An Intelligent Decision Support System Architecture for Key Account Manager Lifecycle Optimization Using Integrated HRIS-CRM and Machine Learning

Andri Fabriansyah
Doctoral Program of Information Systems, Postgraduate School, Universitas Diponegoro, Semarang, Indonesia
andrifabriansyah@students.undip.ac.id (corresponding author)

Aghus Sofwan
Department of Electrical Engineering, Universitas Diponegoro, Semarang, Indonesia
asofwan@elektro.undip.ac.id

Kardison Lumban Batu
Department of Management, Universitas Diponegoro, Semarang, Indonesia
kardisonlumbunbatu@undip.ac.id

Sarah Nazly Nuraya
Faculty of Computer Science, Universitas Indonesia, Depok, Indonesia
sarah.nazly21@ui.ac.id

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ABSTRACT

Key Account Manager (KAM) lifecycle management requires a Decision Support System (DSS) that can integrate workforce and customer performance data to support strategic decision-making. This study develops an intelligent DSS architecture that integrates Human Resource Information Systems (HRIS) and Customer Relationship Management (CRM) data to support lifecycle-based KAM performance management. The proposed framework encompasses system architecture design, end-to-end data integration, and regression-based machine learning analytics using Random Forest and XGBoost models on preprocessed HRIS-CRM data. The regression models generate standardized continuous KAM performance scores that capture performance variability across lifecycle stages, enabling adaptive managerial decision-making. By embedding predictive analytics into structured decision workflows, the proposed DSS bridges analytical modeling and operational implementation. The findings indicate the practical applicability of a regression-based, lifecycle-aware DSS framework for guiding data-driven managerial decisions in complex B2B environments, consistent with the established methodological advantages of ensemble learning in predictive organizational analytics.

Keywords-Key Account Manager (KAM); Decision Support System (DSS); Human Resource Information System-Customer Relationship Management (HRIS-CRM) integration; machine learning; performance risk prediction; regression-based analytics

I. INTRODUCTION

In Business-to-Business (B2B) environments, organizational performance is strongly influenced by how effectively information systems support strategic human resource management. KAM functions as the primary interface between the organization and high-value strategic customers [1, 2]. Long-term customer relationship sustainability, revenue continuity, and service stability depend on how KAMs are recruited, developed, evaluated, and managed throughout their career lifecycle [3, 4]. However, many organizations still rely on subjective assessments and fragmented information systems in managing KAM performance, which may result in inconsistent and suboptimal decision-making.

KAM effectiveness is not determined solely by sales outcomes, but also by competencies developed across multiple lifecycle stages, including selection, onboarding, operational execution, evaluation, and professional development [5, 6]. Although lifecycle-based perspectives provide a structured understanding of KAM progression, prior studies frequently examine isolated performance phases rather than adopting an integrated lifecycle approach. This limitation complicates the identification of the appropriate timing and mechanisms for managerial interventions aimed at sustaining long-term performance.

From an information system perspective, organizations rely primarily on HRIS and CRM systems to manage internal workforce data and external customer performance data [7, 8]. HRIS maintains structured employee information, such as training records, certifications, competency assessments, and career development history, while CRM captures customer interaction metrics, sales growth, account profitability, and revenue indicators. However, these systems are often implemented in a fragmented manner, limiting effective cross-functional integration [9]. As a result, organizations frequently lack a systematic mechanism to connect workforce competencies with business performance outcomes. Machine learning advancement presents new opportunities for analyzing complex, high-dimensional enterprise datasets. Machine learning techniques have demonstrated substantial predictive effectiveness across domains such as sales forecasting, customer churn prediction, and HR analytics, particularly through ensemble-based approaches [10-12]. Algorithms such as Random Forest and XGBoost are capable of modeling nonlinear relationships within structured organizational data [13, 14]. Nevertheless, recent forecasting studies emphasize comparative performance evaluation using statistical accuracy metrics (e.g., MAE, RMSE) [15], with comparatively less attention paid to embedding predictive outputs into structured operational decision workflows.

In the context of KAM management, lifecycle-based frameworks describe structured career progression. However, limited research has examined how lifecycle-aware KAM data can be operationalized within an intelligent DSS that integrates HRIS, CRM, and machine learning analytics. Existing DSS research largely focuses on general AI-driven architectures and methodological developments [16, 17], with insufficient emphasis given on integrated HRIS-CRM system design, tailored to lifecycle optimization. Overall, there is a limited presence of lifecycle-aware information system architectures that systematically connect human resource and customer data within KAM management. Although predictive modeling has advanced considerably, the translation of analytical outputs into actionable managerial decision processes remains underexplored. To address this gap, the current study proposes and empirically validates an intelligent DSS architecture for lifecycle-based KAM management. The proposed framework integrates HRIS and CRM data within a unified analytical environment and employs the Random Forest and XGBoost models to generate continuous performance prediction scores. By embedding machine learning inference into structured decision workflows, the architecture establishes a direct link between predictive analytics and operational management processes, enabling organizations to align workforce development strategies with customer performance outcomes in a systematic and data-driven manner.

II. METHODOLOGY

This study employs an information systems engineering approach using the Design Science Research (DSR) method to analyze the problem domain and to design, implement, and evaluate system artifacts for optimizing the KAM lifecycle. The developed artifacts include: (i) an integrated HRIS-CRM DSS architecture, (ii) a machine learning–based analytical pipeline using Random Forest and XGBoost, and (iii) a rule-based decision inference engine. The overall research stages are illustrated in Figure 1.

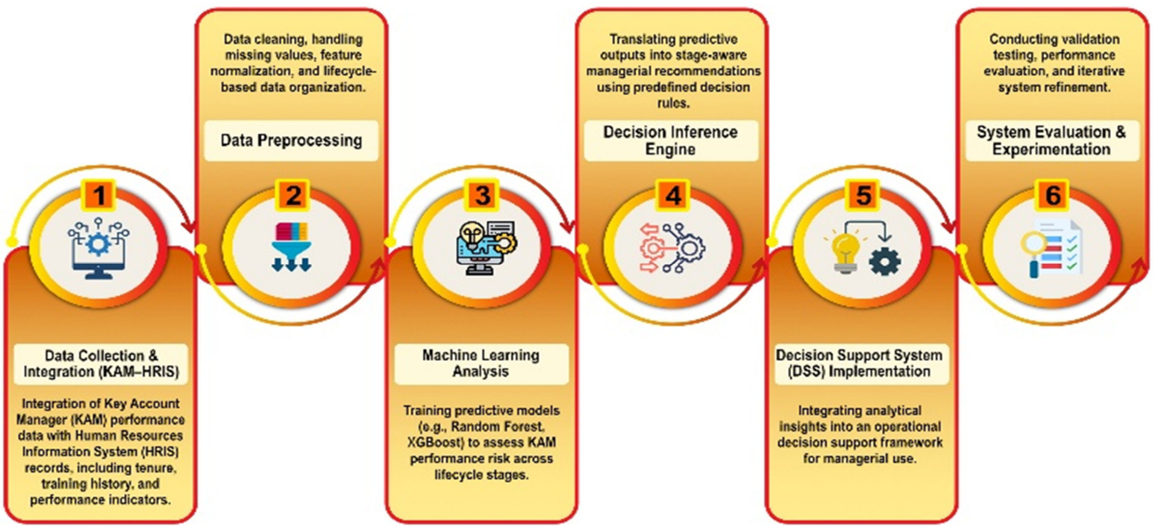

Fig. 1. Research stages.

The research process begins with collecting KAM career data from the HRIS system and customer performance data from the CRM system. These heterogeneous data sources are integrated using a Python-based application-level Extract, Transform, Load (ETL) pipeline, implemented within the DSS backend to form a unified analytical dataset. During the transformation stage, missing values are handled, categorical variables are encoded, and numerical features are normalized using min-max scaling to a range of [0, 1] to ensure consistent and reliable input quality for subsequent analysis. The Random Forest and XGBoost models are then trained on the preprocessed HRIS-CRM dataset to generate continuous KAM performance prediction scores. The models are implemented using Python's scikit-learn framework and selected due to their robustness in handling structured multidimensional data and nonlinear relationships, making them suitable for complex organizational performance modeling.

A. Data Collection and Integration (HRIS-CRM)

The first stage involved collecting and integrating data from the HRIS and CRM systems. The dataset consisted of 200 KAMs, responsible for managing 3100 large customers that contribute approximately 80% of the company's total revenue. Only representative sample records are presented in the tables for illustration purposes. HRIS provided data on KAM career details, such as profiles, training history, and performance evaluations, while CRM tracked external performance indicators, including customer interactions, strategic accounts, and revenue realization. These data sources were combined through an ETL process to create a centralized database for analysis.

Table I shows the HRIS dataset on KAM's career traits and skills, describing their internal conditions across their career cycle, which serves as the main source of independent variables in the DSS. The HRIS dataset contains internal career-related information for KAMs, including variables such as KAM_ID, Career_Stage, Training_Hours, Performance_Score, and Experience_Years. The Career_Stage variable represents the lifecycle of a KAM, consisting of five stages: selection, onboarding, task execution, evaluation, and development.

KAM_ID uniquely identifies each KAM, linking the HRIS data with customer performance in the CRM system. Age indicates the KAM's age, reflecting professional maturity and the influence of experience on performance. Education represents the highest formal education level, impacting analytical and decision-making abilities.

The Years_Experience reflects the KAM's professional years, indicating knowledge and skills. The Training_Hours shows the total training hours, representing the organizational investment in competence. The Certification_Level classifies certification from Basic to Expert, evidencing technical and functional skills. The Performance_Score is an internal evaluation generated by the HRIS system, reflecting the KAM's past performance and used in machine learning model training and decision assessments. The Career_Stage groups KAMs into stages, like Onboarding, On-Duty, Performance, Evaluation, and Development, to model performance dynamics.

The KAM journey is operationalized through these five lifecycle stages. The Onboarding stage represents newly assigned KAMs focusing on initial capability building, while the On-Duty stage reflects active operational execution and customer engagement. The Performance stage indicates KAMs with stable business contribution, followed by the Evaluation stage for periodic performance assessment and gap identification. The Development stage represents advanced KAMs prioritized for strategic account management and long-term capability enhancement. This lifecycle structure provides contextual grounding for subsequent performance prediction and decision inference in the DSS.

Table II displays KAM's external performance data from the CRM system. This dataset shows the role of KAMs in the management of strategic accounts and business performance. Variables include the number of customers (Num_Customers), total account value (Account_Value_USD), annual sales growth (Sales_Growth_%), interaction frequency (Interaction_Frequency), and customer satisfaction (Customer_Satisfaction). The Year variable maintains consistency. Before normalization, Account_Value_USD ranged from USD 300,000 to USD 1,600,000, while Sales_Growth_% ranged from 3.8% to 13.7%. Customer_Satisfaction was measured on a 1-5 Likert scale. These original value distributions justified the application of min–max normalization to ensure comparability across indicators. The processed data were then integrated with the HRIS dataset to support predictive analytics and decision-making within the proposed DSS.

TABLE I. HRIS DATASET (KAM CAREER DATA)

KAM_ID	Age	Education	Years_Experience	Training_Hours	Certification_Level	Performance_Score	Career_Stage
KAM01	32	Bachelor	6	120	Intermediate	82	On-Duty
KAM02	41	Master	15	200	Advanced	91	Performance
KAM03	29	Bachelor	4	80	Basic	74	Onboarding
KAM04	37	Master	10	160	Advanced	88	Evaluation
KAM05	45	Bachelor	18	220	Expert	94	Development

TABLE II. HRIS-CRM DATASET

KAM_ID	Num_Customers	Account_Value_USD	Sales_Growth_%	Interaction_Frequency	Customer_Satisfaction	Year
KAM01	12	480,000	6.5	Medium	4.1	2024
KAM02	20	1,200,000	11.2	High	4.6	2024
KAM03	8	300,000	3.8	Low	3.9	2024
KAM04	15	820,000	8.4	Medium	4.3	2024
KAM05	25	1,600,000	13.7	High	4.8	2024

TABLE III. PREPROCESSED HRIS-CRM DATASET

KAM_ ID	Exp_Yrs_ Norm	Train_Hours_ Norm	Perf_Score_ Norm	Account_Value_ Norm	Sales_Growth_ Norm	Cust_Sat_ Norm	Interaction_ Score	KAM_Lifecycle_ Stage
KAM01	0.29	0.38	0.53	0.30	0.34	0.40	0.5	On-Duty
KAM02	0.71	0.63	0.79	0.75	0.69	0.65	1.0	Performance
KAM03	0.14	0.25	0.29	0.19	0.20	0.28	0.0	Onboarding
KAM04	0.48	0.50	0.68	0.51	0.49	0.53	0.5	Evaluation
KAM05	0.86	0.75	0.89	1.00	0.85	0.80	1.0	Development

B. Data Preprocessing

In this stage, the integrated dataset was preprocessed to enhance quality and analytical readiness. Missing values were handled using mean imputation for numerical variables and mode imputation for categorical variables. Categorical features were encoded using one-hot encoding, and numerical features were normalized using min–max scaling to a range of [0, 1] to ensure comparability across indicators. Data formats were aligned to maintain consistency between HRIS and CRM structures. Subsequently, the processed data were mapped to defined KAM lifecycle stages, including initial assignment, operational phase, performance evaluation, and development to capture performance dynamics over time. Table III presents the preprocessed HRIS-CRM dataset. The dataset presented in Table III was preprocessed, including data cleaning, missing value handling, normalization, and format alignment, to ensure consistency and readiness for subsequent machine learning analysis. All numeric variables, including Years of Experience, Training Hours, Performance Score, Account Value, Sales Growth, and Customer Satisfaction, were normalized to the [0, 1] range using min-max normalization to eliminate scale bias. The categorical variable Interaction_Frequency was converted to a numerical form (Low=0, Medium=0.5, High=1) for model processing. Each KAM was mapped to a simplified life cycle stage (Onboarding, On-Duty, Performance, Evaluation, and Development), which allowed for analyzing performance dynamics over time and career development.

C. Machine Learning Analytics

In this stage, the preprocessed dataset was used to train models to predict KAM performance at each cycle stage. Input variables included normalized internal and external KAM indicators, such as work experience, training hours, performance scores, account value, sales growth, customer satisfaction, and interaction intensity. This study used the Random Forest and XGBoost algorithms to model the non-linear relationship between KAM traits and customer performance based on HRIS-CRM data. These ensemble methods were selected due to their robustness in handling high-dimensional structured datasets and their ability to model nonlinear feature interactions without imposing strong parametric or distributional assumptions [18, 19]. Specifically, Random Forest regression was implemented using scikit-learn's RandomForestRegressor with *n_estimators* = 100, while XGBoost employed gradient-boosted decision trees to enhance predictive performance. The output was a standardized prediction score representing the estimated relative KAM performance, used as input to the decision inference engine in the DSS.

D. Decision Inference Engine

The KAM performance prediction scores from the Random Forest and XGBoost models were translated into managerial decisions through inference rules based on the KAM lifecycle stages. This engine combined performance predictions with the KAM cycle context to generate operational decisions, such as training needs, performance evaluations, account adjustments, or competency priorities. Decision rules used threshold-based, stage-aware methods to ensure that recommendations were relevant to the KAM's career cycle position. Specifically, a rule-based mechanism was applied to map the standardized prediction scores into actionable recommendations. If the predicted performance score was greater than 0.7, the KAM was classified in the Development stage; scores between 0.4 and 0.7 indicated the Evaluation stage; and scores below 0.4 suggested a need for improvement in performance. These threshold values were empirically defined based on score distribution analysis and managerial consultation to ensure interpretability and practical relevance within the DSS.

E. Decision Support System Implementation

All analytical components and decision inference engines were integrated into an operational system. This system combined predictions from the Random Forest and XGBoost models and recommendations from the Decision Inference Engine into an interactive managerial dashboard. The dashboard displays KAM performance, lifecycle status, and decision recommendations clearly for decision makers. This DSS enabled management to use analytical results directly for strategic and operational decisions regarding KAM lifecycle management. Figure 2 presents the KAM Lifecycle DSS dashboard.

F. System Evaluation and Experimentation

The DSS was evaluated for its technical performance and decision effectiveness in KAM lifecycle management through two main components.

- System integration testing ensured HRIS-CRM data flow (ETL), preprocessing, and connectivity of the prediction modules (Random Forest and XGBoost) with the decision inference engine.
- Validated prediction models using a train-test split with accuracy, precision, recall, F1-score, AUC for classification, and MSE for regression to ensure prediction score reliability.

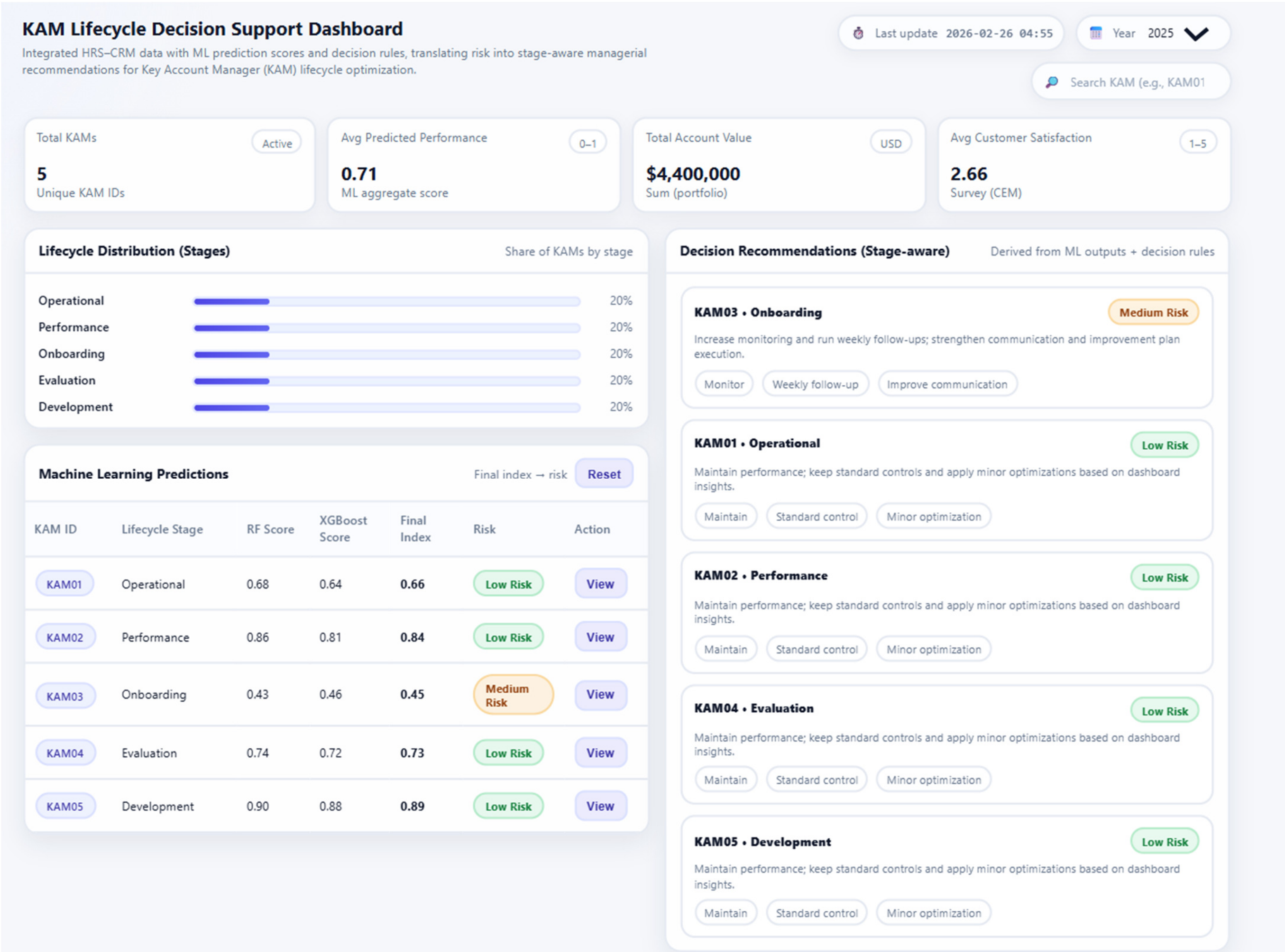

Fig. 2. Dashboard of the KAM lifecycle DSS.

III. RESULTS AND DISCUSSION

The evaluation focuses on two aspects: the reliability of system integration and the performance of Random Forest and XGBoost prediction models to support KAM decision-making.

A. System Integration Testing

In this scenario, the tests focused on verifying the end-to-end data processing flow to ensure that the DSS could operate consistently before model performance evaluation. The pipeline tested included the ETL process to integrate HRIS data (career and KAM development indicators) and CRM data (customer performance and revenue contribution indicators), followed by preprocessing (data cleaning, missing value handling, normalization, and format alignment), to the execution stage of the Random Forest and XGBoost prediction modules and the delivery of prediction outputs to the decision inference engine.

The success criteria were determined through a series of data integrity and inter-module compatibility checks, including: (i) consistency of schemas and data types between ETL results and preprocessing inputs; (ii) completeness of features required by the prediction model (no missing or shifted features); (iii) validity of the post-normalization value range (e.g., all numeric features are within the specified range); and (iv) functional connectivity between modules, namely the system's ability to generate prediction scores for each KAM entity and forward them to the decision inference engine without execution failure. Table IV portrays the System Integration Testing results, which assess end-to-end system integration for predicting KAM performance, where the final performance index is normalized on a scale of [0, 1], with values closer to 1 indicating higher predicted performance and lower performance risk.

TABLE IV. OUTPUT OF SYSTEM INTEGRATION TESTING FOR KAM PERFORMANCE PREDICTION

KAM_ID	RF_Score	XGB_Score	Final_Performance_Index
KAM01	0.463	0.500	0.482
KAM02	0.838	0.875	0.856
KAM03	0.174	0.167	0.170
KAM04	0.692	0.750	0.721
KAM05	0.941	0.999	0.970

The test results show that the integrated system can predict performance between KAMs. KAM05 scored the highest

(0.9697), indicating excellent, consistent performance and low risk, making it a priority for development or account assignments. KAM02 also performed well (0.8563), showing stability and positive contributions. KAM03 had the lowest final performance index (0.1703) with low RF and XGBoost scores, indicating high risk and a need for intervention, such as training or evaluation. KAM01 and KAM04 demonstrated moderate performance and require selective monitoring and improvement.

B. Regression-Based Model Evaluation

The predictive performance of the Random Forest and XGBoost regression models was evaluated using the integrated HRIS-CRM dataset. The dataset was divided into training and testing subsets to ensure objective evaluation on unseen data. Model performance was assessed using regression metrics, including MSE and RMSE, which quantify the average deviation between the predicted and actual performance scores. Lower MSE and RMSE values indicate better predictive accuracy and generalizability.

Figure 3 illustrates the comparative MSE results of the Random Forest and XGBoost regression models. The Random Forest model achieved a lower MSE value (0.018) compared to XGBoost (0.022), indicating smaller average squared prediction errors. This result suggests that Random Forest demonstrates slightly better predictive accuracy and stronger generalization capability when modeling the multidimensional HRIS-CRM dataset. The relatively close MSE values between the two ensemble models indicate that both approaches are capable of capturing nonlinear relationships within integrated workforce and customer performance data. However, the lower error magnitude of Random Forest implies a more stable performance estimation, supporting its suitability as the primary regression engine within the proposed DSS.

To further validate the robustness of the regression models, the evaluation was extended using RMSE, which provides an error measure on the same unit scale as the predicted performance index. Figure 4 presents the RMSE comparison between the Random Forest and XGBoost regression models.

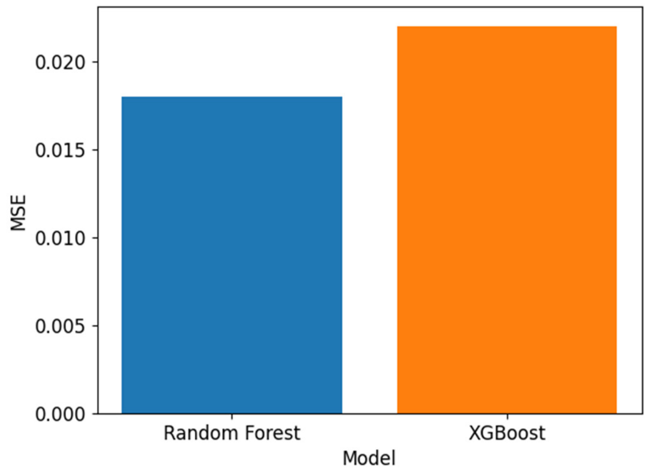

Fig. 3. Comparative MSE performance of Random Forest and XGBoost regression models.

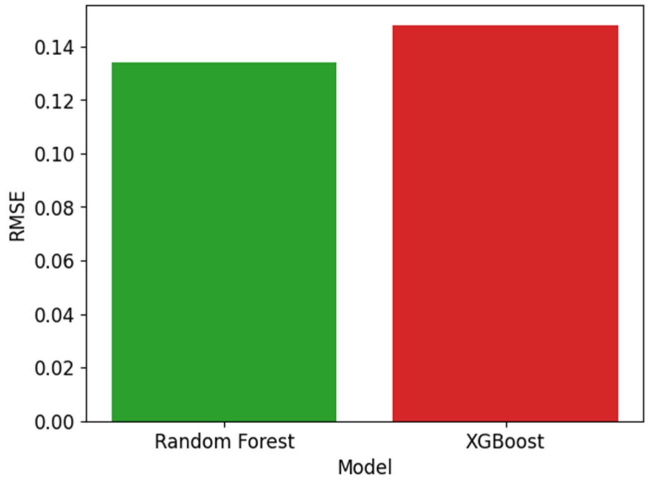

Fig. 4. RMSE comparison of Random Forest and XGBoost models.

The Random Forest model obtained a lower RMSE value (0.134) compared to XGBoost (0.148), indicating smaller prediction deviations and stronger generalization capability. The consistency between the MSE and RMSE results further reinforces the robustness of the regression-based framework in generating stable and continuous performance predictions within the integrated DSS architecture.

C. Decision Inference and DSS Implementation

A regression-based framework was adopted to develop an intelligent DSS for KAM lifecycle management. The regression models generate continuous performance scores, providing a detailed and quantitative representation of KAM performance levels. Unlike discrete evaluation mechanisms, continuous performance indices allow management to interpret each KAM's position along a performance spectrum rather than relying on rigid categorical labels.

The predicted performance scores are subsequently processed by the decision inference engine, which translates analytical outputs into structured managerial recommendations. The inference mechanism applies rule-based reasoning using predefined performance thresholds to generate actionable insights, such as training interventions, performance monitoring, strategic account prioritization, or career development planning. In this way, the DSS functions not only as a predictive analytics tool but also as an operational decision-support mechanism that connects model outputs with managerial workflows, consistent with recent perspectives on AI-driven DSS integration in operational environments [20]

The empirical results indicate that continuous regression-based scoring enables clearer lifecycle-aware differentiation of KAM performance. The continuous performance values generated (e.g., predicted annual revenue outputs prior to threshold categorization) preserve quantitative variation across KAM profiles, allowing detailed interpretation beyond rigid categorical labels. The standardized performance index integrates multidimensional HRIS and CRM indicators, reflecting measurable differences across career stages and customer engagement contexts. Compared to previous performance-oriented studies that primarily emphasized temporal forecasting and predictive accuracy evaluation [15], the proposed framework provides a more flexible and operationally embedded evaluation mechanism. Furthermore, integrating regression analytics with a structured decision inference engine enhances the alignment between analytical modeling and strategic management decisions. Figure 5 presents the regression-based DSS interface integration of HRIS-CRM inputs and decision inference. Figure 5 displays how multidimensional HRIS-CRM inputs are transformed into a standardized continuous performance score and a predicted annual revenue value within the DSS interface. In the illustrated case, the regression model generated a predicted annual revenue value of $329.76, accompanied by a performance grade of A+ and a "High Potential" status classification. The continuous regression output is subsequently processed by the rule-based decision inference engine, which applies predefined thresholds to produce structured managerial recommendations. In this example, the "High Potential" status triggered a recommendation for enrollment in the Global Talent/Fast Track program.

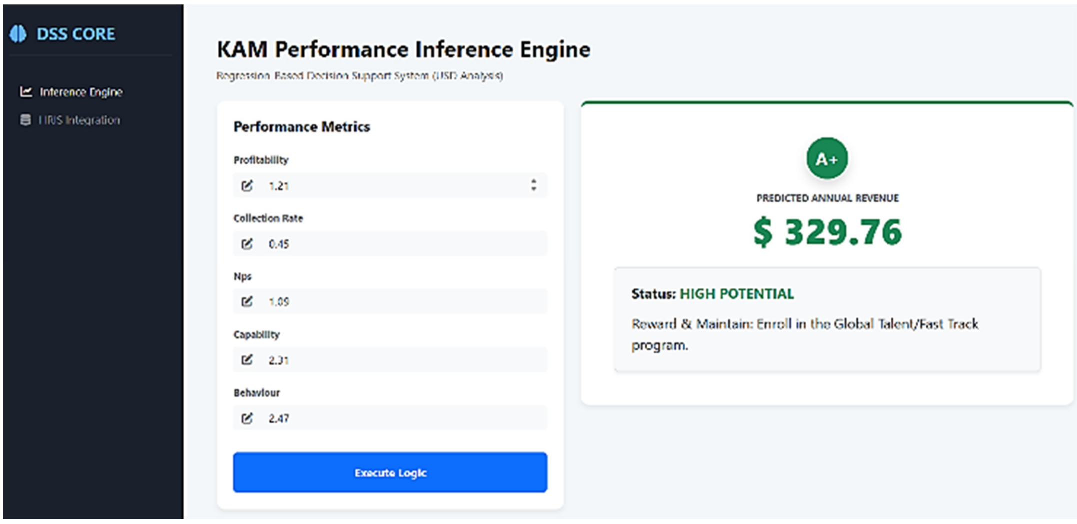

Fig. 5. Regression-based DSS interface and KAM performance inference output.

IV. CONCLUSION

This study proposed and empirically validated an intelligent Decision Support System (DSS) framework for lifecycle-based Key Account Manager (KAM) management by integrating Human Resource Information Systems (HRIS) and Customer Relationship Management (CRM) data within a unified analytical architecture. By adopting a regression-based modeling approach, the system generates standardized continuous performance scores that allow granular differentiation across KAM lifecycle stages and customer engagement contexts.

The continuous performance index captures the multidimensional variation in KAM performance, supporting spectrum-based managerial interpretation rather than rigid categorical assessment. Ensemble learning techniques enhance predictive stability and modeling robustness, ensuring reliable estimation of performance scores. The structured decision inference engine subsequently translates regression outputs into actionable managerial recommendations, thereby embedding predictive analytics within operational decision workflows. Despite its contributions, this study is limited by its organizational scope and single-period dataset. KAM performance remains influenced by complex behavioral and contextual dynamics that may require richer longitudinal and interaction-based data for improved modeling precision.

Future research should explore the incorporation of longitudinal and real-time data streams to better capture lifecycle evolution patterns. The integration of Explainable Artificial Intelligence (XAI) techniques would enhance transparency and managerial trust in DSS recommendations. Additionally, investigating hybrid ensemble-deep learning architectures and validating the framework across diverse industries would further strengthen the effectiveness and generalizability of the proposed lifecycle-aware DSS model.

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DATA AVAILABILITY STATEMENT

The dataset used in this study is not publicly available due to confidentiality agreements with the collaborating organization. The data contain sensitive organizational and customer performance information. Access to anonymized data may be granted upon reasonable request and subject to institutional approval.

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