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A Random Forest-Based AI Decision Support System for an Integrated Indonesian Civil Service Information System

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Abstract: Digital transformation in public administration increases the need for personnel information systems that can consolidate fragmented civil-service records and turn them into timely, transparent, and actionable decision support. This study developed SIPINTAR (Integrated, Adaptive, and Responsive Interactive Personnel Intelligence System), an artificial intelligence-based platform designed to integrate civil-service personnel information and support administrative decision-making within an Indonesian government institution. The study adopted a Research and Development approach and implemented the system through a Waterfall-based Software Development Life Cycle. Personnel data from multiple source systems, representing 5,320 civil servants and more than 42,000 historical records for 2019–2025, were integrated using Application Programming Interfaces (APIs) and Extract, Transform, and Load (ETL) processes. The integrated data were then subjected to cleaning, transformation, feature engineering, and Random Forest modeling. Model performance was assessed using accuracy, precision, recall, and F1-score, whereas system acceptance was examined through a User Acceptance Test. The strongest reported result was obtained for employee-performance prediction, with 87.24% accuracy, 86% precision, 85% recall, and 85.5% F1-score. Feature-importance analysis as the explainable artificial intelligence component identified performance score, competency level, and years of service as the three most influential variables. The integrated dashboard and AI Assistant provided consolidated access to analytical information, and the UAT result reached 91.40%. Overall, the findings suggest that SIPINTAR can move personnel information management beyond historical record keeping toward predictive and explainable decision support. Nevertheless, the results should be validated with baseline models and broader institutional datasets before being generalized across agencies.

Keywords: Artificial Intelligence; Random Forest; Civil Service; Human Resource Information System; Explainable Artificial Intelligence; Decision Support System.

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1. Introduction

Digital transformation in government increasingly requires institutions to connect information resources, digital procedures, and analytical functions so that administrative decisions can be made more effectively and with better traceability. In Indonesia, the Electronic-Based Government System (SPBE) provides a policy and institutional basis for linking government processes and information resources rather than maintaining isolated digital services. Evidence from recent studies suggests that artificial intelligence (AI) can improve administrative productivity, responsiveness, and accountability, but its value depends on organizational preparedness, data quality, governance, and appropriate human oversight (Madan & Ashok, 2023; OECD, 2024, 2025; Vial, 2021). The G7 Toolkit similarly places reliable data, governance safeguards, transparency, and human control among the conditions required for responsible public-sector AI adoption (OECD & UNESCO, 2024). Civil-service human resource management is a particularly relevant setting because personnel decisions rely on information generated across many stages of the employee lifecycle, including recruitment, service history, appraisal, competency development, attendance, training, promotion, and organizational assignment. Studies of AI-supported HRM have reported applications in performance assessment, talent management, learning, and workforce analytics (Dima *et al.*, 2024; Pereira *et al.*, 2023; Qamar *et al.*, 2021). At the same time, the literature remains divided among technological, managerial, and organizational perspectives. Recent reviews consequently argue that AI capability should be considered together with human expertise, governance, and organizational processes instead of being treated as an independent technological solution (Chowdhury *et al.*, 2023; Malik *et al.*, 2023; Pan & Froese, 2023). This research focuses on the problem created when civil-service personnel information is distributed among separate applications. In such an environment, officials may have to combine records manually before examining performance, promotion readiness, competency needs, or disciplinary conditions. Conventional systems consequently tend to function as repositories of past administrative events rather than as integrated environments for identifying patterns and anticipating future conditions. AI-based analytics offers a means of extending this role by learning from structured personnel records and producing predictive indicators. Its use in government, however, also introduces concerns about automation bias, excessive reliance on algorithmic advice, privacy, and unequal outcomes (Alon-Barkat & Busuioc, 2023; Madan & Ashok, 2023).

Interpretability is an additional requirement because personnel predictions can influence career development, advancement, and access to organizational opportunities. When the basis of a prediction is opaque, managers may find it difficult to scrutinize or justify the resulting recommendation. Research on explainable AI (XAI) in high-stakes environments therefore emphasizes the provision of interpretable evidence that enables users to examine model behavior while preserving meaningful human oversight (Sahoh & Choksuriwong, 2023). Public-sector AI guidance likewise associates trustworthy deployment with transparency, accountability, and continued human control (OECD, 2024, 2025; UNESCO, 2021). Three gaps emerge from this body of work. First, research on AI adoption in public administration and HRM frequently concentrates on particular functions or organizational conditions instead of an integrated personnel-information architecture (Chowdhury *et al.*, 2023; Votto *et al.*, 2021). Second, studies demonstrate the potential of data-driven public-sector decision support, yet practical implementations that connect multiple personnel sources, predictive analytics, and operational dashboards remain less visible in the literature (Madan & Ashok, 2023; van Noordt & Misuraca, 2022). Third, transparency is often discussed at the level of governance principles, whereas an operational personnel system needs a concrete way to expose influential attributes alongside predictions (Sahoh & Choksuriwong, 2023). The present study addresses these gaps by embedding Random Forest and feature-importance analysis in an integrated civil-service information environment rather than evaluating the predictive model independently. SIPINTAR was developed in response to these gaps as an integrated platform for personnel decision support. Its design combines heterogeneous data integration, centralized analytical storage, Random Forest prediction, feature-importance analysis for XAI, managerial visualization, and an AI Assistant. The study does not claim that Random Forest is intrinsically superior to other classifiers. Instead, its contribution is the implementation of an established ensemble method inside a government personnel-information workflow while making the principal attributes emphasized by the model visible to authorized users. The resulting contribution is therefore centered on practical integration and decision support, with comparative benchmarking, cross-agency validation, and broader fairness analysis left for subsequent research. Four measurable objectives guide the study: 1) construct a personnel-information platform capable of consolidating heterogeneous civil-service records; 2) assess Random Forest for predicting employee performance, promotion opportunity, and disciplinary risk; 3) determine the attributes most influential to model outputs through feature-importance analysis; and 4) evaluate user acceptance through a User Acceptance Test. The empirical study was conducted in an Indonesian government institution identified as Institution X and used personnel information from 2019–2025.

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2. Related Work

The literature relevant to SIPINTAR can be viewed through four connected themes: the adoption of AI and creation of public value in government; AI-supported HRM and personnel analytics; explainability and responsible AI in high-impact decisions; and machine learning for structured tabular data. This thematic arrangement clarifies both the foundations of the study and the point at which the proposed system extends prior work. AI in public administration. Public-sector AI research indicates that implementation is shaped by institutional and governance factors as well as technology. Madan and Ashok (2023) synthesized studies of AI adoption and diffusion and reported recurring tensions involving fairness, transparency, privacy, human rights, and public value. van Noordt and Misuraca (2022) mapped government AI applications and identified internal management as an area of potential use. Charles *et al*. (2022) described the growing role of AI-supported data-driven governance while calling for stronger empirical evidence. From a behavioral perspective, Alon-Barkat and Busuioc (2023) showed that algorithmic advice can produce automation bias and selective adherence. Collectively, these findings imply that effective public-sector AI should augment accountable human judgment rather than simply automate decisions. AI in HRM and personnel analytics. AI applications have expanded across multiple HR activities. Votto *et al*. (2021) identified data-intensive functions such as performance management in their review of tactical HR information systems, while Qamar *et al*. (2021) synthesized AI-HRM applications and highlighted ethical considerations. Pereira *et al*. (2023) showed that workplace outcomes have been examined from several process perspectives, leaving the research field distributed across HR functions. Chowdhury *et al*. (2023) linked AI value in HRM to organizational resources, human capability, governance, and interaction between employees and AI. Malik *et al*. (2023) likewise positioned AI-assisted HRM within a broader strategic framework. More recent studies emphasize that AI changes the responsibilities of HR professionals and requires coordinated human–AI work rather than unrestricted automation (Dima *et al*., 2024; Fenwick *et al*., 2024; Zhai *et al*., 2024).

Explainability and responsible AI. Interpretability is especially important when model outputs can affect personnel-related decisions. A systematic review by Sahoh and Choksuriwong (2023) emphasizes that high-stakes AI requires evidence that users can inspect and question. This requirement is consistent with public-sector guidance that associates responsible AI with transparency, accountability, and human oversight (OECD, 2024, 2025; UNESCO, 2021). SIPINTAR implements a practical interpretation layer through feature importance. The analysis identifies attributes that the Random Forest model relies on more strongly, but these rankings are treated as evidence of model dependence rather than proof that the attributes cause the predicted outcomes. Machine learning for structured personnel data. Random Forest provides a practical option for heterogeneous tabular information because the ensemble combines multiple decision trees and can capture nonlinear interactions without assuming a linear predictor–outcome relationship. Prior studies also show that feature selection and balancing strategies may affect Random Forest performance when class distributions are uneven (Gu *et al*., 2022; Prasetiyowati *et al*., 2022). TabNet offers another relevant direction because its attentive architecture was designed for interpretable learning from tabular datasets (Arik & Pfister, 2021). These approaches establish a useful comparison space for future experiments; they do not justify an unsupported claim that Random Forest is the optimal algorithm for this application. Comparison and positioning. The comparison in Table 1 places the study at the intersection of four strands of prior research. Existing studies generally examine government AI adoption, AI-supported HRM, explainability, or predictive methods as separate concerns. SIPINTAR instead combines personnel-data integration, Random Forest prediction, feature-importance analysis, and managerial interfaces within a single civil-service information environment.

Table 1. Comparative Positioning of Related Studies

No	Author(s)	Year	Research Title	Method	Main Findings	Research Gap
1	Alon-Barkat & Busuioc	2023	Human–AI interactions in public sector decision making	Experimental study	Examined automation bias and selective adherence to algorithmic advice.	Not focused on integrated personnel systems.
2	van Noordt & Misuraca	2022	Artificial intelligence for the public sector	Landscape study	Mapped government AI use, including internal management applications.	Does not provide an integrated civil-service implementation model.

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3	Charles, Rana & Carter	2022	Artificial intelligence for data-driven decision-making and governance in public affairs	Editorial/special-issue synthesis	Highlighted the growth of AI-enabled data-driven governance and the need for stronger empirical evidence.	Limited operational personnel-system detail.
4	Madan & Ashok	2023	AI adoption and diffusion in public administration	Systematic literature review	Identified adoption factors and tensions involving fairness, transparency, privacy, and public value.	Focuses on adoption rather than an integrated personnel platform.
5	Votto *et al.*	2021	Artificial intelligence in tactical human resource management	Systematic literature review	Mapped AI across tactical HRIS functions such as performance and discipline management.	Does not implement a unified government personnel platform.
6	Qamar *et al.*	2021	When technology meets people: The interplay of AI and HRM	Systematic review	Synthesized AI applications in HRM and their implications for decision-making.	Does not address Indonesian civil-service data integration.
7	Pereira *et al.*	2023	AI and workplace outcomes: A multi-process perspective	Systematic review	Showed that AI-HRM research spans multiple functions and organizational outcomes.	Limited operational architecture for public HRM.
8	Chowdhury *et al.*	2023	AI capability framework for HRM	Systematic/bibliometric review	Emphasized organizational resources, skills, governance, and AI–employee integration.	Does not specify an integrated civil-service decision-support implementation.
9	Malik *et al.*	2023	AI-assisted HRM: An extended strategic framework	Systematic review	Proposed a strategic framework for AI-assisted HRM.	Framework-oriented rather than system implementation.
10	Pan & Froese	2023	An interdisciplinary review of AI and HRM	Systematic interdisciplinary review	Identified fragmentation across technical and managerial AI-HRM research.	Does not operationalize the findings in government personnel systems.
11	Sahoh & Choksuriwong	2023	Explainable AI in high-stakes decision-making systems	Systematic review	Established the importance of explanations for high-stakes AI decisions.	Not specific to civil-service HR data.
12	Arik & Pfister	2021	TabNet: Attentive interpretable tabular learning	Deep-learning method	Introduced an interpretable deep model for tabular learning.	Alternative algorithm; not evaluated in this study.
13	Prasetiyowati *et al.*	2022	Random Forest with feature selection and balancing	Empirical ML study	Showed that feature selection and balancing can improve Random	Different datasets and problem domain.

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					Forest performance on imbalanced data.	
14	Dima *et al.*	2024	AI effects on HR activities and the HR triad	Scoping review	Showed changes in HR activities and the need to coordinate human and AI roles.	Does not provide an integrated public-sector implementation.
15	This Study	2026	Random Forest-Based AI for Decision Support in an Integrated Indonesian Civil Service Information System	R&D and system implementation	Integrates multi-source civil-service data, Random Forest prediction, XAI feature importance, dashboards, and AI Assistant.	Baseline comparison and cross-agency validation remain for future

Based on the comparison presented in Table 1, the present study is positioned at the intersection of four strands of prior research. Existing studies generally examine government AI adoption, AI-supported HRM, explainability, or predictive methods as separate concerns. SIPINTAR instead combines personnel-data integration, Random Forest prediction, feature-importance analysis, and managerial interfaces within a single civil-service information environment.

3. Methodology

A Research and Development (R&D) design was used to construct and evaluate SIPINTAR. The software project adopted a Waterfall-based Software Development Life Cycle because requirements, approvals, integration activities, and testing needed to follow a controlled and documented sequence. The stages consisted of requirements analysis, system design, implementation, testing, and deployment. Figure 1 presents the research sequence, whereas Figure 2 depicts the operational software-development flow. To support this process, the system uses a centralized logical Data Lake architecture to receive personnel information from several source applications. Data are transferred through Application Programming Interfaces (APIs) and Extract, Transform, and Load (ETL) processes from SIMPEG, SIKERJA, the Talent and Competency Management System, ULAPEG, and SLKS/Digital ASN Services. The integrated layer supplies the preprocessing and feature-engineering stages before predictions are delivered to analytical and decision-support interfaces. The retained project documentation specifies the logical flow but does not contain physical Data Lake parameters such as node quantity, partition dimensions, replication settings, or storage-retention rules; these characteristics are therefore not claimed in this paper.

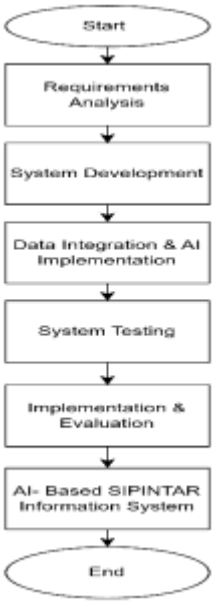


Figure 1. Research Stages Using the System Development Life Cycle (SDLC) Method

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Figure 2. Waterfall-Based System Development Process

System requirements were established through interviews, document examination, and direct observation with personnel administrators, system operators, and organizational decision-makers. These activities produced requirements for multi-source integration, centralized personnel administration, AI-supported decision making, analytical dashboards, timely information access, role-based authorization, and secure API connectivity. The system design covered the database, user interface, integration services, AI module, and data-flow model. The implemented application uses Laravel and communicates with existing personnel systems through RESTful APIs. Functional tests addressed personnel management, data integration, AI prediction, and dashboard functions, after which User Acceptance Testing (UAT) was conducted with administrators, personnel officers, and management representatives. The functional and non-functional system requirements are summarized in Table 2.

Table 2. Functional and Non-Functional System Requirements

Requirement	Description	Implementation Evidence
Multi-source integration	Consolidate personnel data from multiple government systems.	API and ETL integration
Centralized information	Provide a unified personnel information environment.	Central analytical/data layer
AI decision support	Generate performance, promotion, and disciplinary predictions.	Random Forest module
Explainability	Expose influential variables used by the model.	Feature-importance analysis
Managerial analytics	Present workforce indicators and analytical outputs.	SIPINTAR dashboard
Natural-language access	Allow conversational personnel information queries.	AI Assistant
Access control	Restrict system access to authorized users.	Role-based access control
Data protection	Protect personnel information through anonymization and controlled use.	Institutional authorization and de-identification

The research dataset driving this system contains 5,320 civil servants and more than 42,000 historical personnel records spanning 2019–2025. The variables cover age, education, rank/grade, years of service, performance score, attendance, competency, training, position, work unit, promotion status, and disciplinary status. Data preparation included cleaning, duplicate removal, missing-value treatment, categorical conversion, normalization, and feature selection. Because the source documentation does not preserve numerical thresholds for missing-data deletion or anomaly detection, no additional threshold is asserted. Institution X authorized the data for the study; the records were anonymized and de-identified and were used for research and decision-support development. The complete list of dataset variables is presented in Table 3.

Table 3. Dataset Variables

Variable	Description
Age	Employee age
Education	Highest educational attainment
Rank/Grade	Civil-service rank and grade
Years of Service	Length of employment
Performance Score	Annual performance appraisal score (SKP)
Attendance	Attendance records
Competency	Competency assessment result
Training	Training and development history
Position	Job position history
Work Unit	Organizational assignment
Promotion Status	Model target label
Disciplinary Status	Model target label

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To implement the system and process the dataset, a specific software environment was established, comprising PHP 8.2, Laravel 11, JavaScript ES6, MySQL 8.0, Python 3.11, scikit-learn 1.5, pandas 2.2, NumPy 1.26, REST API, Visual Studio Code 1.95, Postman 11, Git 2.47, and a GitLab/GitHub repository. Laravel handled the application layer, MySQL stored structured application data, and Python with scikit-learn supported model development. pandas and NumPy were used for data preparation and numerical processing. This combination matched the requirement for a maintainable web application linked to a Python-based machine-learning workflow. Table 4 details the software tools and technologies used in this study.

Table 4. Software Tools and Technologies

Category	Technology	Version	Purpose
Programming Language	PHP	8.2	Backend development
Framework	Laravel	11	Web application framework
Front-End	JavaScript	ES6	Interactive functionality
Database	MySQL	8.0	Structured data storage
AI Development	Python	3.11	Model development
ML Library	Scikit-learn	1.5	Random Forest implementation
Data Processing	pandas	2.2	Preprocessing and analysis
Numerical Computing	NumPy	1.26	Numerical operations
API Integration	REST API	-	System integration
Development Environment	Visual Studio Code	1.95	Source code development
API Testing	Postman	11	API validation
Version Control	Git	2.47	Source code management
Repository Platform	GitLab/GitHub	Latest	Collaboration and version tracking

The predictive stage of the system uses a Random Forest Classifier formed from an ensemble of decision trees. Given an input vector x, the forest prediction is expressed as the majority vote of T trees, as shown in Equation (1):

$$y^{\wedge} = mode\{ht(x)\} for\ t = 1, \dots, T \quad (1)$$

Feature-importance analysis was used as the Explainable AI (XAI) mechanism to order the attributes most strongly associated with the model's decisions. The available experimental record identifies performance score, competency level, and years of service as the three leading variables. This global model-dependence information gives personnel managers a basis for examining the attributes emphasized by the model instead of viewing only an unexplained prediction. Numerical importance magnitudes were not preserved in the original experiment, so the manuscript reports the ranked attributes without manufacturing percentages or a quantitative importance chart. The evaluation considered three prediction tasks: employee performance, promotion opportunity, and disciplinary risk. An 80% training and 20% testing split was used, with stratified five-fold cross-validation during model development. Predictive performance was measured using accuracy, precision, recall, and F1-score. Separately, system acceptance was examined through a Likert-scale UAT covering functionality, usability, information quality, and user satisfaction. Since the original experiment did not contain a baseline classifier, the Random Forest results are reported as absolute values rather than as evidence of improvement over Decision Tree, Logistic Regression, Support Vector Machine, or XGBoost. The dataset partitioning is shown in Table 5.

Table 5. Dataset Partitioning

Dataset	Percentage
Training Set	80%
Testing Set	20%

The three predictive scenarios were retained as the classification scope. Retirement identification was handled as a rule-based administrative process and was not modeled with Random Forest. The implementation uses 100 trees, maximum depth 10, minimum split size 2, minimum leaf size 1, and random_state = 42. The specific Random Forest parameters applied are listed in Table 6.

Table 6. Random Forest Parameters

Parameter	Value
n_estimators	100
max_depth	10
min_samples_split	2

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min_samples_leaf	1
random_state	42
Cross-validation	Stratified 5-fold

The Random Forest configuration was retained from the original experiment. The documented settings resulted from preliminary experimentation and were intended to maintain a balance between model complexity and computational cost. The depth and minimum-sample constraints were retained as controls over tree complexity, while cross-validation was used to limit dependence on one train-test partition. The original experimental record contains no documented use of class weighting, SMOTE, or another explicit resampling method; consequently, no active class-imbalance correction is claimed. The revision does not add an undocumented hyperparameter search space or an unrecorded class-balancing procedure. To ensure the integrity of the study, several procedures were used to support reliability: the same 80:20 partitioning scheme, stratified five-fold cross-validation, repeated validation during development, and multiple predictive metrics. Model performance and system acceptance were treated as different evidence categories so that user perceptions would not be mistaken for predictive validity. Validity was supported by aligning the selected variables, prediction targets, and evaluation measures with the intended personnel decision-support functions. Data governance was addressed through institutional authorization, anonymization, de-identification, access control, and restricted use of personnel information for the stated research and development activities. Finally, the overall artificial intelligence implementation flowchart within the integrated personnel information system is illustrated in Figure 3.

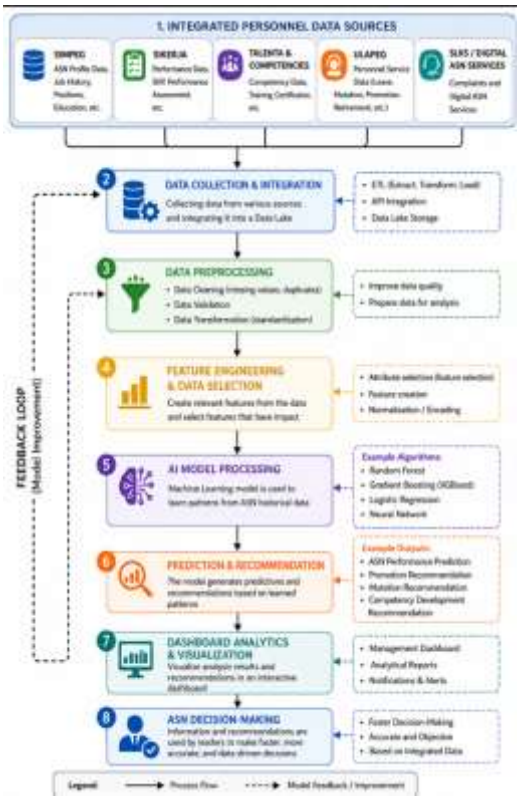


Figure 3. Artificial Intelligence Implementation Flowchart in the Integrated Personnel Information System

As depicted in the flowchart, the implementation sequence tightly couples data ingestion from multiple government platforms with the machine-learning pipeline. This end-to-end integration ensures that the predictive models and explainability features operate directly on updated civil-service records, thereby providing actionable and transparent insights for the subsequent decision-support interfaces.

4. Results and Discussion

4.1 Results

The implemented SIPINTAR application successfully functions as an integrated web-based personnel information environment. Data from SIMPEG, SIKERJA, the Talent and Competency Management System, ULAPEG, and SLKS/Digital ASN Services are brought together through API and ETL mechanisms. The resulting

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flow links source collection, integration, preprocessing, feature engineering, model execution, prediction, dashboard presentation, and human review. Thus, the predictive component is embedded in the information-processing workflow rather than operated as a separate analytical tool. The visual interface of this integrated environment is illustrated in Figure 4.

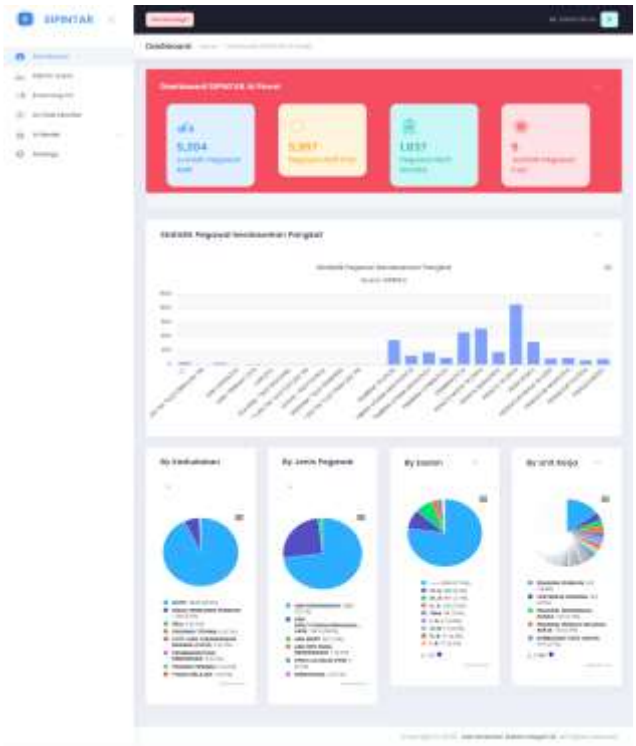


Figure 4. SIPINTAR Application Management Dashboard

The SIPINTAR management dashboard, as shown in Figure 4, consolidates indicators and visual summaries for employee distribution, rank, position, organizational unit, competency, promotion readiness, and disciplinary risk. Presenting these outputs through a common management interface allows the analytical results to support routine monitoring and workforce-planning activities. To support these analytical outputs, the Random Forest algorithm was evaluated for three specific prediction tasks. Employee-performance prediction produced the strongest reported result, with 87.24% accuracy, 86.00% precision, 85.00% recall, and an 85.50% F1-score. Promotion-opportunity prediction reached 85.00% accuracy, 84.71% precision, 83.00% recall, and an 83.50% F1-score. Disciplinary-risk prediction produced 82.00% accuracy, 82.00% precision, 81.92% recall, and an 80.50% F1-score. The model therefore generated usable predictive signals for all three tasks, although the observed performance differed by prediction objective. A complete summary of the model evaluation results is provided in Table 7.

Table 7. Random Forest Model Evaluation Results

Prediction Type	Accuracy	Precision	Recall	F1-Score
Employee Performance Prediction	87.24%	86.00%	85.00%	85.50%
Promotion Opportunity Prediction	85.00%	84.71%	83.00%	83.50%
Disciplinary Risk Prediction	82.00%	82.00%	81.92%	80.50%

Beyond predictive accuracy, feature-importance analysis formed the Explainable AI (XAI) layer and identified the attributes most strongly associated with model outputs. Performance score, competency level, and years of service ranked as the three leading variables. This ranking gives managers additional information for reviewing a prediction and understanding which recorded attributes receive greater emphasis. It should not, however, be interpreted as a causal explanation. Because numerical importance values were not retained in the source experiment, the revised manuscript reports only the ranked variables and does not introduce unsupported quantitative values. The decision-support component places this model-derived information alongside managerial monitoring and workforce-planning functions. Recommendations generated from the analytical layer are presented for examination by authorized personnel before they are considered in personnel actions. Furthermore, a Natural Language Processing (NLP)-based AI Assistant was incorporated into SIPINTAR. Users can formulate personnel-information requests in ordinary language and retrieve information from integrated services without moving through multiple application menus. Its contribution in this study is

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primarily related to accessibility and self-service retrieval. Because the available experiment does not contain an independent NLP accuracy evaluation, no quantitative performance claim is made for the assistant. To evaluate system acceptance, User Acceptance Testing (UAT) was conducted with administrators, personnel officers, and management representatives. The evaluation results, detailed in Table 8, show scores of 92.10% for functionality, 90.80% for usability, 91.60% for information quality, and 91.10% for user satisfaction, yielding an overall mean of 91.40%. These scores indicate strong perceived acceptance of the implemented system. The UAT results are interpreted as evidence of user acceptance rather than as evidence of predictive validity, and the two evaluation dimensions remain separate.

Table 8. User Acceptance Testing Results

Evaluation Aspect	Score (%)
Functionality	92.10
Usability	90.80
Information Quality	91.60
User Satisfaction	91.10
Average Score	91.40

The 91.40% overall UAT value represents the mean of the four assessed dimensions. SIPINTAR demonstrates an integrated operational sequence in which source applications feed a centralized analytical layer, task-specific models generate predictions, and dashboards make the resulting information available to authorized decision-makers.

4.2 Discussion

The results indicate that SIPINTAR addresses the central integration problem by linking heterogeneous personnel sources with predictive analytics and managerial interfaces. The approach complements findings in public-sector AI and HRM literature that emphasize the importance of organizational readiness, data integration, and human involvement in realizing AI value (Madan & Ashok, 2023; Votto *et al.*, 2021). The system therefore represents an operational pathway from fragmented records to a centralized decision-support environment, responding directly to the fragmentation often described in public-sector AI adoption. The study shows that SIPINTAR can consolidate heterogeneous civil-service records and connect the resulting information with machine-learning-based decision support. The strongest Random Forest result was 87.24% accuracy for employee-performance prediction, followed by 85.00% for promotion-opportunity prediction and 82.00% for disciplinary-risk prediction. Feature-importance analysis placed performance score, competency level, and years of service among the most influential attributes. The dashboard and AI Assistant extend access to these analytical outputs, while the UAT assessment produced an overall acceptance score of 91.40%. While the Random Forest results provide useful predictive signals across the three defined tasks, the reported performance should not be interpreted as proof that Random Forest is the best available classifier. Because the original experiment did not include a baseline model, direct comparisons with Logistic Regression, Decision Tree, Support Vector Machine (SVM), or XGBoost cannot be made from the present evidence. This distinction is important when interpreting the 87.24% accuracy obtained for employee-performance prediction.

A further consideration is the risk of bias inherited from historical personnel evaluations. If past appraisal practices systematically favored or disadvantaged particular groups, a predictive model trained on those records could reproduce the same patterns while presenting them in numerical form. The current experiment did not retain subgroup fairness measurements, so this risk cannot be quantified here. Future evaluation should therefore examine error rates and predictive performance across relevant employee subgroups before the system is used for high-impact personnel decisions. Ultimately, the study's main contribution is the operational combination of multi-source personnel-data integration, Random Forest prediction, feature-importance-based explanation, and managerial visualization within an Indonesian government setting. This architecture demonstrates how a personnel information system can be extended from historical record administration toward predictive and explainable decision support. The contribution concerns integration and implementation; it should not be read as evidence that Random Forest outperforms all competing algorithms.

5. Conclusion and Recommendations

Interpretation of the findings in this study is subject to several constraints. The data originate from one anonymized government institution, limiting direct transferability to other agencies. No baseline classifier was included in the original experiment, preventing measurement of the additional value of Random Forest relative to alternative methods. The source experiment also did not retain numerical feature-importance values, subgroup fairness measures, or explicit numerical thresholds for data-cleaning decisions. Furthermore, physical

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Data Lake characteristics and large-scale operational performance were not tested experimentally. These limitations restrict the broad generalization of both the predictive metrics and the User Acceptance Testing (UAT) results.To address these limitations, future research should begin with controlled benchmarking against alternative algorithms such as Logistic Regression, Decision Tree, Support Vector Machine (SVM), XGBoost, and TabNet using identical data partitions, repeated cross-validation, and metrics that account for class imbalance. Fairness analysis should then compare performance and error rates across relevant employee subgroups and examine whether historical appraisal practices introduce systematic bias. Additionally, interpretable tabular models like TabNet can be evaluated as alternatives for improving both predictive and explanatory capabilities (Arik & Pfister, 2021). Federated learning offers another avenue for cross-agency analysis when raw personnel records cannot be centralized, provided that suitable privacy and security controls are maintained. Finally, longitudinal monitoring should be implemented to detect concept drift, recalibrate models, and preserve human oversight in high-impact personnel decisions.

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