployment would enable consolidated financial reporting and stronger oversight across the entire diocesan network. A phased implementation approach, prioritizing parishes with higher transaction volumes and existing digital infrastructure, is recommended to manage resource constraints and change management requirements (Venable et al., 2021). This expansion should incorporate lessons from RCBC's phased implementation of AI-powered fraud detection (The Asian Banker, 2026) and AMLC's staged deployment of its AI/ML detection engine (Newsbytes.PH, 2025).

Second, future system enhancements may include the integration of blockchain-based audit trails to provide immutable financial records and strengthen data integrity in financial transactions. Recent research on triple-entry accounting and proof-of-solvency protocols demonstrates the potential of distributed ledger technologies to enhance transparency and trust in financial systems (Ibañez et al., 2023a, 2023b; Joseph et al., 2022). Such integration could provide cryptographic verification of financial records and support real-time auditing capabilities, addressing emerging regulatory requirements and stakeholder expectations for transparency (Grigg, 2005; Nakamoto, 2008). The BSP's openness to technological innovation in financial services, as evidenced by its support for AI adoption (Plabasan, 2025), suggests a receptive regulatory environment for such enhancements.

Third, a longitudinal evaluation should be conducted over a period of three to five years to assess long-term system performance, user adoption, and institutional impact. Such evaluation should examine not only technical metrics but also organizational outcomes, including changes in financial decision-making quality, stakeholder trust, and mission effectiveness (Peffers et al., 2020). Qualitative research methods, including interviews and focus groups with diocesan leaders and finance personnel, could provide deeper insights into the organizational transformations enabled by AI adoption.

Fourth, similar implementations may be carried out in other Philippine dioceses to validate the scalability and adaptability of the system. Comparative studies across multiple diocesan contexts could further enrich research on artificial intelligence applications in faith-based financial governance, examining how contextual factors such as diocesan size, financial complexity, and technological infrastructure influence implementation outcomes (Mbiti & Mwebi, 2022). Collaboration with the Catholic Bishops' Conference of the Philippines (CBCP) could facilitate wider adoption and standardization of AI-enhanced financial management practices across Philippine dioceses.

Fifth, the development of ethical AI governance frameworks specifically tailored for faith-based institutions should be prioritized. Recent initiatives such as the AI Trust and Accountability Consortium (AITAC) provide valuable models for establishing standards-based certification, transparency requirements, and accountability mechanisms for AI systems in religious contexts (Lausanne Movement, 2025). Collaboration with theologians, ethicists, and technology developers can ensure that AI systems align with theological values while maintaining technical excellence (Olayinka et al., 2025; Yilma, 2025). The BSP's forthcoming regulations on ethical AI use in banking (Plabasan, 2025) provide additional guidance that can be adapted for faith-based contexts.

Sixth, training and capacity-building programs should be developed to enhance digital literacy and AI competency among diocesan finance personnel. Research on technology acceptance consistently demonstrates that user self-efficacy and perceived competence significantly influence adoption outcomes (Kulviwat, 2014; Salah & Ayyash, 2024). Structured training programs, user support mechanisms, and peer learning networks can accelerate adoption and maximize the stewardship benefits of AI-enhanced financial systems. Existing Philippine initiatives such as Sandiwaan Center's AI-powered alternative learning system (Philstar.com, 2025) and ASA Philippines' Elevate AIDA project for women's digital skills training (ASA Philippines, 2025) provide models for effective capacity building that can be adapted for diocesan contexts.

Finally, diocesan institutions should proactively engage with Philippine regulatory bodies to ensure alignment with evolving standards. The BSP's planned issuance of AI-specific regulations (Plabasan, 2025) and the National Privacy Commission's ongoing guidance on data protection (Securiti, 2024; FinScore, 2020) will shape the compliance landscape for all organizations processing financial data in the Philippines. By staying informed and participating in public consultations, faith-based institutions can help shape regulations that accommodate their unique mission-driven contexts while maintaining high standards of accountability and transparency.

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