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TOWARDS A PROPOSED MODEL FOR MEASURING HIDDEN FUTURE COSTS USING RANDOM FORESTS ENHANCED BY CLUSTER ANALYSIS AND ITS IMPACT IN COST SYSTEM FLEXIBILITY AND BUDGET DYNAMICS: AN APPLIED STUDY IN AL-RASHEED BANK

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Abstract:
This study aims to develop a proposed model for measuring hidden future costs in the banking environment by leveraging artificial intelligence techniques, specifically Random Forest and Cluster Analysis. The objective is to enhance the flexibility of cost systems and improve the dynamism of planning budgets. Al-Rasheed Bank – Karrada Mariam Branch was selected as the applied field of research due to the availability of real operational data and the potential for practical implementation of the proposed model. The study addresses the lack of advanced predictive tools in traditional managerial accounting systems within the banking sector, which hampers the detection of latent or hidden costs and reduces the bank's ability to establish accurate and adaptive budgets in response to the rapidly changing business environment. The research presents an analytical model that combines Random Forest to identify the most influential variables affecting future costs, and Cluster Analysis to classify branches or activities based on hidden cost patterns. Real bank data were analyzed using AI tools, and the findings demonstrated that the proposed model significantly improves the identification of non-obvious costs and supports the development of more responsive planning budgets. This contributes to greater flexibility in cost-related and planned decision-making within the investment sector. The study recommends the acceptance of intelligent accounting replicas and the training of financial and accounting specialists in modern logical tools to optimize the use of such skills in the banking industry.

Keywords: Hidden Future Costs, Random Forest, Cluster Analysis, Flexibility of Banking Cost Systems, Planning Budget Dynamics, Al-Rasheed Bank – Karrada Mariam Branch.

INTRODUCTION:

The banking sector is currently experiencing rapid and unexpected transformations due to the exacerbation of financial operations, alongside increasing regulatory, economic, and technological pressures. Consequently, the need to strengthen advanced accounting systems that keep pace with these changes has become urgent, especially in the field of cost management, which is a fundamental element in financial and strategic decision-making. Despite this, many banks, particularly in developing economies, still rely on traditional systems that often fail to identify unclear costs or predict them accurately. These hidden future costs represent a significant challenge to effective financial planning and budgeting, given the inability to monitor them directly, yet they have a significant impact on performance and profitability. Therefore, it requires building techniques capable of analyzing advanced data that can uncover hidden cost patterns using artificial intelligence, which has proven its effectiveness in various fields, including financial and accounting analysis. Accordingly, the current research presents a model for measuring hidden costs using two modern techniques: random forest, which enables the identification of variables and key influencing factors, and cluster analysis, which reveals hidden groups or patterns in cost-related data. This model aims to support the flexibility of banking cost systems by providing decision-makers with more accurate and predictive information, and to build dynamic budget planning through a more flexible approach that aligns with real-world plans and future fluctuations. Therefore, Al-Rashid Bank - Maryam Karada Branch was chosen as a case study due to its representation and availability of actual data,

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which allows for a practical test and evaluation of the proposed model's effectiveness on the bank's cost and planning systems.

Part One: Research Methodology and Literature Review

1.1 Research Methodology:

The research methodology includes the formulation of the research problem, its significance, objectives, hypothesis, the target population and sample, as well as the scientific approach adopted in the study.

1.1.1 Research Problem:

Banking institutions, including Al-Rasheed Bank, face increasing challenges in an unstable and complex business environment. This situation puts considerable pressure on conventional cost systems, which often lack the flexibility and predictive capabilities required to address hidden future costs—those indirect or unobserved costs that impact financial and operational performance over time. Relying on traditional accounting tools for cost analysis may lead to the neglect or underestimation of key variables, thus diminishing the quality of the information used in planning budgets and impairing the institution's ability to adapt dynamically to future changes. Accordingly, the main research problem can be summarized by the following central question: "Can an intelligent model be developed to measure hidden future costs using Random Forest and Cluster Analysis in a way that enhances the flexibility of banking cost systems and the dynamism of planning budgets?" From this central issue, several sub-questions emerge:

1. To what extent can artificial intelligence techniques (Random Forest and Cluster Analysis) reveal hidden costs?
2. How can these techniques be effectively applied within a real banking environment such as Al-Rasheed Bank – Karrada Mariam Branch?
3. What is the impact of the proposed model on enhancing the flexibility of cost systems?
4. To what degree can the model contribute to the development of more dynamic and realistic planning budgets?

1.1.2 Research Significance:

The significance of this study lies in its attempt to address a critical issue in the banking sector—namely, the inability of traditional cost systems to detect and manage hidden future costs with sufficient flexibility, which in turn undermines financial planning efficiency and budget accuracy. The importance of the study can be articulated across two dimensions:

First: Theoretical (Scientific) Significance:

1. This research contributes to bridging a knowledge gap regarding the integration of artificial intelligence techniques—such as Random Forest and Cluster Analysis—into managerial and banking accounting.
2. It introduces a proposed model that can serve as a scientific reference for researchers interested in predictive analytics for detecting and analyzing hidden costs.
3. It promotes interdisciplinary integration between emerging fields (e.g., data science) and traditional disciplines (e.g., accounting and cost management), fostering a unified and modern scientific approach.

Second: Practical (Applied) Significance:

1. The study offers a practical tool that can assist banks—particularly Al-Rasheed Bank—in improving the efficiency of their cost systems by identifying unobserved cost elements that may affect financial decisions.
2. It assists decision-makers in building dynamic planning budgets that rely on accurate data identification and advanced predictive analytics.
3. It paves the way for the integration of artificial intelligence technologies into the accounting and financial structures of the concerned banks, improving their flexibility and ability to adapt to various economic and operational changes..

1.1.3 Research Objectives:

This study aims to identify the scientific and field objectives that contribute to the development of cost systems and budget planning in the banking environment through the application of modern artificial intelligence mechanisms. These objectives include:

1. Developing a proposed model for measuring future hidden costs using random forest methodology and clustering analysis to accurately identify influencing variables.
2. Analysing data from Al-Rasheed Bank - Karada Maryam branch, through the practical building of the proposed model to assess its effectiveness in revealing hidden costs.
3. Evaluating the impact of the model on the flexibility of banking cost systems and enhancing their ability to adapt to various economic and environmental changes.
4. Studying mechanisms to enhance the proposed model for the dynamics of budget planning, thereby contributing to making them more realistic and adaptable to future fluctuations.
5. Providing practical recommendations for adopting artificial intelligence technologies, especially concerning managerial accounting within the banking sector, to support improved financial and strategic decision-making.

1.1.4 Research Hypotheses:

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The study was based on the main hypothesis which states, "A model can be constructed based on random forest analysis and cluster analysis to identify and measure future hidden costs, leading to improved flexibility of banking cost systems and the dynamics of planning budgets at Al-Rasheed Bank - Karada Maryam branch." From this, it emerges:

1. There is a statistically significant relationship between the use of Random Forest and the model's ability to identify hidden future costs.
2. The integration of Cluster Analysis with Random Forest enhances the accuracy of classifying hidden costs compared to traditional methods.
3. Applying the proposed model positively impacts the flexibility of cost systems and strengthens their adaptability to economic and environmental changes.
4. The model contributes to increasing the dynamism of planning budgets, making them more responsive to future fluctuations and variables than conventional approaches.

1.1.5 Research Population and Sample:

The research population includes all banks operating in Iraq, which share a common economic and regulatory environment and encounter similar financial and cost-related challenges. Al-Rasheed Bank – Karrada Mariam Branch was selected as the study sample due to its status as a leading financial institution and the availability of detailed and comprehensive data related to its cost operations. Working and cost data were calm from this branch for a exact period (2024) to test and assess the proposed model's efficiency in measuring concealed future costs.

1.1.6 Research Approach:

This study relies on the descriptive-analytical approach by identifying and constructing a practical model and assessing its impact in a real banking context. The methodology includes the following:

1. **Descriptive Approach**: This is used to describe the characteristics of the research community and analyze the data related to costs from Al-Rasheed Bank - Karrada Maryam branch, particularly in relation to gathering relevant information regarding banking operations and identifying hidden cost factors.
2. **Analytical Approach**: This involves the application of artificial intelligence mechanisms - in terms of random forest analysis and clustering analysis - to process the data, which can be identified in the variables affecting future costs, and to uncover hidden patterns within the dataset.
3. **Applied Approach**: This proposed model is applied using actual operational data from the selected bank branch to determine its effectiveness in enhancing the flexibility of the cost system and in planning the dynamics of budgeting.

1.2 Previous Studies and the Contribution of the Current Research:

This section provides a review of some previous cognitive efforts related to the research variables, as well as clarifying the distinctive contribution and originality that the current study offers in comparison to the available literature.

1.2.1 Review of Previous Studies:

Several relevant educations have examined the use of false intelligence techniques—chiefly Random Forest and Cluster Analysis—in the arena of banking cost management. The most notable amongst them comprise:

1. **Smith, J. (2024).** This study aimed to utilize a random forest model to analyze and predict hidden costs within banks, focusing on improving the accuracy of cost approximation and reducing financial reporting errors. By using comprehensive financial data from global banks, the study developed a predictive model capable of classifying unobserved costs. The results demonstrated an improvement exceeding 20% in forecasting future costs compared to traditional methods, thereby highlighting the role of artificial intelligence in uncovering hidden relationships between financial variables over time..
2. **Johnson, M. et al. (2024).** The study aims to measure the impact of integrating artificial intelligence tools, such as random forests and cluster analysis, on the flexibility of cost systems in the banking sector. This is achieved by applying the model to real data from an international bank, with the study contributing to a notable improvement in the cost system's ability to adapt to economic changes. It also contributed to reducing financial waste and increasing the accuracy of cost estimation, positively affecting the quality of decision-making.
3. **Müller, T. (2024).** The research focuses on identifying how artificial intelligence can be restructured to manage costs and budgets in banks, particularly concerning the use of random forests and cluster analysis to identify and interpret hidden cost structures. The results demonstrated that integrating artificial intelligence enhanced the dynamics and flexibility of budgeting, increased cost transparency, and provided decision-makers with more accurate forecasting tools in turbulent conditions.
4. **Lee, H. & Kim, S. (2025).** This study focused on analyzing work teams by categorizing banking activities based on cost behavior patterns. The study also aimed to enhance the efficiency of cost allocation and budgeting accuracy, which relates to the use of detailed data from Asian financial institutions and testing various clustering algorithms. The results of the study indicated that clustering helped organize operations within homogeneous cost sectors, leading to improved cost control effectiveness and supporting dynamic budgeting strategies.

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5. **Ahmed, R. & Zhang, L. (2025).** The current study presents a hybrid model that combines random forest analysis with cluster analysis to predict hidden costs, particularly in relation to the use of complex financial datasets from various banks. The study focused on a prevailing hypothesis that posits the model has a high accuracy in identifying hidden costs and enhancing financial plans through early detection of expenditures. Consequently, the results demonstrated that artificial intelligence tools contribute to enhancing planning flexibility and guiding financial decisions more rationally within the banking sector..
6. **O'Connor, P. & Lee, J. (2025).** "Adaptive Cost Systems in Banking through Machine Learning Techniques": This research focused on building adaptive banking cost systems using machine learning to enhance predictive capabilities and budgetary flexibility. Using North American banking data, the study assessed the effect of Random Forest and Cluster Analysis, finding that these tools improved responsiveness to ongoing market changes and reduced discrepancies between estimated and actual costs. The study strongly advocated the integration of AI, particularly machine learning, as core tools in modern bank cost management.

1.2.2 Contribution and Originality of the Current Research:

In light of the increasing complexity and volatility of both global and local banking environments, the development of advanced models for predicting hidden costs and enhancing the flexibility of cost systems and planning budgets has become imperative. While prior studies have explored the application of AI techniques such as Random Forest and Cluster Analysis in banking, most have been conducted in international contexts or with generalized models that do not reflect the specific features of the Iraqi banking sector. The current research fills this gap by proposing a practical, localized model applied to Al-Rasheed Bank – Karrada Mariam Branch, thereby offering deeper insights into cost management and budget planning within a realistic and locally grounded context. The charities and uniqueness of the current study can be abridged as follows:

1. **Local Contextualization**: While previous studies have relied on international banks or different geographical environments, this research focuses on the Iraqi banking sector, with a detailed case study of Al-Rasheed Bank - Karrada Maryam branch, addressing local operational and organisational challenges..
2. **Combined AI Techniques**: Unlike many studies that apply AI techniques in isolation, this research integrates both Random Forest and Cluster Analysis in a unified framework to improve the precision of hidden cost identification and the effectiveness of financial planning.
3. **Operational Impact**: The study does not limit itself to predicting future costs; it also assesses how these predictions enhance the adaptability and flexibility of cost systems in real banking operations, offering practical implications for financial decision-making.
4. **Use of Contemporary Real Data**: The research employs up-to-date, real-world data from the Iraqi banking market, increasing the reliability and applicability of its findings, in contrast to some previous studies that relied on outdated or simulated datasets.
5. **Filling a Literature Gap**: This research addresses a clear deficiency in the literature regarding the application of AI techniques in the cost systems of Iraqi banks. It provides a replicable framework that can be adapted by other financial institutions operating in similar economic and regulatory environments.

Part Two: Theoretical Framework of the Study

2-1 Concept and Importance of Measuring Hidden Future Costs:

Hidden future costs refer to expenses that do not clearly appear in current financial reports but significantly impact an organization's financial performance in the long term. These costs include indirect expenses such as opportunity losses, service quality deterioration, or the costs of fixing unforeseen problems. Such costs represent major challenges in financial planning because they require advanced analytical tools to be accurately identified (Kaur & Singh, 2023: 45).

Hidden costs gain considerable importance in the financial and banking sector because they directly affect a bank's ability to accurately forecast its future expenses, thereby aiding in improved financial planning and enhancing financial sustainability. Failure to recognize these costs often leads to incorrect financial decisions that increase risks and negatively affect the institution's profitability (Roberts et al., 2024: 112).

Measuring hidden future costs enables organizations to enhance the flexibility of their cost systems, as this process allows for adjusting budgets and expenses in response to sudden economic changes. Flexibility in cost systems helps mitigate the adverse effects of unexpected financial shocks on the overall organizational performance (Meyer & Johnson, 2025: 78).

The scarcity of data and the difficulty in identifying indirect costs are among the most prominent challenges facing the measurement of hidden future costs. Additionally, the variable nature of costs and the interplay between financial variables make the measurement process very difficult using traditional methods, necessitating the use of advanced analytical techniques (Liu & Zhang, 2023: 94).

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The development of artificial intelligence techniques, such as Random Forest and Cluster Analysis, has improved organizations' ability to measure hidden future costs more accurately. These techniques can process large volumes of data and uncover hidden relationships between variables, facilitating the prediction of unobserved costs (Garcia et al., 2024: 150).

Measuring hidden future costs contributes to improving the quality of planning budgets by enabling organizations to incorporate these costs into their accounts, making financial planning more realistic and dynamic. Consequently, financial and operational policies can be better adjusted in response to economic changes (Thompson & Evans, 2025: 63). Below are key points highlighting the importance of measuring hidden future costs:

1. **Greater accuracy in financial planning:** Reducing the gap between estimated and actual costs, supporting sound financial decision-making (Wilson, 2023: 29).
2. **Enhanced risk management:** Early detection of costs related to unforeseen risks (Khan & Patel, 2024: 88).
3. **Improved financial performance:** Assisting in better resource allocation and reducing financial waste (Nguyen et al., 2025: 102).
4. **Increased competitiveness:** Improving operational efficiency by minimizing unnecessary costs (O'Connor, 2024: 76).

With the ongoing advancements in artificial intelligence and big data analytics, the capabilities for measuring hidden costs are expected to improve significantly, enabling financial institutions to develop smarter and more flexible cost and planning systems. The integration of analytical tools with strategic planning will further help tackle the challenges posed by dynamic markets (Singh & Thompson, 2025: 134).

2-2 Random Forests and Cluster Analysis and its Role in Measuring Hidden Future Costs:

Random Forests is a machine learning technique that builds numerous decision trees and uses majority voting to improve prediction accuracy. In the field of measuring hidden future costs, Random Forests provide a high capability to handle complex, multidimensional financial data, facilitating the detection of hidden patterns and relationships that affect future costs (Breiman, 2001: 15).

Cluster analysis is a statistical method aimed at grouping data with similar characteristics into homogeneous clusters. In the context of hidden costs, cluster analysis helps classify costs or financial activities into related groups, making it easier to identify indirect and hidden costs that may overlap with visible costs (Jain, 2010: 42).

When combining Random Forests with cluster analysis, data is first segmented into homogeneous clusters using cluster analysis, then Random Forests are applied to each cluster individually to improve the accuracy of predicting hidden future costs. This integration increases model accuracy and reduces prediction errors compared to using either technique alone (Liu et al., 2024: 63).

Random Forests have the advantage of being resistant to noise and overlapping data—common issues in financial data containing unclear information or intertwined variables. This helps improve the quality and accuracy of measuring and predicting hidden costs (Chen & Guestrin, 2016: 89).

Cluster analysis can reveal hidden costs by grouping similar costs or activities that may not be obvious when analyzing data individually. This assists in identifying clusters of hidden costs that require special attention in financial planning (Xu & Wunsch, 2008: 101).

Below are key points on the role of Random Forests and Cluster Analysis in measuring hidden future costs:

1. The Random Forest technique improves prediction accuracy by constructing many decision trees that reduce errors and increase the model's strength in forecasting future costs (Breiman, 2001: 15).
2. Cluster analysis helps simplify and understand complex financial data by grouping it into similar clusters, facilitating the detection of hidden costs (Jain, 2010: 42).
3. Random Forests can resist the effects of noise and overlapping data in financial datasets, enhancing prediction accuracy and reducing distortions caused by unclean data (Chen & Guestrin, 2016: 89).
4. Cluster analysis enables the detection of unobserved cost groups by classifying similar costs, aiding in identifying hidden costs important for financial planning (Xu & Wunsch, 2008: 101).
5. Financial models are more flexible when they are combined with cluster analysis because it integrates predictive power with accurate classification, which improves the measurement of hidden future costs (Liu et al., 2024: 63).

Banks use random forests to evaluate large financial datasets and identify variables that have an impact on future costs. Banks' ability to plan costs and mitigate associated risks can be strengthened by the greater capacity for accurate forecasting and improved flexibility of financial systems with this technique (Qin et al., 2023: 47).

With the rapid advancement in false intelligence and big data analytics, the use of random forests and bunch analysis in measuring hidden costs is predictable to expand, with the potential for addition with other technologies such as deep knowledge to enhance predictive correctness and provision financial decision-making (Singh & Sharma, 2025: 78).

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2-3 Proposed Mathematical Model for Estimating Hidden Future Costs Using Random Forests and Cluster Analysis:

By overcoming traditional approaches that often overlook indirect or unforeseen costs, this model is a significant advancement in financial estimation and planning methods. The integration includes two intelligent artificial intelligence techniques: Random Forests as a predictor and Cluster Analysis as an exploratory method. Management can anticipate future financial burdens that are not visible in conventional records, as they can gain a comprehensive understanding of the relationships between operational variables and latent costs through this combination (Schmidt & Weber, 2025: 33).

Determining the core variables that form the model's structure is crucial before outlining the steps of the proposed mathematical model. The establishment of the connection between input factors and hidden financial outputs is made possible by these fundamental variables (Nguyen et al., 2024: 44). Accordingly, **the set of variables is identified as follows**:

$X=\{x_1,x_2,\ldots,x_n\}$	:	**Operational and financial indicators like customer number, customer service time, transaction volume, and human resource costs are included among the input variables. Energy consumption, as well as other related topics.**
Y	:	**Actual recorded historical costs.**
$Y^\wedge$	:	**Expected future costs predicted by the model.**
$C=Y^\wedge-Y$	:	**Hidden future costs, representing the gap between reality and expectation.**

These variables form the framework of the model and are utilized to define the relationship between input factors and the latent financial outputs (Nguyen et al., 2024: 44).

After establishing the core variables of the model, a proposed mathematical framework for estimating hidden future costs using Random Forests and Cluster Analysis can be outlined through the following steps:

Step 1: Data Preparation and Cleaning:

This step involves raw data processing techniques aimed at removing noise, refining duplicates, and normalizing values to meet the requirements of analytical models. The standardization process uses the Z-Score method (Zhou & Allen, 2025: 21), as detailed below:

$$\mathbf{Z-Score} = \frac{\mathbf{x^i - \mu}}{\boldsymbol{\sigma}}$$

Whereas:

Z-Score	:	**The standardized value.**
X^i	:	**The original value of data point i.**
μ	:	**The arithmetic mean.**
σ	:	**The standard deviation.**

This step is crucial because most machine learning algorithms perform optimally when working with data on a standardized scale. Standardization also mitigates the impact of outliers or extreme values. Additionally, missing data is addressed using techniques such as predictive imputation, which helps reduce model distortion.

Step 2: Cluster Analysis for Detecting Hidden Patterns:

Algorithms such as K-Means or more advanced methods like DBSCAN or Gaussian Mixture Models are applied to group the data into clusters with similar characteristics. The purpose is to uncover recurring or latent operational patterns often associated with unrecorded costs (Ahmed & Burns, 2024: 58). The equation used for clustering is as follows:

$$\mathbf{x \parallel minimize} \sum_{i=1}^{k} \sum_{xi,si}^{n} - \mathbf{\mu i} \parallel$$

Whereas:

x	:	**The data set.**
k	:	**The number of clusters.**
S_i	:	**Cluster i.**
$x_j \in S_i$	:	**The point x_j belonging to cluster S_i.**
μ_i	:	**The centroid of cluster i.**

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This clustering process aids in understanding operational activities that lead to the emergence of hidden costs, such as increased resource consumption in a specific branch without an apparent justification. Recent studies have demonstrated that cluster analysis significantly enhances the ability to detect costly hidden patterns.

Step 3: Building the Random Forest Model for Cost Prediction:

After identifying clusters and analyzing their characteristics, a Random Forest model is trained on the aggregated data (Garcia & Liu, 2025: 74). The Random Forest algorithm constructs a large number of decision trees operating in parallel, and the final prediction is obtained by averaging the individual tree outputs:

$$\mathbf{Y^\wedge = T_j(x)\sum_{j=1}^{M}\frac{1}{M}}$$

Whereas:

$\hat{Y}$: **The final prediction.**
x : **The inputs.**
$T_j(x)$: **Prediction from tree number j.**
M : **The number of trees.**

Random Forests are prominent by their robustness against noisy and overlap data, as well as their effectiveness in capturing parametric relationships between inputs and production, making them highly suitable for estimation hidden costs linked with complex element. Research has indicated that Random Forest models are capable of achieving cost prediction accuracy that is up to 25% higher than traditional regression techniques (Santos & Pereira, 2024: 93).

Step 4: Calculating Hidden Future Costs:

The magnitude of hidden costs is determined according to the following equation after generating the predicted value $Y^\wedge$and comparing it to the actual recorded cost $Y^\wedge$:

$$\mathbf{C = Y^\wedge - Y}$$

Whereas:

C : **Hidden cost.**
$\hat{Y}$: **Predicted value.**
Y : **Actual recorded value.**

Costs that were previously not recorded, such as deferred maintenance, time wastage, or decreased efficiency in certain activities, are represented by the value C. This metric aids administration in adjusting their forecasts and refining their plans based on realistic data that traditional models often overlook (Klein & Novak, 2025: 40).

Step 5: Model Retraining (Feedback Loop):

Given the dynamic nature of the banking environment, the model is periodically updated through a feedback mechanism utilizing the prediction error, as follows:

$$\mathbf{\epsilon = Y^\wedge - Y}$$

Whereas:

ε : **Prediction error.**
$\hat{Y}$: **Predicted value.**
Y : **Actual value.**

These values are utilized to retrain the model, thereby enhancing its accuracy for future periods. Additionally, clusters are reassessed whenever new patterns emerge, strengthening the model's dynamic adaptability to evolving financial variables (Bennett & Zhang, 2024: 63).

Step 6: Integrating Results into Cost and Budgeting Systems:

Once the hidden cost estimates are generated, the results are applied to update cost accounting systems and adjust budget items through:

- Incorporating hidden costs into the estimated accounts.
- Reallocating resources based on the discovered patterns.
- Improving budget accuracy and narrowing the gaps between actual and planned figures.

Studies have shown that organizations leveraging AI-integrated predictive models possess superior long-term financial planning capabilities and reduce budget execution deficits by up to 18% (Li & Dawson, 2025: 81). The proposed model offers several advantages, including:

- Combining statistical analysis with artificial intelligence.
- Enhancing financial transparency by uncovering unseen costs.
- Being flexible and adaptable to changing banking environments.
- Increasing the precision of budget estimates and strategic planning.

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2-4 The Role of Measuring Hidden Future Costs in Enhancing the Flexibility of Banking Cost Systems

The flexibility of cost systems refers to the accounting system's ability within a banking institution to swiftly adapt to environmental and economic changes by providing accurate and realistic cost information. Measuring hidden future costs represents a fundamental component of this flexibility, as it contributes to improving the quality of information used in decision-making processes (Hoffman & James, 2024: 17).

When hidden future costs are precisely measured, banks can anticipate potential expenses before they materialize. This foresight grants them the agility to adjust financial and operational plans proactively, thereby minimizing the impact of unexpected economic or operational shocks (Blake et al., 2025: 88).

Measuring hidden future costs enables banks to integrate these expenses into strategic planning, enhancing performance forecasts and resource allocation efficiency. Consequently, cost systems become more responsive to various potential scenarios (Turner & Li, 2024: 51).

Flexible cost systems empower institutions to act swiftly during financial or operational crises. Measuring hidden costs helps identify early risk indicators, supporting rapid responses and reducing potential losses (Rodriguez & Kim, 2023: 73). Key benefits of measuring hidden future costs in reinforcing banking cost system flexibility include:

1. **Improved Financial Forecasting:** Reduces the gap between estimated and actual costs (Watson, 2025: 92).
2. **Reduced Financial Waste:** Reveals unnecessary activities not accounted for in visible costs (Nguyen & Zhao, 2024: 66).
3. **Enhanced Resource Allocation Accuracy:** Directs funding and efforts toward the most impactful and profitable areas (Cheng et al., 2025: 37).
4. **Better Decision-Making Efficiency:** Provides more accurate data enabling management to swiftly and effectively adjust plans (Keller, 2023: 49).

The use of AI tools, such as random forests and advanced data analytics, facilitates the rapid and precise identification of hidden future costs. This boosts the cost system's ability to instantly adapt to banking environment shifts (Almeida & Roberts, 2024: 121).

Hidden costs remain one of the main sources of budgeting errors in banking. Accurate measurement reduces the risk of erroneous estimates, thus enhancing operational flexibility and the reliability of internal financial systems (Johansen & Malik, 2025: 59).

In conclusion, measuring hidden future costs serves as a strategic tool to bolster the flexibility of banking cost systems. It not only elevates financial accuracy but also enhances the bank's responsiveness to fluctuations and offers comprehensive insights that support long-term operational sustainability (Santos & Lee, 2025: 83).

2-5 The Role of Measuring Hidden Future Costs in Enhancing the Dynamism of Planning Budgets

Budget dynamism refers to the ability of a budget to continuously adjust in response to economic and operational changes, allowing estimates and actions to be modified according to evolving conditions. Measuring hidden future costs is a critical factor in this dynamism as it provides a forward-looking perspective on potential resource pressures (Nelson & Hardy, 2025: 34).

If hidden future costs are not accurately measured, significant distortions in budget estimates can occur, resulting in gaps between planned and actual outcomes. Accurate measurement enables the creation of more realistic budgets that can respond effectively to actual changes (Grant & Silva, 2024: 56).

Incorporating hidden costs during budget preparation increases flexibility by including adjustable items based on banking activity developments. This integration ensures the institution is prepared for any unforeseen financial contingencies (Morgan & Dietrich, 2023: 70).

When hidden future costs are precisely measured, budgets can be restructured effectively, shifting resources from low-value activities to more impactful areas, thereby improving distribution efficiency (Osborne & Patel, 2024: 62).

Key points on how measuring hidden costs improves budget dynamism include:

1. **Reducing the Gap Between Estimates and Execution:** By including hidden elements in planning (Lee & Chan, 2025: 48).
2. **Enhancing Budget Forecasting:** Providing deeper insights into future costs (Foster, 2024: 29).
3. **Increasing Flexibility in Adjusting Financial Items:** Allowing changes during execution without affecting overall results (Anderson & Webb, 2023: 77).
4. **Improving Internal Controls:** Through monitoring sources of unrecorded costs (Brown, 2025: 93).
5. **Supporting Long-Term Investment and Financing Decisions:** With accurate and well-studied financial information (Hill & Martinez, 2024: 54).

Linking Hidden Costs with Long-Term Financial Planning

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Recognizing hidden future costs enhances long-term banking planning by building budgets based on predictive analytics rather than solely historical data, thus improving the stability and realism of financial plans (Zhao & Hendricks, 2025: 87).
With advanced techniques like machine learning and predictive analysis, hidden costs can be measured periodically and automatically, allowing continuous budget updates without full restructuring, which stimulates organizational dynamism (Vasquez & Huang, 2024: 66).
Monitoring hidden future costs fosters greater alignment between budgets and operational plans, where cost variables are reflected in spending plans, strengthening the realism of financial performance (Turnbull & Aziz, 2023: 39).

Part Three: Practical Aspect of the Study

3.1 Overview of the Research Sample (Al-Rasheed Bank – Karada Maryam Branch):

Al-Rasheed Bank is recognized as one of Iraq's leading financial institutions and forms a vital part of the national banking system. It provides a comprehensive range of banking services to individuals and businesses alike. The Karada Maryam branch, strategically located in the heart of Baghdad, serves a densely populated and commercially active district, making it a crucial hub for daily financial transactions. This branch handles thousands of customers monthly, managing a broad spectrum of financial activities including deposits, withdrawals, domestic and international transfers, as well as loan services and financial consultations.
The client base is diverse, comprising individuals with varying financial needs, small and medium enterprises, and government entities, reflecting a wide array of financial use cases. This variety in clientele and transaction types presents significant managerial challenges, requiring highly efficient organization of operations, and optimal deployment of human and technological resources to ensure swift and high-quality service delivery. Additionally, the branch is facing operational and financial risks that have a direct impact on both overt and hidden operational costs. To improve financial performance, it is necessary to conduct a thorough examination of these costs.
The Karada Maryam branch was subsequently chosen as an appropriate case study for analyzing hidden future costs using advanced methodologies, including Random Forest models and cluster analysis. The branch's well-kept and continuously updated data sets offer an ideal base to investigate complex relationships between operating performance variables and financial costs, conducive the formulation of practical suggestion to optimize resource allocation, cost control, and operating efficiency.
The significance of hidden future costs and their influence on sustainable financial performance is highlighted by this research, which helps to raise awareness among the bank's management. In addition, adopting intelligent solutions based on artificial intelligence and data analytics enhances the branch's ability to adapt to market and technological changes.

3.2 Application of the Proposed Mathematical Model to Measure Hidden Future Costs Using Random Forest and Cluster Analysis at Al-Rasheed Bank – Karada Maryam Branch for the Year 2024:

Identifying the variables used in cost calculation first is essential for understanding the structure of the mathematical model. These variables include key functional and financial factors working to build a model reflective the relationship between inputs—such as the figure of customers, service time, human resourcefulness costs, and others—and the financial outputs symbolizing actual historical costs alongside hidden future costs. The Karada Maryam branch in 2024 is portrayed in the table below with their estimated values summarized:

Table 1: Key Model Variables and Estimated Values at Al-Rasheed Bank – Karada Maryam Branch for the Year 2024

Symbol	Definition	Estimated Value (2024)	Unit
X_1	Monthly number of customers	9200	Customers
X_2	Average transaction service time	13.6	Minutes
X_3	Monthly transaction volume	41500000000	Iraqi Dinar (IQD)
X_4	Human resource costs	250000000	IQD
X_5	Monthly energy consumption	72000	kWh
X_6	Monthly number of complaints	170	Complaints
X_7	Number of repeated transactions	680	Transactions
Y	Actual historical costs	390000000	IQD
$\hat{Y}$	Expected future costs	430000000	IQD

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$C = \hat{Y} - Y$	Hidden future costs	40000000	IQD

By approximately 40 million IQD per month, the table displays that the anticipated future costs are higher than the historical costs, which suggests that there are unrecorded hidden costs. Analysis of factors like increased customer volume or complaint rates can be facilitated by these operational variables, which may lead to rework or delays, resulting in cost increases.

The proposed mathematical model for measuring hidden future costs using Random Forest and Cluster Analysis can be implemented at the Karada Maryam branch for the year 2024 through the following steps:

Step 1: Data Preparation and Cleaning:

This step involves preparing the data for modeling by removing noise and standardizing values using the Z-Score method, which measures how many standard deviations a value is from the mean. Missing data is addressed using the KNN-Imputer technique (with k=5), which estimates missing values based on the average of the five nearest neighbors. This step relies on raw data preprocessing techniques aimed at noise reduction, duplication removal, and value normalization to meet analytical model requirements. The standardization process using Z-Score is applied as follows:

$$\mathbf{Z - Score} = \frac{\mathbf{x^i - \mu}}{\boldsymbol{\sigma}}$$

Whereas: μ represents the mean, and σ denotes the standard deviation. This step is crucial because most machine learning algorithms perform optimally when the data is standardized, reducing the impact of outliers or extremely large values. Missing data is handled using predictive imputation techniques, which help minimize model distortion. The following table illustrates this process:

Table 2: Standard Statistical Analysis of Operational Data at Al-Rasheed Bank – Karada Maryam Branch for 2024

Variable	Mean (μ)	Standard Deviation (σ)	Recorded Value in 2024 (x_i)	Z-Score
Number of Customers	9000	450	9200	0.44
Service Time (minutes)	14.2	1.5	13.6	-0.40
Number of Repeated Transactions	620	150	680	0.40
Number of Complaints	155	35	170	0.43

The Z-Score values indicate that the number of customers slightly exceeds the average, while the average service time is somewhat below the mean, which may reflect system pressures to accelerate service delivery. The increase in repeated transactions and complaints signals weaknesses in process quality, contributing to elevated hidden operational costs.

Step 2: Cluster Analysis to Detect Hidden Patterns:

To analyze operational costs and identify hidden factors leading to increased expenses, the K-Means clustering algorithm was employed as a statistical tool to categorize banking transactions into three main clusters based on multiple criteria such as transaction size, operational cost, number of repeats, and human intervention frequency. This classification groups transactions with similar operational characteristics into clusters to pinpoint the primary sources of hidden costs within daily operations at the Al-Rasheed Bank Karada Maryam branch.

The purpose of this analysis is to differentiate efficiency levels across transaction clusters, isolate high-cost categories, and enable management to target the clusters that have the greatest cost impact. While K-Means was primarily utilized, more advanced clustering algorithms like DBSCAN or Gaussian Mixture Models can also be applied to segment data into groups sharing similar traits.

The objective is to uncover recurring or unreported operational patterns often associated with unaccounted costs. The clustering is mathematically defined by the following equation:

$$\mathbf{x \parallel minimize} \sum_{\mathbf{i=1}}^{\mathbf{k}} \sum_{\mathbf{xi,si}}^{\mathbf{n}} - \boldsymbol{\mu}\mathbf{i} \parallel$$

Whereas: Si represents each cluster, and μi denotes its centroid. This clustering approach aids in understanding the operational processes that contribute to hidden costs, such as excessive resource consumption in a specific branch without clear justification. Recent studies have demonstrated that cluster analysis significantly enhances the detection of costly hidden patterns. The results of this analysis are summarized in the following table:

Table 3: Classification of Transactions by Cost and Operational Efficiency at Al-Rasheed Bank – Karada Maryam Branch for 2024

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Cluster	Number of Transactions	Percentage of Total	Average Cost per Transaction (IQD)	Remarks
Cluster 1	3500	27%	9000	Regular transactions with high operational efficiency
Cluster 2	4200	32%	13400	Moderate efficiency, frequent human intervention
Cluster 3	1500	11%	22100	High-cost transactions, main source of hidden costs

The table highlights a clear disparity in cost and operational efficiency across the three clusters, detailed as follows:

- **Cluster 1:** Constituting 27% of total transactions, this cluster is characterized by high operational efficiency and a low average cost of 9000 IQD per transaction, representing best practices within the branch. The attributes of this cluster can serve as a benchmark for improving other clusters.
- **Cluster 2:** Comprising 32% of transactions, this cluster suffers from repeated human interventions, driving costs up to 13400 IQD per transaction. It reflects a moderate efficiency level and indicates the need for process automation and reduction of human errors.
- **Cluster 3:** Though accounting for only 11% of transactions, its high average cost of 22100 IQD per transaction results in this cluster being responsible for 41.1% of the total monthly operational costs. This alarming indicator suggests that Cluster 3 contains inefficient transactions that are the primary source of hidden future costs.

Focusing on mitigating the causes of high costs in Cluster 3 could lead to a substantial reduction in overall expenses. Improving process quality within this cluster alone could reduce hidden costs by at least 40%. Cluster analysis provides management with clear, data-driven insights into sources of waste and operational inefficiencies, forming a foundation for targeted and effective improvement initiatives.

Therefore, it is recommended to extend this analysis to other branches, linking cluster results to performance enhancement and training plans—especially concerning procedures classified under Cluster 3—while emphasizing the automation of complex processes and minimizing manual interventions.

Step 3: Developing the Random Forest Model for Cost Prediction:

To improve the accuracy of predicting hidden future costs and reduce the influence of bias and noise in the data, a Random Forest model consisting of 100 trees was employed. The result of multiple decision trees is aggregated by this advanced machine learning technique to generate more stable and precise predictions.

By partitioning the data into many subsets, building independent decision trees for each, and then aggregating the outcomes, the model can improve its generalization capability and minimize overfitting. The model's explanation of a significant portion of the cost variance is possible with this approach, which also reduces discrepancies between predicted and actual values.

After identifying clusters and analyzing features, the Random Forest model is trained with aggregated data. Random Forests operate by assembling a large group of decision trees that are executed simultaneously, with the final prediction being the average of all individual tree outputs, as expressed by:

$$\mathbf{Y^\wedge} = \mathbf{T_j(x)} \sum_{\mathbf{j=1}}^{\mathbf{M}} \frac{\mathbf{1}}{\mathbf{M}}$$

Whereas: Where: M is the number of trees, and Tj is the prediction from tree j. Random forests are characterised by their adaptability in the face of noisy and overlapping data, in addition to their ability to detect nonlinear relationships between inputs and outputs. Their capacity to measure hidden costs related to complex factors is a distinctive advantage. The table summarises the random forests model:

Table 4: Performance Metrics of the Random Forest Model at Al-Rasheed Bank – Karada Maryam Branch for 2024

Metric	Value	Interpretation
Number of Trees	100	Enhances prediction accuracy and reduces over fitting
Coefficient of Determination R^2	0.89	Explains 89% of variance in costs
Mean Absolute Error (MAE)	6200000 IQD	Minimal error margin relative to actual values
Root Mean Square Error (RMSE)	7850000 IQD	Balanced metric for model comparison and performance evaluation

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Improvement Over Linear Regression	**+23%**	**Significant accuracy gain compared to traditional methods**

It is clear from the table that using one hundred trees in the random forest model has significantly improved prediction accuracy. The high R^2 value of 0.89 indicates that the model represents 89% of the variance in cost data, which is a strong indication of its effectiveness in capturing real data patterns. Additionally, the mean absolute error (MAE) of approximately 6.2 million Iraqi dinars demonstrates a very small discrepancy between the expected and actual costs compared to the total cost volume, which averages in the hundreds of millions. This confirms the credibility and reliability of this model in making predictions.On another note, the root mean square error (RMSE) value of 7.85 million Iraqi dinars provides a balanced assessment by accounting for large error deviations, which presents a useful benchmark for comparing this model with proposed alternatives and evaluating its operational performance.Moreover, the 23% improvement compared to traditional linear regression methods shows that the random forest pattern significantly reduces prediction errors and enhances predictive capability, making it an ideal tool for estimating related future concealed costs..

Step 4: Calculating Hidden Future Costs:

Hidden costs are calculated by subtracting actual costs from projected monthly costs, taking into account the influencing factors for each period. After generating the expected value Y^, it is compared to the recorded actual cost Y to determine the amount of hidden costs, according to the following formula:

$$C = Y^{\wedge} - Y$$

Value C represents costs that have not been previously accounted for, such as deferred maintenance, wasted time, or reduced efficiency in certain activities. This metric assists management in adjusting their expectations and improving their plans based on real data that is often overlooked by traditional models. The following table illustrates this concept.:

Table 5: Actual, Predicted, and Hidden Costs at Al-Rasheed Bank – Karada Maryam Branch for 2024

Month	Actual Costs Y (IQD)	Predicted Costs Y^ (IQD)	Hidden Costs C (IQD)	Notes
January	380000000	410000000	30000000	Delays in financial transfer settlements
February	375000000	405000000	30000000	Increased auditing activities
March	400000000	435000000	35000000	Operational bottlenecks in the bank
April	395000000	430000000	35000000	Financial system updates
May	395000000	445000000	50000000	Seasonal surge in requests
June	390000000	440000000	50000000	Poor internal coordination
July	385000000	425000000	40000000	Temporary technical issues
August	388000000	430000000	42000000	Increase in customer complaints
September	385000000	420000000	35000000	Errors in paperwork procedures
October	390000000	435000000	45000000	High workload pressure
November	395000000	440000000	45000000	System updates
December	400000000	445000000	45000000	Elevated seasonal requests

It is observed that hidden costs range between 30 and 50 million Iraqi dinars monthly, with a noticeable increase in May and June due to heightened seasonal demand and poor internal coordination. These gaps highlight the need for continuous corrective measures.

Step 5: Model Retraining (Feedback Loop):

Based on the experiential discrepancies between the predictable and actual costs, the model undergoes recalibration through reeducation and updating the key variables to enhance predictive accuracy. Given the lively nature of the banking setting, the model is periodically updated via a response loop using the forecast error, as follows::

$$\epsilon = Y^{\wedge} - Y$$

These values are used to reeducate the model and improve its accuracy in future periods. Clusters are also re-evaluated when new designs emerge, which reinforces the model's dynamic flexibility to altering financial variables. This procedure can be illustrated in the next table:

Table 6: Impact of Retraining on Model Accuracy at Al-Rasheed Bank – Karada Maryam Branch for 2024

Month	Prediction Error (Million IQD)	Resulting Adjustment	Retraining Outcome

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January	**30**	**Improved quality of complaint data**	**MAE reduced by 5%**
February	**30**	**Adjusted service time variable**	**Prediction accuracy increased to 0.88**
March	**35**	**Enhanced "number of repeated transactions" variable**	**MAE reduced by 8%**
April	**35**	**Added new HR variable**	**R^2 increased to 0.90**
May	**50**	**Updated weights for Cluster 3**	**Prediction accuracy raised to 0.91**
June	**50**	**Adjusted energy consumption variable**	**Overall model stability improved**
July	**40**	**Improved seasonal transaction model**	**RMSE reduced by 7%**
August	**42**	**Updated complaints database**	**Increased prediction accuracy**
September	**35**	**Adjusted paperwork criteria**	**Model accuracy stabilized**
October	**45**	**Added workload pressure variable**	**Performance improved in high-pressure months**
November	**45**	**Retrained with new data**	**Prediction accuracy reached 0.92**
December	**45**	**Comprehensive model improvement with feedback**	**Lowest MAE of the year**

The retraining data show important development in prediction accuracy, especially after concentrating on powerful variables such as repeated transactions and human resources. These changes led to discounts in Mean Absolute Error (MAE) and increases in the coefficient of determination (R^2), ornamental the replica's effectiveness in predicting future costs.

Step 6: Integrating Results into Costing and Budgeting Systems:

The evaluation beforehand and after applying the model demonstrates improved accuracy in operational finances and a discount in annual deficits, alongside significant financial resource reorganizations permitted by uncovering hidden costs. After predicting hidden costs, consequences are rummage-sale to update costing systems and regulate financial items by joining hidden costs into estimated controls, moving resources based on discovered patterns, and refining cheap accuracy to reduce gaps between actual and deliberate values. This is abridged in the next table:

Table 7: Comparison of Key Indicators Before and After Model Implementation at Al-Rasheed Bank – Karada Maryam Branch for 2024

Indicator	Before Implementation	After Implementation	Difference
Budget Prediction Accuracy (%)	**76**	**91**	**+15%**
Hidden Costs Ratio (%)	**12**	**3**	**-9%**
Annual Savings (IQD)	**—**	**480,000,000**	**—**

The proposed mathematical model, combining Random Forests and Cluster Analysis, successfully uncovers hidden future costs with high precision, provides accurate data for annual operational budget planning, improves resource allocation efficiency, reduces financial waste, supports strategic decision-making with intelligent forecasting capabilities, and is continuously updated through retraining based on new and updated data over time.

Step 7: Forecasting Hidden Future Costs for 2025:

Following full implementation of the proposed mathematical model at Al-Rasheed Bank – Karada Maryam Branch for 2024, hidden future costs for 2025 will be estimated using this model. Table 8 provides a detailed monthly forecast of hidden costs from January through December 2025, based on the model combining Random Forests and Cluster Analysis. The model trusts on actual and foretold costs for each month, with the change on behalf of hidden costs that are not obvious in traditional accounting. The table shows once-a-month hidden costs ranging between 35 million and 50 million IQD, representative an unreported financial load hindering working efficiency.

For instance, May and June demonstration mountains of 50 million IQD due to augmented dealings, seasonal requests, and sustained poor interior coordination, resulting in higher imperceptible expenses. Conversely, months like January, February, July, and September exhibition comparatively lower hidden costs (~35 million IQD), reflecting working developments or reduced challenges. These monthly variances underline the rank of a dynamic model that adapts to working vicissitudes and provides precise predictions helping better budget planning.

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Table 8: Monthly Forecast of Hidden Future Costs at Al-Rasheed Bank – Karada Maryam Branch for 2025

Month	Expected Actual Costs Y (IQD)	Expected Predicted Costs Y^ (IQD)	Expected Hidden Costs C=Y^−Y (IQD)	Notes and Additional Forecasts
January	395000000	430000000	35000000	Continued operational challenges
February	390000000	425000000	35000000	Anticipated increase in seasonal complaints
March	405000000	445000000	40000000	Seasonal demand increases pressure on system
April	400000000	440000000	40000000	Software updates may cause temporary delays
May	410000000	460000000	50000000	Noticeable surge in transactions and requests
June	405000000	455000000	50000000	Ongoing internal coordination weaknesses
July	400000000	435000000	35000000	Relative improvement in some processes
August	398000000	438000000	40000000	Expected increase in customer complaints
September	395000000	430000000	35000000	Corrective actions to improve operations
October	405000000	445000000	40000000	High workload pressure toward fiscal year-end
November	410000000	450000000	40000000	System updates and improvements ongoing
December	415000000	460000000	45000000	Peak seasonal demand at year-end

Key Insights from Table 8:

1. **Annual Average Hidden Costs:** The financial planning quality and resource allocation efficiency are significantly impacted by a total annual hidden cost estimate of around 460 million IQD, with monthly hidden costs ranging between 35 and 50 million IQD.
2. **Monthly Distribution:** In May and June, hidden costs increase because of peak activity seasons that call for focused administrative control to manage costs and operational challenges such as weak internal coordination.
3. **Improved Performance in Lower Hidden Cost Months:** During months with lower hidden costs (January, February), operational improvements or stabilization of workflow are associated, indicating efficient management interventions to reduce hidden costs.
4. **Effectiveness of the Proposed Model:** The model is capable of detecting hidden costs early and accurately, which allows the bank to take corrective measures before they accumulate and have a negative impact on budgets.
5. **Importance of Monthly Notes:** The notes that accompany them pinpoint probable causes of hidden expenses, such as software updates, increased complaints, and fiscal year-end pressures, which aid management in developing proactive plans for each scenario. To conclude, the proposed model provides accurate monthly monitoring of hidden expenses for 2025, pointing out periods that need more intense managerial attention. To prevent financial shortfalls and improve operational efficiency, it is important to incorporate an average monthly hidden cost of approximately 39 million IQD (over 460 million IQD annually) into annual budgets. By providing quantitative insights into invisible costs, this forecasting tool assists in strategic decision-making, improving resource allocation and reducing financial waste within the bank being studied.

3-3- Measuring the Flexibility of Cost Systems at Al-Rasheed Bank – Karada Mariam Branch for the Year 2024:

Accounting and operational frameworks are flexible in cost systems because they can adapt quickly and efficiently to changes in operational transactions without compromising service quality. The cost system's responsiveness to

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operational changes, particularly in a dynamic financial environment like Iraq, is a key indicator of flexibility in the context of Al-Rasheed Bank's Karada Mariam Branch.

To evaluate this flexibility, an analysis was conducted on the monthly operational costs associated with key expenditure components—such as human resources, energy consumption, customer complaints, and transaction volume—throughout 2024. These costs were compared against changes in workload and the number of transactions.

The table below details the monthly operational cost data alongside transaction volume and client numbers, with calculated cost flexibility coefficients for each cost element.

Table 9: Monthly Operational Costs and Transaction Volume at Al-Rasheed Bank – Karada Mariam Branch for 2024

Month	Number of Clients	Transaction Volume (Billion IQD)	Human Resource Costs (IQD)	Energy Consumption (kWh)	Number of Complaints	Cost-to-Transaction Ratio (%)	Cost Flexibility Coefficient
January	9100	40.8	248000000	71500	165	0.61	0.95
February	8900	39.5	245000000	70800	160	0.62	0.90
March	9300	42.0	251000000	72000	172	0.60	1.05
April	9250	41.7	250500000	71900	168	0.60	1.02
May	9400	42.5	252000000	72200	175	0.59	1.10
June	9,350	42.3	251500000	72100	170	0.60	1.08
July	9200	41.0	249000000	71700	165	0.61	0.96
August	9150	40.7	248500000	71600	162	0.61	0.94
September	9100	40.5	247800000	71400	160	0.61	0.93
October	9200	41.2	249500000	71800	165	0.60	0.97
November	9300	41.8	250700000	72000	168	0.60	1.03
December	9,400	42.4	251900000	72,300	170	0.59	1.07

From the table, it is evident that both the number of clients and transaction volumes fluctuate moderately throughout the year, providing an opportunity to assess the cost system's responsiveness to these variations. Human resource costs range between 245 and 252 billion IQD monthly, while energy consumption remains relatively stable, fluctuating slightly between 71,400 and 72,300 kWh. The cost-to-transaction ratio varies narrowly from 0.59% to 0.62%, indicating a relative stability of operating costs in relation to transaction volume—a preliminary sign of system flexibility.

Changes in transaction volume and client numbers allow the system to adjust costs, which is reflected in the cost flexibility coefficient. The calculated coefficients are ranging from 0.90 to 1.10, and if they are closer to 1, they suggest high flexibility, which means that costs change proportionally to transaction volume.

The flexibility coefficient reached 1.10 in May, when the branch was responsible for handling 9,400 clients and a transaction volume of 42.5 billion IQD. The system was able to effectively optimize cost control relative to workload, demonstrating heightened responsiveness to operational changes that month. The flexibility coefficient in February was 0.90, which means there was less responsiveness and Although transaction volume was lower, there was still rigidity in cost adjustments.

Overall, the conclusion show that the cost system at the Karada Mariam branch hold laudable flexibility in adapting to operating transfer throughout 2024, enhancing the bank's ability to handle expenditure and improve operational efficiency while preserving high-grade quality customer service.

3-4- Measuring the Dynamism of Budget Planning at Al-Rasheed Bank – Karada Mariam Branch for 2024:

The ability of the financial and administrative systems to continually update and adjust budgets in line with operational and economic changes during the annual planning period is reflected in the dynamism of budget planning. This capability is vital to make sure that resources are allocated efficiently, financial gaps are minimized, and decision-making is based on accurate and up-to-date data.

To gauge this dynamism, monthly planned budgets were scrutinized against actual budgets and operational costs during 2024, emphasizing accuracy in planning and the extent of budget adjustments in response to changes. The table below gives a comprehensive comparison of planned and actual budgets, including the financial resources and operational costs allocated for each month.

Table 10: Comparison of Planned vs. Actual Budgets at Al-Rasheed Bank – Karada Mariam Branch for 2024

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Month	Planned Budget (IQD)	Actual Budget (IQD)	Variance (IQD)	Variance (%)	Operational Cost (IQD)	Operational Cost as % of Actual Budget
January	1200000000	1250000000	50000000	4.17%	740000000	59.2%
February	1180000000	1220000000	40000000	3.39%	735000000	60.2%
March	1250000000	1300000000	50000000	4.00%	745000000	57.3%
April	1240000000	1280000000	40000000	3.23%	750000000	58.6%
May	1260000000	1310000000	50000000	3.97%	760000000	58.0%
June	1255000000	1295000000	40000000	3.18%	755000000	58.3%
July	1230000000	1270000000	40000000	3.25%	745000000	58.7%
August	1225000000	1265000000	40000000	3.27%	740000000	58.5%
September	1220000000	1260000000	40000000	3.28%	735000000	58.3%
October	1235000000	1275000000	40000000	3.24%	745000000	58.4%
November	1245000000	1290000000	45000000	3.62%	750000000	58.1%
December	1260000000	1320000000	60000000	4.76%	760000000	57.6%

Table 10 reveals a recurring variance between the planned and actual budgets throughout the year, with the deviation percentage ranging from 3.18% to 4.76%. According to the suggestion, the budgeting system at Al-Rasheed Bank's Karada Mariam Branch is displaying a reasonable level of dynamism by regularly altering budgets to meet the needs of the situation. Despite fluctuation during the month, the operational costs maintain a consistent cost ratio of between 57.3% and 60.2% of the actual budget, indicating efficient cost control within available resources. However, there is still room for improvement in reducing this ratio and increasing profitability.

Analyzing monthly variances and budget adjustment rates executed by the financial planning department and their impact on resource utilization efficiency helped refine the assessment of budget planning dynamism. The following table stands key indicators of allocation vigour, including the monthly adaptation rate, correction portion relative to the prior month, number of every month adaptation, and an overall vigour index rated on a scale from 1 to 10.

Table 11: Indicators of Budget Adjustment Dynamism at Al-Rasheed Bank – Karada Mariam Branch for 2024

Month	Budget Adjustment Rate (%)	Correction vs. Previous Month (%)	Number of Monthly Adjustments	Dynamism Index (1-10)
January	4.17	–	2	7
February	3.39	-18.7	1	6
March	4.00	+18.0	3	8
April	3.23	-19.25	1	6
May	3.97	+22.9	3	8
June	3.18	-19.9	2	6
July	3.25	+2.2	1	6
August	3.27	+0.6	1	6
September	3.28	+0.3	1	6
October	3.24	-1.2	1	6

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November	**3.62**	**+11.7**	**2**	**7**
December	**4.76**	**+31.5**	**3**	**9**

Table 11 shows that the budget adjustment rate fluctuates between 3.18% and 4.76%, with a significant increase in December (+4.76%) that indicates an effective response to resource realignment before the fiscal year-end. The system's flexibility in responding to sudden operational changes or updated forecasts can be seen in the variability of correction percentages compared to the previous month, with May and December showing strong increases exceeding 20%. every month number adaptation monthly adjustments ranges between 1 and 3, while the dynamism index scores between 6 and 9 out of 10, point out that the management at Karada Mariam Branch sensitive an budget and responsive budget review capable of frequent revisions to ensure that budgetary truth with actual financial realities.

To sum up, these indicators demonstrate a high level of financial flexibility and potential for continual improvement, which can enhance the efficiency of financial planning and reduce the risks associated with market and operational changes.

3-5- Testing the Research Hypotheses:

This study is based on a main hypothesis concerning the building of an integrated model combining Random Forest and Cluster Analysis procedure to estimation hidden future costs and its impact on the flexibility of cost systems and the dynamic of allocation planning at Al-Rasheed Bank – Karada Mariam Branch. Empirical data can be used to test the subsidiary hypotheses statistically.

1. Testing the First Subsidiary Hypothesis:

According to this hypothesis, the use of the Random Forest technique is statistically significant for detecting hidden future costs in the model. To confirm this hypothesis, we used Pearson's correlation coefficient and the coefficient of determination to measure the relationship between the Random Forest model's performance and the detection of hidden future costs (R^2). Actual and predicted cost data were collected monthly over 12 months, and the differences (hidden costs) were calculated. The significance of the relationship between predictions and actual expenditures was then tested. The results are summarized in the following table:

Table 12: Testing the First Subsidiary Hypothesis – Relationship Between Random Forest Technique and Hidden Costs

Indicator	Value	Interpretation	Significance Level (p-value)
Pearson Correlation (r)	0.92	Very strong correlation between predictions and actual costs	<0.001
Coefficient of Determination (R^2)	0.85	Model explains 85% of the variance in hidden costs	—
t-test for correlation	10.45	Highly significant, confirming validity of relationship	<0.001

The results indicate a very strong correlation ($r = 0.92$) between the Random Forest model's predictions and actual costs, demonstrating the model's high accuracy in detecting hidden future costs. The R^2 value of 0.85 further confirms that 85% of the variance in hidden costs can be explained by the model, supporting the hypothesis. The p-value < 0.001 confirms that this relationship is statistically significant and unlikely due to chance.

2. Testing the Second Subsidiary Hypothesis:

This hypothesis states: "Integrating Cluster Analysis with Random Forest improves the accuracy of classifying hidden costs compared to traditional methods." To test this hypothesis, the performance of the integrated model (Random Forest combined with Cluster Analysis) was compared with that of a traditional Linear Regression model in classifying and predicting hidden costs. Prediction accuracy metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the improvement percentage in performance were calculated. The results are shown below:

Table 13: Comparison of Hidden Cost Classification Accuracy Between Proposed and Traditional Models

Indicator	Proposed Model (Random Forest + Clustering)	Traditional Model (Linear Regression)	Improvement (%)
MAE (IQD)	6200000	8050000	+23%
RMSE (IQD)	7850000	10200000	+23%
Prediction Accuracy (R^2)	0.89	0.72	+23%

Table 13 clearly shows a significant improvement in hidden cost classification accuracy when using the proposed model. The MAE decreased from 8,050,000 IQD to 6200000 IQD, a 23% reduction. Similarly, RMSE showed a 23% reduction,

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indicating more reliable and less dispersed predictions. The increase in R^2 from 0.72 to 0.89 demonstrates the superior effectiveness of the proposed approach compared to traditional methods.

3. Testing the Third Subsidiary Hypothesis:

This hypothesis states: "The application of the proposed model positively affects the flexibility of banking cost systems and enhances their ability to adapt to economic and environmental changes." The flexibility of cost systems was evaluated by comparing efficiency and financial adjustment indicators before and after applying the model, using measures such as the operational budget deficit ratio, unexpected costs ratio, and the amount of reallocated resources. An independent-samples t-test was employed to assess the statistical significance of differences between the two periods. The results are summarized below:

Table 14: Impact of Model Application on Cost System Flexibility

Indicator	Before Application	After Application	Difference (%)	Significance Level (p-value)
Operational Budget Accuracy (%)	78	91	+13	0.002
Annual Deficit Ratio (%)	16	7	-9	0.001
Reallocated Resources (IQD)	0	460,000,000	—	—
Unexpected Costs Ratio (%)	12	4	-8	0.005

Table 14 demonstrates significant improvements in the flexibility of cost systems following the model's implementation. Operational budget accuracy increased by 13%, while the annual deficit ratio declined by 9%. Additionally, resources worth 460 million IQD were successfully reallocated. The unexpected costs ratio dropped from 12% to 4%, indicating a greater capacity to adapt to changes and reduce financial risks. The p-values (< 0.01) confirm the statistical significance of these improvements.

4. Testing the Fourth Subsidiary Hypothesis:

This hypothesis states: "The model contributes to increasing the dynamism of budget planning and makes it more responsive to future fluctuations and variables compared to traditional methods." To measure the dynamism of budgets, the monthly budget adjustment rate, number of adjustments, and system responsiveness over 12 months were analyzed and compared with the traditional budgeting system, which relies solely on annual planning. An Analysis of Variance (ANOVA) test was employed to compare differences between the two systems. The results are presented in the following table:

Table 15: Comparison of Budget Planning Dynamism Between the Proposed Model and the Traditional System

Indicator	Traditional System	Proposed Model	Difference (%)	Significance Level (p-value)
Monthly Budget Adjustment Rate (%)	1.2	3.8	+216.7	< 0.001
Number of Annual Adjustments	1	15	+1400	< 0.001
System Responsiveness Index (1-10)	3	8	+166.7	< 0.001

Table 15 illustrates that the proposed model significantly increases the dynamism of budget planning. The monthly budget adjustment rate rose from 1.2% to 3.8% (+216.7%), with a substantial increase in the number of annual adjustments from a single adjustment in the traditional system to 15 in the new model. Additionally, the system responsiveness index increased from 3 to 8, reflecting a greater capacity to absorb changes and fluctuations. All differences were highly statistically significant ($p < 0.001$), supporting the hypothesis.

PART FOUR: CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusions:

This study reached the following conclusions:

1. The Random Forest model demonstrated a high capability to accurately predict hidden future costs at Al-Rasheed Bank – Karada Mariam Branch, achieving an R^2 of 0.89. This indicates that the model explains 89% of the variance in cost data, enhancing confidence in relying on it to analyze unseen costs that are difficult to estimate using other methods.

2. Combining Cluster Analysis with Random Forest techniques improved classification and estimation quality, with the model achieving a 23% reduction in Mean Absolute Error (MAE) compared to traditional methods. This integration allowed clear differentiation among categories of hidden costs, facilitating more precise and effective managerial decisions.
3. Implementing the model increased the flexibility of the bank's cost systems, where the accuracy of operational budgets improved from 78% to 91%, and the annual deficit ratio dropped from 16% to 7%. These figures reflect an enhanced ability to control costs and adapt to economic and environmental changes, reducing financial risks and increasing resource management efficiency.
4. Budget planning became more responsive and flexible to variables and fluctuations, with the annual number of budget modifications rising from a static state to 15 targeted adjustments. The model's active and adaptive support in financial planning is reflected in this shift, resulting in the reduction of gaps between forecasts and financial reality.
5. The model identified monthly hidden costs that amount to approximately 42 million Iraqi Dinars, which totals an estimated 504 million annually. This important discovery highlights the existence of expenditures that were previously unaccounted for and have an impact on the bank's financial performance. Integrating these costs into budgets is necessary to prevent financial surprises and improve decision-making.
6. The model's sustainability and effectiveness over the long term are enhanced by feedback mechanisms and periodic retraining that enable continuous adaptation to changes in operational data. This enables the model to be a flexible and advanced tool that assists in continuously improving cost and budget systems within the bank.

4.2 Recommendations:

The education recommends the following:
1. The Random Forest model's outstanding ability to accurately predict hidden future costs at the Karada Mariam branch should be generalized to all Al-Rasheed Bank branches. Management will be able to gain a clear and up-to-date understanding of hidden expenses across different branches, which will lead to better financial planning and data-driven decision-making.
2. The study revealed that the accuracy of cost classification and analysis can be enhanced by integrating Cluster Analysis with forecasting techniques. The bank's financial analysis procedures should routinely incorporate this approach, which will enable management to efficiently classify and analyze costs and uncover hidden patterns that affect financial performance.
3. To ensure the continued flexibility and adaptability of cost systems to economic and environmental variables, it is recommended to establish clear mechanisms for periodically reassessing and updating cost data and predictive models. Continuous updates will allow handling emerging changes promptly and reduce estimation errors that may affect the bank's financial performance.
4. Given the observed increase in budget dynamism after applying the model, it is advised to transform the budgeting system into a flexible framework allowing frequent adjustments in response to new data and changes in the operating environment. This will enhance estimate accuracy and reduce gaps between actual and planned performance, thereby boosting the bank's financial efficiency.
5. Due to the importance of hidden future costs and their impact on financial performance, they should be formally incorporated into annual budgets and financial performance reports. This measure will enhance cost comprehensiveness, provide accurate data for future planning, and improve financial risk assessment.
6. To maximize the benefits of advanced techniques such as Random Forest and Cluster Analysis, it is recommended to develop specialized training programs targeting staff in financial and planning departments. This training will raise technical skills and improve understanding of analytical tools, ensuring successful and sustainable model implementation for more accurate and effective outcomes.

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