

An Integration of Decision Support System Using Classification Techniques and Time Series Analysis for Loan Disbursement in Financial Services

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Abstract: The study designed, developed, and implemented a Decision Support System (DSS) that integrates Time Series Analysis and Forecasting techniques to enhance decision-making and loan disbursement efficiency within the financial sector. A quantitative research approach was utilized, employing the Rapid Application Development (RAD) model for building the system, alongside the Knowledge Discovery in Databases (KDD) process for data mining activities. Classification algorithms enabled the DSS component, while historical data were analyzed through time series methods for forecasting purposes. The classification model recorded an accuracy of 92.3%, while the forecasting component performed consistently well, with a Mean Absolute Percentage Error (MAPE) of 6.4%.

System performance and user satisfaction were assessed using the ISO/IEC 25010:2011 quality model, producing an overall weighted mean score of 4.26, reflecting a high level of user acceptance. The integration of classification and forecasting within the DSS contributed to improved efficiency of loan processing, more accurate decision outcomes, and enhanced operational procedures. To ensure the system's continued effectiveness and scalability, the study recommends ongoing model updates and retraining, improvements in system security, and the adoption of a scalable infrastructure capable of handling growing data volumes and user activity.

Keywords: Decision Support System, ISO 25010, Integration, Loan Disbursement, Financial Services, Time Series Analysis, Forecasting

I. Introduction

Information Systems (IS) are integral to modern organizations, as they support efficient business operations, strengthen competitive advantage, and contribute to increased revenue. IS, in its turn, requires consistent and efficient Information Technology infrastructure that is made up of the best components that work together to produce the best outcomes for business. The rise of digitalization and digital transformation is significantly increasing the role and adoption of Information and Communications Technology (ICT) and information science in business operations. Many organizations are increasingly relying on ICT and big data analytics to adapt rapidly to change and maintain their competitive advantage (Hamad et al., 2020).

In 2019, the Philippines enacted Republic Act (RA) No. 11293, also referred to as the Philippine Innovation Act, to position innovation as a central force for national progress and to improve the country's global competitiveness. The law aims to promote broad-based economic development and strengthen the global presence of Micro, Small, and Medium Enterprises (MSMEs). It also requires the allocation of funding to support innovation-related programs. To advance these goals, the government promotes the creation of innovation centers and institutions in collaboration with private sector partners, academic institutions, and research entities. These initiatives aim to support technology transfer, industry partnerships, supplier capacity building, access to financing, and market expansion.

As a result, businesses and organizations are increasingly leveraging technologies and analytical strategies to evaluate both current and historical data. This empowers them to make more informed strategic decisions and achieve a competitive advantage. It also helps for data optimization, which is the process of gathering and effectively using organization's data to maximize the efficiency and accuracy of information extraction, analysis, and utilization (Niu et al., 2021). It might also be accomplished by utilizing the features of data mining that is built into a system, technology, or applications. Furthermore, utilizing technology for the improvement of service processes in financing services enables organizations to enhance their operational efficiency and leads to better outcomes for both borrowers and loan providers (Aniceto et al., 2020). Nonetheless, without a clear understanding the goals of the optimization objectives and the present situation of the organization, it is hard to improve the performance of it. So, it is important to think back on the most recent performance and consider where it might improve. By the implementation of an information system, it will help the productivity and achieve the effectiveness and efficiency level of a business's operations. Moreover, the systematic analysis of these systems can positively influence on a business's competitiveness.

In response to these needs, this study proposes the integration of a Decision Support System (DSS) with time series analysis to enhance loan disbursement and financing services. By offering predictive insights into cash flow patterns, borrower behavior, and market trends, the integration enables organizations to make more informed and timely financial decisions. Forecasting techniques can be embedded within the system to anticipate loan demand, manage liquidity, and optimize loan distribution according to seasonal and economic fluctuations. Additionally, classification algorithms can be employed to develop models that assess borrower eligibility by analyzing risk levels, income stability, and financial profiles.

The study aims to explore the integration of a Decision Support System (DSS) with time series analysis and forecasting to enhance and make efficient the decision-making process within a unified financial system. The proposed system is expected to provide data-driven support for forecasting loan trends, improving allocation strategies, and minimizing financial risk. Furthermore, the study seeks to assess user satisfaction with the system based on the ISO/IEC 25010:2011 Software Quality Criteria. The evaluation focused on functional suitability, which measures the effectiveness of the system in performing its intended functions; performance efficiency, which evaluates responsiveness and resource usage; compatibility, which looks at interoperability with various environments; usability, which assesses the ease of use; reliability, which examines stability and fault tolerance; security, which ensures protection of data and system integrity; and portability, which refers to the ease of system adaptation and deployment across different platforms.

II. Literature Review

This section presents a review of related literature and prior studies conducted by various researchers, which are considered relevant and significant to the context and objectives of this study.

Decision Support Systems (DSS)

Decision Support Systems (DSS) have become essential in helping organizations navigate complex decision-making processes. Most researchers agree that these systems are interactive, computer-based tools developed to support decisions involving unstructured or semi-structured problems. They combine data, analytical methods, and intuitive interfaces to assist users in making informed choices at different levels within an organization. Literature often highlights DSS as flexible and intelligent platforms that can analyze operational data and generate practical, data-driven recommendations (Fairlie, 2023; Power et al., 2023; Hou et al., 2023).

Decision support systems have evolved to lessen the human burden in analyzing organizational information (Sanjay, 2023). It offers brief decisions primarily based on the available data that may help to improve the organization particularly within a short period of time. In view of this, high-quality records define the satisfaction of an organization in order that decisions might be taken at the proper time, which diverts organization growth along the right path. Decision support systems are capable of selecting the data and analyzing it to achieve the proper trends in order for techniques and solutions to be framed. Records are the main element in the decision process in order for the support system to summarize the statistics either graphically or textually through the use of its professional artificial intelligence. Decision support systems collect everyday information such as assets, legacy, and relational data and prepare comparative analyses as assumptions of future trends in a particular context. Consequently, many organizations have integrated decision support systems in their daily operations.

Kumar (2020) stated that decision support systems accumulate statistics, conduct analysis, and restructure the records to derive valuable strategic selections. Typically, decision support systems are divided into two categories: passive and active. Passive systems are designed to compile and structure data effectively, without offering interpretations or decision-making support. Alternatively, active decision support systems not only collect information but also process it to generate solutions and strategies. Meanwhile, collecting and examining records with human interactions refines solutions to provide the best strategies in decision support systems. The decision support systems are categorized based on their applications such as:

Data Driven decision support system. In this application, begins with the critical step of data collection, as gathering relevant information enables faster and more informed decision-making. After collecting the data, it is processed and customized according to user needs, taking into account that the data may be either structured or unstructured, and sourced both internally and externally. Time series techniques can be applied to handle and analyze this data when appropriate. This type of system typically provides straightforward file access, allowing users to retrieve information through queries. Key contributors in a data-driven model include managers, employees, product suppliers, and service providers, all of whom play a vital role by supplying valuable data inputs.

Communication driven decision support system. It focuses on facilitating collaboration among individuals working together on a common task or process. It emphasizes shared activities and teamwork, where specific collaborators are intentionally grouped to improve strategic outcomes. This model primarily targets internal teams and partners, aiming to enhance communication and coordination. Typically, communication-driven systems rely on technologies such as internet-based, web-based, or client-server platforms to support and improve the efficiency of decision-making processes.

Document driven decision support system. It conducts operations based on a user group. In document driven models, the procedure is searching the internet for pertinent documents for a specified set. Document retrieval and analysis in these models depend on technology adaptation and storage. In document driven models, a variety of document kinds, including text documents, database

records, spreadsheets, etc., are processed to derive decisions. Similar to communication-driven systems, document-driven systems also use client-server or web-based technologies to gather decisions.

Model driven decision support system. It includes the option of modifying and manipulating financial data or information to determine the best answer for the growth of the organization. Since model driven decision support systems do quantitative analysis and offer basic functionality utilizing small parameters, they typically do not require large datasets. Model-driven decision support systems, which can run on client-server networks or standalone computers, are primarily designed to assist individuals who engage with the organization such as managers, staff, and other key personnel.

Knowledge driven decision support system. It includes a wide user base within an organization that allows for collaboration with other users. In knowledge-driven models, management guidance is an essential phase so that the organization may choose the best services or products. It may also offer ideas and recommendations to the managers. Knowledge-driven models are similar to personal computers with problem-solving capabilities, making it simple to grasp and identify problems in a given subject.

Time Series Analysis

Time series analysis involves uncovering meaningful insights from data recorded over time by examining its structure, identifying patterns, and using these patterns to forecast future events (Ma et al., 2022). Time series data is widely used and represents events or phenomena that change or evolve over time (Wen et al., 2021). For data to be considered a time series, it must be recorded at consistent time intervals such as every second, minute, hour, day, or month. One essential aspect of time series data is its frequency, referring to how often data points are recorded. This represents one of the common features found in time series datasets.

Seasonality. It is the term used to describe recurring cycles or patterns in time series data that take place over set time intervals and frequently correlate to seasons or other discrete time periods. For instance, retail sales may rise annually over the holiday season. The analyzing of visual data or applying statistical approaches can be used to determine seasonality, which can have a predictable pattern.

Trend. In time series analysis, a trend describes a long-term shift or direction observed in the data over time. It shows whether the values tend to rise, decline, remain steady, or display no definite pattern. Identifying a trend involves evaluating the overall direction and behavior of the data throughout the observed period.

Cycles. It represents a long-term pattern in time series data that is less regular and harder to predict than seasonality. The economic, social, or natural factors can be influenced of this cycle, like business cycles with periods of expansion and recession, or sunspot cycles that affect weather patterns and other non-seasonal aspects may also contribute in this cycle.

Correlation. It refers to the extent to which current values in a time series are related to their past values or to other variables. Understanding these relationships can be highly useful across fields such as finance, economics, environmental science, and social sciences, as it supports more informed decision-making and accurate forecasting.

These are the crucial aspects of time series data, and a thorough understanding of them is necessary for efficient analysis and modeling. These aid in finding trends, generating projections, and learning about the underlying dynamics of the data (Kumar (2023)). The two main forms of time series data are known as stationary and non-stationary.

Stationary time-series data. It refers to data whose statistical properties, like mean and variance, stay consistent over time. This means the data doesn't show any trends, seasonal effects, or other systematic patterns that would change these characteristics. Variability in the dataset occurs only due to random influences. Examples of stationary data could be the number of people visiting a library on a typical weekday or the daily closing price of a stable, well-established stock that doesn't experience major shifts.

Non-stationary time-series data. This time series contains identifiable patterns either seasonal or trending so its fluctuations are not purely due to randomness. In this case, reliable modeling and forecasting require further pre-processing to remove the non-stationary, such as detrending or differencing, considering the annual sales data of a business that has been expanding consistently over time, which clearly demonstrate a trend. Similarly, monthly temperature readings in a city show a seasonal pattern as temperatures fluctuate throughout the year. Another example is the sharp upward trend in the stock prices of a rapidly growing startup, which also demonstrates non-stationary behavior.

Time series analysis involves extracting meaningful insights from time-based data by applying data visualization techniques, statistical tools, and mathematical modeling methods (Fernández et al., 2020). These results can be used to understand and explore the past as well as predict the future.

Moraffah et al., (2021) emphasize the importance of time series data in various domains like medicine, agriculture, and finance. Time series data are essentially a sequence of observations arranged chronologically. Over the years, several studies have developed various methods including classification, forecasting, and clustering to analyze the data. These techniques help in making valuable of the information contained in time series data.

Moreover, time series data are valuable for studying the impact of interventions or changes in a situation over time. As a result, time series data can be used to explore causal relationships and patterns within different domains. Moraffah et al., highlight the versatility of time series data, which are used for a range of tasks and provide valuable insights into various fields.

Time series data is one of the most common ways to record and analyze information over time (Dama and Sinoquet, 2021). It involves collecting observations that are ordered by timestamps, which helps us understand how a particular measurement changes historically in fields that rely on time-based data from sources like sensors, surveys, or transaction logs. Because time series data is so widespread, there is a growing need to perform various tasks on it, such as visualizing trends, identifying repeating patterns, uncovering correlations, classifying and grouping data, detecting anomalies, segmenting the series, making predictions, and even simulating new data.

Moreover, Moraffah et al. (2021) defines a time series as a collection of observations of a random variable. They explain that a time series consists of observations recorded at evenly spaced time intervals, typically collected in chronological order. These observations are recorded at precise time intervals and are often taken sequentially across time. The study and modeling of such data sequences' statistical features, patterns, and trends constitute time series analysis. The main goal of Moraffah et al.'s research is to apply these ideas to financial time series data, which is crucial in the fields of finance and economics.

In the book of Abdalla et al. (2023) comprehensively discuss time series analysis. This involves studying and predicting data that's collected over time, like stock prices or temperature readings. One important aspect he covered in the book is the use of traditional methods. These methods rely on parametric models, which mean they make assumptions about the underlying patterns in the data. These assumptions are based on the knowledge and expertise of the domain or subject area. Here are some commonly used time series analysis models based on specialized knowledge within a specific field that emphasize using parametric methods.

III. Methodology

The study used a quantitative research approach for development and integration of Decision Support System (DSS) and loan disbursement with time series analysis and forecasting aimed at enhancing financial services operations within a unified system. The development process adheres to the Rapid Application Development (RAD) model, which prioritizes iterative prototyping, user involvement, and rapid implementation. The research is organized into three sequential phases: system design, model development, and system evaluation.

The results of both the classification and forecasting models were integrated into a unified system, developed through iterative prototyping in line with the RAD model. The system delivers decision support recommendations and forecasting insights through an interactive dashboard, enabling financial decision-makers to quickly interpret results and respond proactively. To evaluate system performance, the study employed the ISO/IEC 25010 software quality model, assessing key quality attributes such as functional suitability, performance efficiency, compatibility, usability, reliability, security, and portability. These criteria provided a structured basis for determining the overall quality and user satisfaction of the system.

The study used total population sampling for the one hundred (100) selected financial institution employees. Total population sampling is a purposive sampling method in which all individuals from a group sharing specific characteristics are included, particularly when the group is small and well-defined (Laerd Dissertation, 2023). In addition, purposive sampling was used to select other qualified respondents, including previous borrowers and selected IT experts and professionals, bringing the total number of respondents to one hundred (100). Purposive sampling involves selecting individuals based on the researcher's judgment, guided by specific experience, knowledge, or qualifications relevant to the study.

Ethical considerations were thoroughly addressed throughout the study. Data privacy was ensured via secure handling practices, and algorithmic fairness was continuously monitored to mitigate potential bias in predictive decision-making processes. This study demonstrates the feasibility and effectiveness of a data-driven decision support system in enhancing operational efficiency and strategic financial planning in the loan management sector.

IV. Results and Discussion

The implementation of the integrated Decision Support System and Time Series Analysis provided significant outputs in terms of predictive performance and system responsiveness.

Figure 1 represents an integrated system that combines a Decision Support System for loan approval with Time Series Analysis for loan disbursement and financing services.

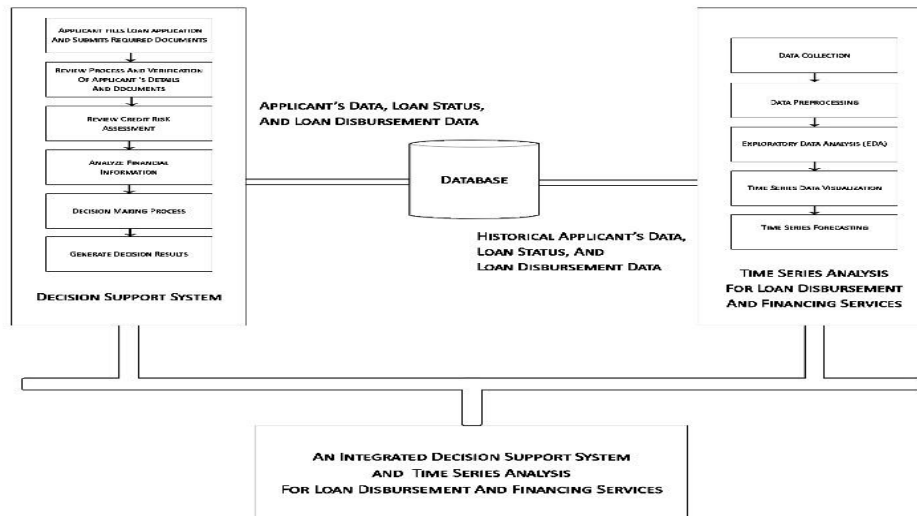


Figure 1. Integrated System Architecture for Loan Disbursement in Financial Services

The two systems are interconnected and contribute to each other in the following ways:

Decision Support System (Left Side):

Applicant Files Loan Application and Submits Required Documents: This is the initial phase where an applicant provides the necessary information and documents for the loan.

Review Process and Verification of Applicant's Details and Documents: The submitted information is thoroughly checked for accuracy and completeness.

Review Credit Risk Assessment: The financial credibility of the applicant is assessed by reviewing and verifying their information and documents.

Analyze Financial Information: An in-depth analysis of the applicant's financial information is conducted to evaluate their loan repayment capacity.

Decision Making Process: Based on the analysis, a decision process is undertaken to conclude on the loan application.

Generate Decision Results: A decision is made at the end of the process, indicating whether the loan is approved or declined.

Database (Center):

This is the core of the integrated system, where all the data related to the applicant, loan status, and disbursement information is stored. It includes both current and historical data.

Time Series Analysis (Right Side):

Data Collection: This step involves gathering relevant information from the database or data repository, including applicant data, loan status, and loan disbursement details. This information is specifically selected for its usefulness in forecasting loan disbursement trends through time series analysis.

Data Preprocessing: The gathered data is refined and structured to ensure it is ready for analysis.

Exploratory Data Analysis (EDA): The early stage of analysis focuses on detecting trends and patterns within the dataset, especially in the context of loan disbursement and financial services.

Time Series Data Visualization: The data is visualized to clearly show trends over time, which is essential for understanding past loan disbursement behavior.

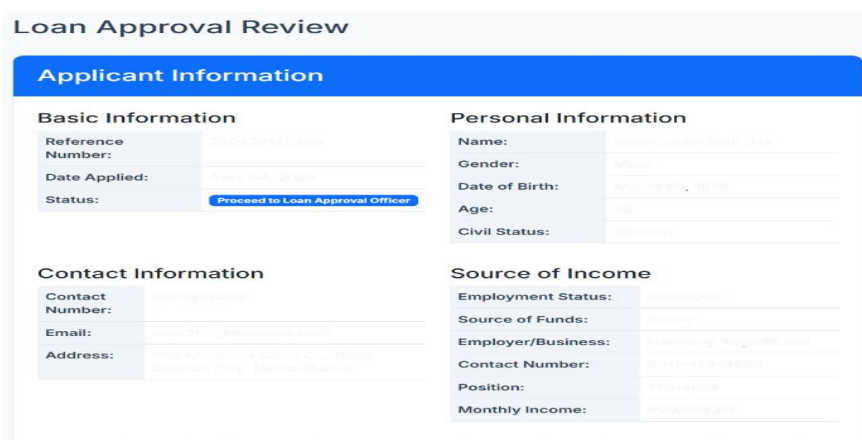
Time Series Forecasting: The forecasting is then performed based on this historical data to predict future trends in loan disbursement.

The integrated system architecture combines a Decision Support System (DSS) and time series analysis into a unified platform aimed at enhancing loan disbursement and financial services. It produces data-driven insights to improve the accuracy of loan approval decisions, efficiently analyzes historical disbursement data, and forecasts future loan trends. A key component of this system is the Automated Classification-Based Decision Support System, which utilizes classification algorithms to evaluate loan applications and automatically generate approval or declined decisions. See Figure 2 for the interface of the Automated Decision Support System.



Figure 2. Automated Decision Support System Interface

This interface displays the system's automated decision-making process for loan applications. The system analyzes submitted data and assesses potential risks to determine whether an applicant is approved or declined. This enables consistent, objective, and accurate evaluations, improving the overall efficiency and reliability of the loan approval process. In addition to automated decision-making, the system features interfaces for reviewing borrower information and uploaded documents. These interfaces provide a centralized digital workspace, enhancing the efficiency of loan processing by ensuring that all necessary information is easily accessible and securely stored.



The image shows a "Loan Approval Review" form with a blue header. The form is divided into two main sections: "Applicant Information" and "Source of Income".

Applicant Information

Basic Information

Reference Number:	1234567890123456
Date Applied:	April 01, 2024
Status:	Proceed to Loan Approval Officer

Personal Information

Name:	John Doe
Gender:	Male
Date of Birth:	March 15, 1990
Age:	34
Civil Status:	Married

Contact Information

Contact Number:	09123456789
Email:	john.doe@example.com
Address:	123 Main Street, New York, NY 10001

Source of Income

Employment Status:	Employed
Source of Funds:	Salary
Employer/Business:	ABC Company Inc.
Contact Number:	09123456789
Position:	Software Engineer
Monthly Income:	\$5,000.00

Figure 3. Applicant's Information Interface

This interface presents essential applicant information for verification and assessment.



The image shows a "Decision Support System" interface with a sidebar on the left containing "Applicant Information" and "Loan Details". The main area displays a "Valid ID" document, which is a Philippine Identification Card (PHL) for a person named "Tirahan, Noval". The card includes a photo, a QR code, and the text "REPUBLICA NG PILIPINAS" and "PAMBANSANG PAGKAKILANLAN".

Loan Details

Loan Type:	New	Valid ID:	View
Loan Purpose:	For Personal Use	Proof of Income:	View
Vehicle Value:	₱400,000.00	Utility Bill:	View
Down Payment:	30.00% (₱120,000.00)		
Loan Amount:	₱280,000.00		

Marketing Officer Remarks

Officer Name:	Marketing Officer
Documents Complete:	Yes
Remarks:	ok, proceed to CI.

Figure 4. Applicant's Uploaded Document Interface

This interface provides access to all relevant borrower documents uploaded during the loan application process.

These features simplify and improve the loan workflow by minimizing the need for manual handling of physical documents. As a result, the system helps prevent errors, reduces processing time, and ensures that all files are securely stored and readily accessible. This contributes to improved efficiency, accuracy, and organization in handling documentation and loan procedures.

Figures 5 to 8 present data visualizations that support time series analysis and forecasting of loan disbursements based on historical data. These visual insights enable financial institutions to enhance financial planning and strategic decision-making by identifying trends, and seasonality in past loan disbursements, helping predict future activity.

Figure 5 presents the raw historical loan disbursement data, where all actual disbursement records will be displayed and can be monitored on a daily basis.



Figure 5. Data Visualization for Historical Loan Disbursements

Figure 6 displays the long-term trend component of the data, which helps identify the general direction of loan disbursements over time.

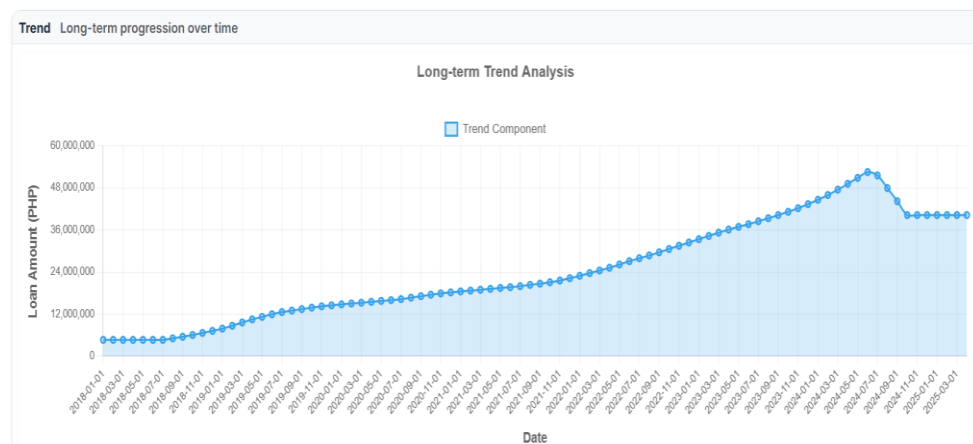


Figure 6. Data Visualization for Long-Term Trend Analysis

Figure 7 shows the seasonal pattern extracted from the data, allowing observation of recurring cycles within specific time intervals



Figure 7. Data Visualization for Seasonal Pattern Analysis

Furthermore, Figure 8 presents the forecasted loan disbursement values, supporting strategic planning by predicting future disbursement activity based on historical trends. This forecasting capability enhances institutional decision-making, allowing for better cash flow management and resource allocation.

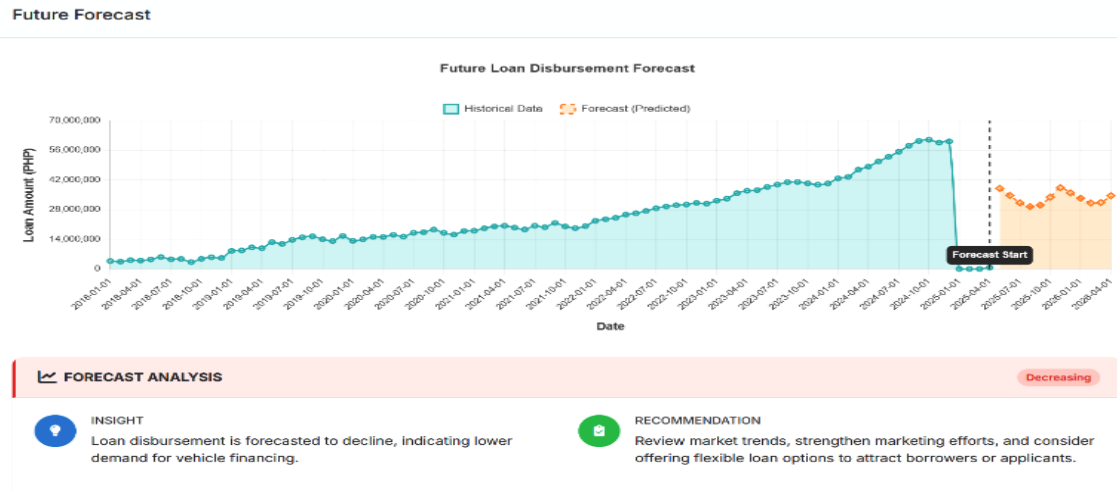


Figure 8. Data Visualization for Forecasting of Loan Disbursement with Insight and Recommendation

The forecasting capability helps institutions manage cash flow more effectively by anticipating loan disbursement demand. It enables better planning by predicting future trends, allowing financial institutions to allocate resources more efficiently, meet anticipated demand, and make more informed decisions that enhance overall financial performance. Historical loan disbursement data was analyzed using time series forecasting. The model achieved a MAPE of 6.4%, indicating strong predictive accuracy. These results demonstrate the system's effectiveness in predicting future loan trends and improving liquidity planning. For the ISO 25010 evaluation, a total of 100 respondents participated in the study, with their distribution detailed in Table 1. Regarding gender, 59% were male, 39% female, and 2% identified as LGBTQ, reflecting a predominantly male respondent base with notable female participation and minimal LGBTQ representation.

Table 1 Respondents' Gender of the Study

Descriptive Statistics	Total Respondents	Frequency	Percentage
Gender	Female	39	39%
	Male	59	59%
	LGBTQ	2	2%
	Total	100	100%

In terms of age, the largest group (45%) was aged 25–34 years, followed by 35% aged 35–44 years, and 14% aged 45–54 years. The remaining respondents were aged 55–64 years (3%), 18–24 years (2%), and 65 years and above (1%). This indicates that most participants are within the productive working-age range, especially young and middle-aged adults. See Table 2.

Table 2 Respondents' Age of the Study

Descriptive Statistics	Total Respondents	Frequency	Percentage
Age	18–24 years	2	2%
	25–34 years	45	45%
	35–44 years	35	35%
	45–54 years	14	14%
	55–64 years	3	3%
	65 years and above	1	1%
	Total	100	100%

Regarding of respondent classification, potential borrowers comprised the largest group at 49%, followed by employees of selected financial institutions at 41%, including loan approval officers, credit investigators, marketing officers, and loan disbursement

officers. IT experts and professionals made up the remaining 10%. This diverse respondent composition provides a well-rounded perspective relevant to the study's objectives. See Table 3.

Table 3 Respondents' Classification of the Study

Descriptive Statistics	Total Respondents	Frequency	Percentage
Respondent	Selected Financial Institution Employees	41	41%
	Potential Borrower	49	49
	IT Expert and Professionals	10	10%
	Total	100	100%

Table 4 shows the respondents' evaluation of the Functionality of the system, with an overall weighted mean score of 4.43, interpreted as "Satisfied." Among the three indicators, Functional Completeness achieved the highest mean score of 4.50, which falls under the "Very Satisfied" category. This is followed by Functional Correctness, with a mean rating of 4.48, and Functional Appropriateness, which recorded a mean score of 4.31.

Table 4 Respondents' Evaluation of the System's Functionality

Criteria	Mean Rating	Verbal Interpretation
Functional Completeness	4.50	Very Satisfied
Functional Correctness	4.48	Satisfied
Functional Appropriateness	4.31	Satisfied
Average Weighted Mean	4.43	Satisfied

Table 5 shows the respondents' evaluation of the Efficiency of the system, with an overall weighted mean score of 4.22, interpreted as "Satisfied." Among the three indicators, Resource Utilization achieved the highest mean score of 4.35, indicating that the system effectively accesses the necessary resources to meet user requirements. This is followed by Time Behaviour, with a mean of 4.23, reflecting acceptable system responsiveness and processing time. Capacity received the lowest score of 4.07, though still within the "Satisfied" range, suggesting that the system is capable of handling multiple user accesses simultaneously.

Table 5 Respondents' Evaluation of the System's Efficiency

Criteria	Mean Rating	Verbal Interpretation
Time Behaviour	4.23	Satisfied
Resource Utilization	4.35	Satisfied
Capacity	4.07	Satisfied
Average Weighted Mean	4.22	Satisfied

Table 6 presents the respondents' evaluation of the Compatibility of the system, with an overall weighted mean score of 4.16, interpreted as "Satisfied." Among the two indicators, Co-existence received a slightly higher mean score of 4.18, indicating that the system can function efficiently alongside other systems within a shared environment. Interoperability followed closely with a mean rating of 4.14, showing that the system is capable of exchanging and utilizing information from other systems.

Table 6 Respondents' Evaluation of the System's Compatibility

Criteria	Mean Rating	Verbal Interpretation
Co-existence	4.18	Satisfied
Interoperability	4.14	Satisfied
Average Weighted Mean	4.16	Satisfied

Table 7 presents the overall weighted mean score for Usability, which is 4.21. Among the six indicators evaluated, User Error Protection received the highest mean score of 4.26. This was closely followed by Learnability at 4.24, and Appropriateness Recognizability at 4.23. User Interaction Aesthetics and Accessibility followed with scores of 4.21 and 4.20, respectively. Operability recorded the lowest mean score among the indicators, with a value of 4.15.

Table 7 Respondents' Evaluation of the System's Usability

Criteria	Mean Rating	Verbal Interpretation
Appropriateness Recognizability	4.23	Satisfied
Learnability	4.24	Satisfied
Operability	4.15	Satisfied
User Error Protection.	4.26	Satisfied
User Interaction Aesthetics	4.21	Satisfied
Accessibility	4.20	Satisfied
Average Weighted Mean	4.21	Satisfied

Table 8 shows the overall weighted mean score for Reliability, which is 4.23. Maturity obtained the highest mean score of 4.34 among the four indicators. This is followed by Availability, with a mean of 4.25. Fault Tolerance and Recoverability recorded mean scores of 4.17 and 4.16, respectively.

Table 8 Respondents' Evaluation of the System's Reliability

Criteria	Mean Rating	Verbal Interpretation
Maturity	4.34	Very Satisfied
Availability	4.25	Satisfied
Fault Tolerance	4.17	Satisfied
Recoverability	4.16	Satisfied
Average Weighted Mean	4.23	Satisfied

Table 9 shows the overall weighted mean score for Security, which is 4.22. The highest mean score among the five indicators was observed in Confidentiality, with a value of 4.31. This is followed by Accountability, with a mean of 4.23. Both Non-repudiation and Authenticity recorded a mean of 4.21, while Integrity received the lowest mean score of 4.16.

Table 9 Respondents' Evaluation of the System's Security

Criteria	Mean Rating	Verbal Interpretation
Confidentiality	4.31	Satisfied
Integrity	4.16	Satisfied
Non-repudiation	4.21	Satisfied
Accountability	4.23	Satisfied
Authenticity	4.21	Satisfied
Average Weighted Mean	4.22	Satisfied

Table 10 shows the overall weighted mean score for Portability, which is 4.33. Among the two indicators, Installability achieved the highest mean score of 4.33, followed closely by Replaceability, with a mean of 4.32.

Table 10 Respondents' Evaluation of the System's Portability

Criteria	Mean Rating	Verbal Interpretation
Installability	4.33	Satisfied
Replaceability	4.32	Satisfied
Average Weighted Mean	4.33	Satisfied

Table 11 presents the summary of the respondents' overall evaluation based on the ISO 25010 Product Quality Model. The average weighted mean score across all seven criteria is 4.26, with a verbal interpretation of "Satisfied". Among the criteria, Functionality received the highest mean rating of 4.43, followed by Portability with a mean of 4.33. Reliability and Security obtained mean scores of 4.23 and 4.22, respectively. Efficiency was rated at 4.22, while Usability and Compatibility recorded the lowest scores of 4.21

and 4.16, respectively. Despite variations in the scores, all criteria were evaluated as "Satisfied," indicating that the system meets quality expectations across all aspects of the ISO 25010 model.

Table 11 Summary of the Respondents' Overall Evaluation in the ISO 25010 Product Quality Model

Criteria	Mean Rating	Verbal Interpretation
Functionality	4.43	Satisfied
Efficiency	4.22	Satisfied
Compatibility	4.16	Satisfied
Usability	4.21	Satisfied
Reliability	4.23	Satisfied
Security	4.22	Satisfied
Portability	4.33	Satisfied
Average Weighted Mean	4.26	Satisfied

The results of the system evaluation, based on the ISO/IEC 25010:2011 Software Quality Model, indicate a level of user satisfaction across various software quality attributes. The system was assessed in terms of functionality, efficiency, compatibility, usability, reliability, security, and portability. User feedback demonstrated that the system effectively met its intended requirements, was easy to use, and provided accurate and timely outputs. These findings validate the system's capability to support decision-making and improve loan disbursement processes in the selected financial institution, confirming its overall quality and practical applicability in a real-world setting.

In conclusion, the Decision Support and Loan Disbursement System improves and simplifies the entire loan processing workflow by integrating data analytics, automation, decision support system, and time series analysis and forecasting. Overall, the development and integration of the Decision Support System and Loan Disbursement System has proven effective in improving loan processing operations, reducing manual errors, and enhancing decision-making. By addressing areas such as system performance during high usage, the system's effectiveness could be further optimized, making it an essential tool for financial institutions looking to improve operational efficiency and user satisfaction in the financial industry.

Based on the results of the study, there are recommendations can be implemented to further improve the Decision Support and Loan Disbursement System. First, it's important to continuously update the system's predictive models and forecasting techniques to keep up with changes in borrower behavior and financial trends. Regularly refining the models will ensure they stay accurate and effective. The security and reliability can also be improved by integrating features such as fraud detection systems. Strengthening data protection through encryption, multi-factor authentication (MFA), and regular security audits will help maintain compliance with industry standards and protect sensitive information. Furthermore, it is recommended to improve scalability to support more simultaneous users, improve system integration for smoother data exchange with other platforms, and strengthen fault tolerance and security, particularly in terms of integrity and non-repudiation. Lastly, providing more user training and support can enhance the user's experience. Regular performance monitoring and system updates should be conducted to address emerging issues and maintain the system's effectiveness over time.

By implementing these recommendations, financial institutions can improve their decision support system, loan disbursement process, increase borrower/applicant satisfaction, reduce costs, and ensure the system's long-term success.

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