IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 6, December 2026, pp. 5448~5463
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i6.pp5448-5463

Predictive assessment of e-Puskesmas using COBIT 2019 and random forest algorithm

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Article Info

Article history:

Received Oct 27, 2025
Revised Aug 10, 2026
Accepted Aug 31, 2026

Keywords:

COBIT 2019
e-Puskesmas
Machine learning
Predictive assessment
Random forest

ABSTRACT

Bekasi City's electronic public health center (e-Puskesmas) system handles thousands of patient records daily, yet its information technology (IT) governance performance for risk and service management had never been assessed predictively. This study combined control objectives for information and related technology (COBIT) 2019 with machine learning (ML) to fill that gap. This study visited 16 community health centers and collected 58 questionnaire responses covering align, plan, and organize 12 (APO12) (managed risk) and deliver, service, and support 02 (DSS02) (managed service requests and incidents) domains. Using random forest (RF), this study built a model that predicts capability levels from yes-or-no answers, achieving an overall accuracy of 0.83. APO12 scored 83.52% at level 2, still one step behind its level 3 target. DSS02 performed better at level 4 with 79.4%, meeting its target. Risk management proved slightly more influential than service management, with importance scores of 0.5172 versus 0.4828. However, the model failed to predict low-maturity cases due to limited data, and the findings are limited to the two assessed management objectives. Future research should expand the assessment to additional COBIT domains, incorporate metric-based measures, and collect more comprehensive data. This predictive approach offers health officials clearer direction for improvements, particularly in documenting risks and setting service resolution targets.

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1. INTRODUCTION

Computers aren't just helpful anymore—they're absolutely essential if we want to see any real forward movement in science and tech now [1], [2]. The ongoing advancement of information and communication technologies, along with their increasingly widespread integration into industrial sectors and the social fabric, is significant [3]. Since the start of the digital era, computers have been widely used for data processing, reporting, and storage [4], [5]. Thus, it can be said that computers have transformed from a tool to a major foundation in today's human civilization [6].

In fact, they correspond to the different types of digital services offered today, free or reserved, under agreements previously concluded, for certain users [7]. The problems that emerge fall under three categories: technology, organizational structure, and the regulatory framework. Hospitals and other health facilities, as government institutions, continue to implement computer-based services for the general public [8]. Understanding these three aspects is crucial for the organizations involved.

These days, digital developments are making their mark on how hospitals operate [9]. The healthcare sector manages massive amounts of patient medical records [10], complete histories of diagnoses and healthcare data among facilities [11]. These days, information technology (IT) is woven into the fabric of most businesses, helping them run more effectively and efficiently [12]–[14]. Organizational sustainability today is closely tied to IT, which enhances both operational speed and business effectiveness [15]. In addition to system evaluation, critical cloud considerations include service models, deployment strategies, and relevant actors [16]. Electronic health record (EHR) systems have revolutionized the healthcare industry by enabling the efficient storage, retrieval, and sharing of patient health information [17]. These days, community clinics rely on the electronic public health center (e-Puskesmas) platform to assist with their healthcare duties. With e-Puskesmas, patient recording and data collection are done electronically [18], mainly related to unauthorized access to EHR when different healthcare service providers maintain records [19], so that the data needed to be used can be immediately processed and informed. Efforts to improve IT services [20], it's necessary to audit governance and services so that in the future there will be no problems. Control objectives for information and related technology (COBIT) 2019, developed and published by Information Systems Audit and Control Association (ISACA), is a framework that can serve as a standard reference for conducting audits and IT governance within an organization [21], [22].

This study focuses on two of the 35 COBIT 2019 management objectives: align, plan, and organize 12 (APO12) and deliver, service, and support 02 (DSS02). These objectives were selected because they represent key operational aspects of the e-Puskesmas system—specifically, risk management and service request handling. Consequently, the study's findings measure the capability maturity levels of only these two management objectives and cannot be generalized to the e-Puskesmas IT governance system as a whole.

The auditing profession is only one of several industries that have seen changes due to the ongoing digital transformation. Emerging technologies such as artificial intelligence (AI), blockchain, data analytics [23], machine learning (ML), and computer science can be connected with audit science so that they can provide new knowledge and help society in general. ML is a subfield of artificial intelligence that may have better prediction performance and higher interpretability than traditional statistical methods for prediction [24]. While they offer descriptive insights, traditional COBIT-based audits are not predictive [25], [26].

Traditional IT governance frameworks like COBIT are indeed important for structured audits and controls; however, their retrospective and descriptive nature is increasingly perceived as inadequate amidst the rapid pace of digital transformation [27]. The dynamic and complex nature of modern IT environments demands a shift from reactive assessments to proactive, predictive insights [28]. This is where the power of ML becomes critical [29]. With predictive algorithms, auditing is no longer merely a matter of compliance; it has become a strategic tool capable of identifying future risks and performance bottlenecks—going beyond the assessment of current conditions [30], [31].

This study presents a ML method that uses the random forest (RF) algorithm [32], [33] to forecast the capability maturity levels of the APO12 and DSS02 domains to improve decision assistance in IT governance evaluation [34]. For social scientists, such developments in algorithms are useful only to the extent that they can access an implementation of the algorithm [35]. Through this integration, audit datasets may be automatically learned from, and important factors influencing APO12 and DSS02 performance can be found.

2. METHOD

Through an integrated ML-based IT audit architecture for better vulnerability prediction, this study improves audit risk modelling accuracy and adaptive anomaly intervention [36], [37]. Effective turnaround was achieved through the introduction of internal controls, strengthening governance and oversight, and the implementation of adequate records management practices [38]. COBIT 2019 is a comprehensive framework aimed at the enterprise as a whole; the results show there are certain aspects of the framework that directly or indirectly relate to digital literacy [39], [40]. While this research is still predictive in nature, it is expected to provide more robust and responsive interventions [41]. Integrating two branches of computer science is essential for addressing the sustainability development goals (SDGs), particularly in relation to knowledge. The integration of cutting-edge ML algorithms with data balancing and feature reduction techniques has sharply enhanced the identification of fraudulent medicare claims [42]. For prediction tasks, why does RF perform better than linear regression? Although this assumption simplifies while interpretable, the model frequently falls short in predictive adaptability [43]. The Puskesmas is a government agency responsible for

handling health complaints. As previously outlined, evaluations and audits will be executed utilizing the COBIT 2019 framework and ML techniques.

The questionnaire items used in this study were developed based on selected process activities from the APO12 and DSS02 domains. For APO12, the assessment covered activities from levels 0 to 3 (6 activities). For DSS02, the assessment covered activities from levels 0 to 4 (14 activities). While these represent a substantial subset of the required activities, it is important to acknowledge that a complete COBIT 2019 assessment would require evaluation of all management practice activities for each objective. The framework and research flow for this research are as shown in Figure 1. The study on e-Puskesmas audits at Bekasi City's community health centers is carried out in four phases: i) requirement analysis; ii) data collection; iii) exploring ML into COBIT 2019; and iv) recommending results. COBIT 2019-based assessment of selected management objectives, this study integrates a ML model using the RF algorithm to perform predictive analysis of capability levels and identify key governance factors within the APO12 and DSS02 domains.

The explanation begins with primary data, then moves on to the ML integration process with COBIT 2019, as shown in Figure 2 (part of Figure 1). The stages begin with preprocessing, which includes data cleaning, gap, and capability calculations. After that, capability level calculations (scoring) are performed, followed by feature selection to obtain indicators from the APO12 and DSS02 domains. These values are used to train the model using the RF algorithm. Finally, the analysis results from both domains are used to compile recommendations and conclusions for e-Puskesmas governance.

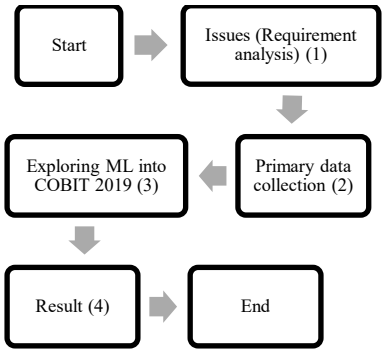


Figure 1. The framework and research flow

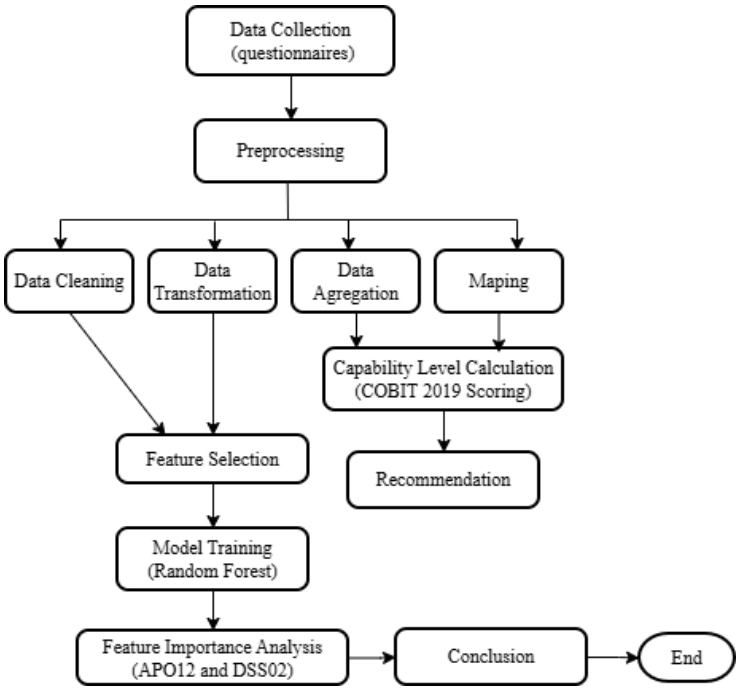


Figure 2. The flowchart of the COBIT 2019 framework and ML-based models

2.1. COBIT 2019 framework

COBIT 2019 is a comprehensive framework for IT governance and management published by ISACA [44]. An IT audit is an independent and objective examination of an organization's IT infrastructure to ensure that information management complies with policies, safeguards assets, maintains data accuracy, and operates effectively and efficiently in achieving organizational goals [45]. To address organizational issues, an evaluation of IT governance and management capability levels will be conducted using the COBIT 2019 framework [46]. This framework consists of documentation and guidelines aimed at helping organizations effectively implement IT governance. COBIT 2019 organizes IT governance into two main categories: evaluate, direct, and monitor (EDM), 5 objectives; management objectives, 35 objectives: i) APO, 13 objectives; ii) build, acquire, and implement (BAI), 10 objectives; iii) DSS, 6 objectives; and iv) monitor, evaluate, and assess (MEA), 6 objectives [47]–[49].

2.2. Capability level

The process capability level is a measure of how well a process is implemented and performed [50]–[52]. Management and calculation of questionnaire data in determining the COBIT 2019 capability level [53], [54] from each activity is calculated and processed [55] using (1).

$$Percentage = \frac{\sum_{i=1}^{n} R_i}{n} \times 100\% \quad (1)$$

In (1) explains the domain achievement score, which is calculated by dividing the number of domains declared "yes or checklist" by the number of indicators/questions within that indicator. Table 1 shows the level of achievement of control and audit processes for each COBIT domain.

Table 1. Capability level interpretation

Level	Interpretation	Score range (%)
1	Not achieved	0 – < 15
2	Partially achieved	15 – < 50
3	Largely achieved	50 – < 85
4	Fully achieved	85 – 100

Based on Table 1, a process reaches the expected capability level only if it achieves a "fully achieved" rating, meaning a score above 85% [56]. After calculating the capability level, the next step is to determine the gap analysis, as per the formula and gap analysis table in (2).

$$GAP = Domain_{to-be} - Domain_{as-is} \quad (2)$$

The gap analysis will reveal the maturity level achieved in the APO12 (target level 3) and DSS02 (target level 4) domains. It is hoped that these results will encourage Puskesmas, as e-Puskesmas providers, to improve services and continuously enhance quality in the future.

2.3. COBIT 2019 and machine learning integration mapping

Integrating COBIT 2019 with ML requires a clear mapping between the framework's components and the analytical approaches applied in this study. Through its governance and management objectives—each encompassing management practices and specific process activities to establish expected performance levels—COBIT 2019 provides a structured framework for assessing IT governance [57]. The relationship between COBIT 2019 components and ML approaches is established through the following mapping, as shown in Table 2.

Table 2. COBIT 2019 and ML mapping

COBIT 2019 component	Study assessment	ML role
Process activities (e.g., APO12.01, DSS02.01)	Questionnaire items (40 questions) representing specific activities	Features (predictor variables)
Management practices	Grouped questions by COBIT levels (0-4)	Feature groups for domain-level analysis
Capability indicators	Yes/No responses encoded as 1/0	Binary feature encoding for model input
Capability level	Percentage scores mapped to levels (0-4)	Target variable for prediction
Scope	APO12 (level 0-3) and DSS02 (level 0-4)	Domain-specific model training and evaluation

2.4. Preprocessing

In general, text cleaning is typically one of the data preprocessing procedures that are completed [58]. The preprocessing can not only improve the quality of data but also shorten the calculation process and effectively improve the accuracy and performance [59] of the information system audit prediction. The preprocessing step included cleaning, encoding [60], and converting qualitative audit data from the COBIT 2019 evaluation into a numerical format suitable for ML analysis. The sequence of data cleaning steps during preprocessing is crucial—it can determine the success or failure of the process, especially given that these steps are sometimes repeated [61]. Data transformation is crucial in modern analytics, involving the cleaning, integration, and preparation of data from diverse sources, as well as addressing missing values, inconsistencies, and redundancies [62]. Furthermore, the discussion covers data aggregation calculations and crucial factors that must be considered in every project—ranging from data quality and scope to data suitability [63]. The historical institutional context of the organization enables both aggregation (sector mapping) and comparison, resulting in contextual and targeted mapping [64]. This study obtained preprocessing data using a questionnaire given to respondents in the community health center environment. The codes for each "Yes" and "No" or checklist response were 1 and 0, respectively. After calculating the percentages for each of the COBIT 2019 domains (DSS02 and APO12), the total audit scores were determined. The COBIT 2019 capacity criteria were then used to map these scores into capability levels (1–4). An RF model was trained using the generated dataset to predict the IT governance competence level (APO12 and DSS02 management) of the e-Puskesmas system.

In this study, preprocessing methods—specifically, data processing from questionnaires—are introduced and validated. The qualitative approach refers to the preprocessing method that collects data through observations and interviews at community health centers using e-Puskesmas. Meanwhile, the quantitative approach refers to the questionnaire distribution method used to collect data, which will then be processed and generated based on capability maturity and decision-making using an RF. The data preprocessing workflow is illustrated in Figure 3.

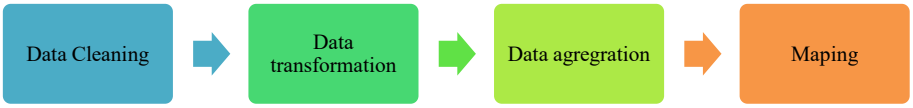


Figure 3. Workflow of data preprocessing

2.5. Feature selection

Feature selection is a procedure that involves using a set of rules to determine the relative importance and ranking of the attributes in a dataset [65]. Feature selection varies across classifiers, as each classifier achieves optimal performance with distinct attribute subsets for more robust results [66]. Chi-square function of a word against a category is obtained from (3) [67], feature selection was performed with the single Chi-square value of a term by summing the Chi-square value of a term for each category with k categories using (4) [68].

$$\chi^2 = \sum_{ri}^{=1} \sum_{j}^{=1c} \left(O_{ij} - E_{ij}\right)^2 / E_{ij} \quad (3)$$

$$E_{ij} = \left(J_i \times K_j\right)/N \quad (4)$$

Where χ^2 is the Chi-square value; O_{ij} is observed frequency in row i, column j; E_{ij} is expected frequency in row i, column j; J_i is total of row i; K_j is total of column j; N is total number of respondents; r is number of rows (2: Yes and No); and c is the number of columns (3: low, medium, high). Random feature selection enhances diversity via the random sampling of predictor variables at each nodal split [69], lowering tree correlation and improving generalization.

2.6. Model training

During model training, the algorithm tracks the total reduction in domain COBIT 2019 impurity each time a variable is used to split high and low, aggregated across all models in the forest [70]. This method constructs an ensemble of decision trees, where each tree is trained on a random subset of the dataset,

reducing overfitting and improving predictive accuracy [71]. The process begins with domain-level sampling, where multiple samples are created from the training data to ensure diversity in the dataset [72].

2.7. Feature importance

Feature importance methods provide useful insights into the data generating process under certain conditions [73]. Some of these tools are model specific, such as feature importance plots or permutation method, while some others are model agnostic, such as Shapley values [74]. Although post-training feature importance approaches assist this interpretation, there is an overall lack of consensus regarding how feature importance should be quantified, making explanations of model predictions unreliable [75].

3. RESULTS AND DISCUSSION

This study used data from an audit of IT governance in the e-Puskesmas system of 58 respondents from several Puskesmas regional technical implementation unit (UPTD) work areas in Bekasi City. The audit was conducted based on the COBIT 2019 framework, focusing on two main domains: manage risk (APO12) and manage service requests and incidents (DSS02). To figure out exactly what the platform needs to do, consult with stakeholders, conduct interviews, and gather feedback through surveys [76]. The collected data is then processed and analyzed quantitatively and qualitatively to produce a comprehensive and objective capability level assessment [77].

The COBIT 2019 terms these design factors—critical considerations for enterprises in tailoring governance systems to optimize IT value realization [48]. This study addresses various serious IT issues such as data loss, project failures, and application errors, as well as issues related to vendor services, regulatory compliance, and IT resource constraints. Other issues discussed in this study include IT projects that often deviate from business needs, innovation implementation that is always delayed due to obstacles in the existing system architecture, and of course the classic problem of data quality and its integration from various sources. So, to measure the level of maturity of IT governance, the research team calculated an audit score based on the average value of two domains, namely APO12 and DSS02, the results of which are presented as a percentage.

So, to predict the maturity level of IT governance, researchers used a RF method with one hundred decision trees. The data itself was taken from audit answers for each item, then divided into two parts: 70% for training and 30% for testing. The results were quite astonishing because the model was able to predict accurately—almost 100% in the test. When checked using a confusion matrix, it turned out that the model's predictions were exactly the same as the actual conditions. This means that this method has proven effective for predictions in conditions like this.

3.1. Preprocessing

Based on the data obtained from the questionnaires, 58 respondents completed them correctly. The questionnaires were distributed to the city and district of Bekasi, covering 16 areas: Pengasinan, Bekasi Jaya, South Tambun, Bojong Menteng, Rawalumbu, Mustika Jaya, Marga Mulya, Sepanjang Jaya, Sukakarya, Bintara, Pondok Gede, Jatimakmur, Pondok Melati, Setu, Jatibening, Jatiasih. In this data preprocessing, based on the questionnaire data obtained, as shown in Table 3.

Table 3. Data questionnaires

Data	Sum
Question	40
Respondents	58
Distribution area	16
Job titles	3

The data in this study were taken from a questionnaire that refers to the COBIT 2019 framework, specifically the APO12 domain levels 0-3 and DSS02 levels 0-4. The respondents were 58 randomly selected Puskesmas officers, consisting of 2 heads/managers, 11 admins, and 45 operators. After the data was collected, data cleaning was carried out by removing unnecessary columns such as timestamps, names, locations, and positions. The goal was to facilitate the data transformation phase. Now, in the transformation phase, "Yes" and "No" answers from the questionnaire were processed into an assessment to measure the level of IT governance maturity in the e-Puskesmas system. Each question actually represents a control activity in the COBIT 2019 domain. For data cleaning and data transformation, it will be processed in feature selection. The data APO12 can be seen in Tables 4 and 5 shows the data DSS02.

Table 4. Data APO12

Domain	Checklist					
	Q1	Q2	Q3	Q4	Q5	Q6
APO12 level 0	56					
APO12 level 1	48					
APO12 level 2	49	50	50	50		
APO12 level 3	27	40	16	25	20	20

Table 5. Data DSS02

Domain	Checklist													
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14
DSS02 level 0	57													
DSS02 level 1	47													
DSS02 level 2	48	48	50	41	47	50	43	50	51	51	42	45	34	45
DSS02 level 3	45	42	40	43	38	45	47							
DSS02 level 4	17	30	34	52	54									

3.2. Capability level calculation

The aggregation and mapping data will be processed to obtain the COBIT 2019 capability level calculation. The data aggregation APO12 is shown in Table 6. Data aggregation DSS02 is shown in Table 7.

Table 6. Data aggregation APO12

Domain	Percentage						Average
	Q1	Q2	Q3	Q4	Q5	Q6	
APO12 Level 0	96.55						96.55
APO12 Level 1	82.76						82.76
APO12 Level 2	84.48	86.21	86.21	77.19			83.52
APO12 Level 3	46.55	68.97	27.59	43.10	34.48	34.48	42.53

Table 7. Data aggregation DSS02

Domain	Percentage														Average
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	
DSS02 level 0	98.3														98.3
DSS02 level 1	81.0														81.0
DSS02 level 2	82.8	82.8	86.2	70.7	81.0	86.2	74.1	86.2	87.9	87.9	72.4	77.6	58.6	77.6	79.4
DSS02 level 3	776	72.4	69.0	74.1	65.5	77.6	81.0								73.9
DSS02 level 4	29.3	51.7	58.6	89.7	93.1										64.5

Table 8 shows the capability level results for the APO12 domain. Level 0 scored 96.66%, meaning it was fully achieved. Levels 1 and 2 were categorized as largely achieved. However, the gap between levels was 42.53%, meaning they were only partially achieved. So, it could be said that the APO12 domain has only reached level 2, even though the evaluation target was level 3. Therefore, improvements will be made in the next evaluation to achieve the target.

Table 8. Capability level APO12

Domain	Score's (%)	Interpretation
APO12 level 0	96.55	Fully achieved
APO12 level 1	82.76	Largely achieved
APO12 level 2	83.52	Largely achieved
APO12 level 3	42.53	Partially achieved

In Table 9 of the capability level maturity DSS02, level 0 obtained a score of 98.3% with interpretation capability fully achieved, for levels 1, 2, 3, and 4 with interpretation capability largely achieved. This means that the capability level maturity DSS02 domain has achieved the level 4 target, so the evaluation is in accordance with the target. The gap analysis results, as shown in Table 10, will be derived from the APO12 and DSS02.

Table 9. Capability level DSS02

Domain	Average (%)	Interpretation
DSS02 level 0	98.3	Fully achieved
DSS02 level 1	81.0	Largely achieved
DSS02 level 2	79.4	Largely achieved
DSS02 level 3	73.9	Largely achieved
DSS02 level 4	64.5	Largely achieved

Table 10. Gap analysis result

Domain	Current capability value (as-is)	Expected capability value (to-be)	Gap
APO12 (manage risk)	Level 2	Level 3	1
DSS02 (manage service requests and incidents)	Level 4	Level 4	0

Looking at Table 10, there's a single-level view. This indicates that the current risk management process (APO12) is operational and under control (level 2), but is not yet mature enough to become a formal, defined standard across all organizational units (level 3). Meanwhile, in domain DSS02 (manage service requests and incidents), there are no gaps; this process is already at the targeted maturity level.

3.3. Recommendation

Based on the findings from the data transformation, several recommendations can be made. For the APO12 level 3 domain, there needs to be a clear division of roles and responsibilities within the e-Puskesmas IT risk management team. Furthermore, there should be documented risk management plans, a structured and regularly updated risk register, and training on IT risk management standard operating procedures (SOPs). Meanwhile, for the DSS02 level 4 domain, there needs to be a resolution timeframe for each e-Puskesmas incident and service request.

3.4. Feature selection

In RF, feature selection is pivotal for identifying attributes with the greatest impact on model performance [78]. Based on data from 58 respondents and 40 questions, the feature selection process was conducted using the Chi-square method. The results obtained from this analysis revealed that there were 30 features containing complaints, as shown in Figure 4.

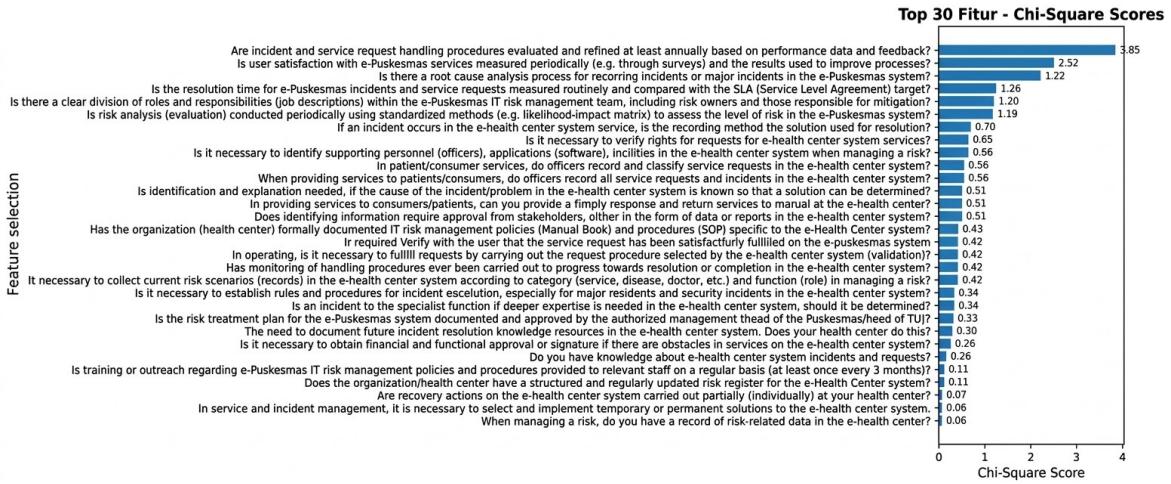


Figure 4. Feature selection 30 features–Chi-square

3.5. Model training

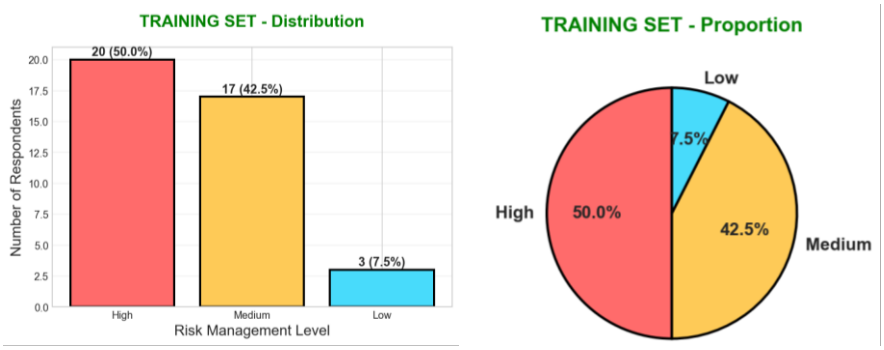
The training model utilizes the training data (44 samples - 70% of total) presented in Table 11 and Figure 5, where Figure 5(a) shows the APO12 and Figure 5(b) shows the DSS02, as well as the testing data (19 samples - 30% of total) presented in Table 12 and Figure 6, where Figure 6(a) shows the APO12 and Figure 6(b) shows the DSS02. Based on Figure 5 and Table 11, the training data consists of 40 respondents grouped by risk management level. Twenty respondents (50%) were at the "high" level, 17 respondents

(42.5%) were at the "medium" level, and only three respondents (7.5%) were at the "low" level. This indicates an imbalanced distribution, with high-risk respondents dominating the training set.

Table 12 and Figure 6 present test data from 18 respondents grouped into three risk management levels. Nine respondents, or half of the total, were at the "high" level, while eight (44.4%) were in the "medium" category, and only one (5.6%) was at the "low" level. This composition indicates that the majority of respondents in the test data came from the high- and medium-risk groups.

Table 11. Training set APO12 and DSS02

Class	Data samples	Training set (%)
Low	3	7.5
Medium	17	42.5
High	20	50.0

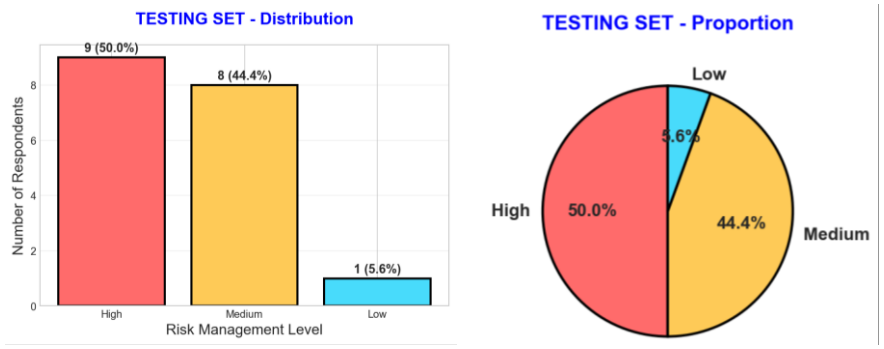


(a) (b)

Figure 5. Training set of (a) APO12 and (b) DSS02

Table 12. Testing set APO12 and DSS02

Class	Data samples	Testing set (%)
Low	1	5.6
Medium	8	44.4
High	9	50.0



(a) (b)

Figure 6. Testing set of (a) APO12 and (b) DSS02

3.6. Feature importance

The feature importance section presents Figures 7 to 10, which show the most influential features along with their importance scores, the number of features selected at the 80% and 90% thresholds, the distribution of importance scores, and the confusion matrix of the classification results. Based on the dataset analysis, the feature importance values were obtained. These results are summarized in Table 13 and Figures 7 to 10. Figure 7 shows the top 20 important features with their importance scores, Figure 8 shows the number of features selected at 80% and 90% thresholds, Figure 9 shows the distribution of feature importance scores, and Figure 10 shows the confusion matrix of the classification results, respectively.

Table 13 shows the classification performance of the RF model for predicting capability levels across the APO12 and DSS02 domains. The model achieved an overall accuracy of 83%, with excellent performance for high (F1-score = 0.88) and medium (F1-score = 0.89) classes. However, the model failed to predict the low class (F1-score = 0.00) due to severe data imbalance, where only 1 out of 18 test samples belonged to the low category. This limitation is acknowledged in the conclusion and addressed as a key direction for future research, including collecting more data from low-capability Puskesmas and applying synthetic minority over-sampling technique (SMOTE) to balance the dataset.

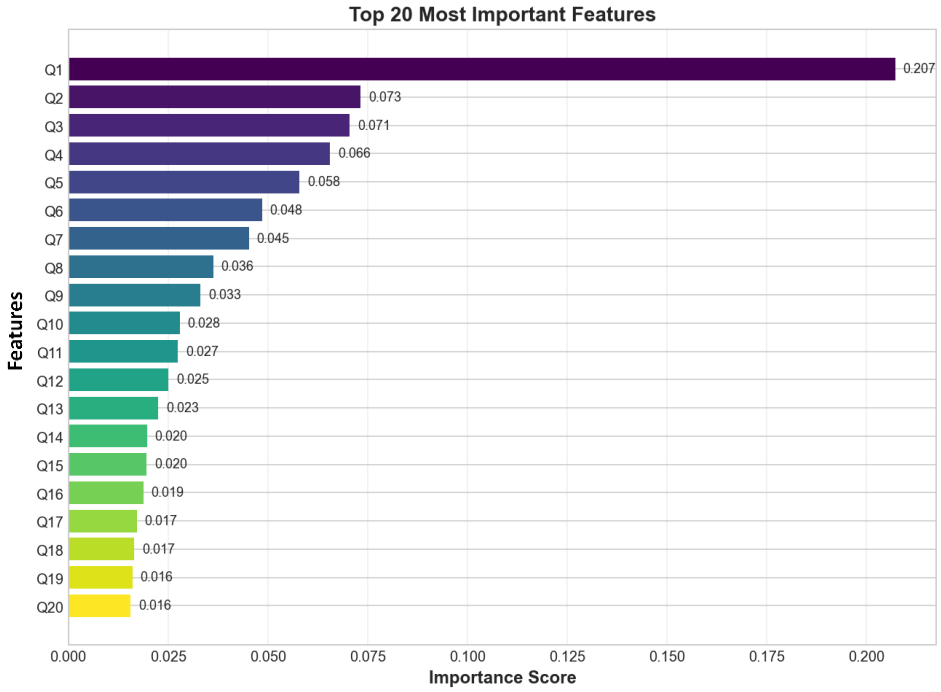


Figure 7. Feature importance analysis from e-Puskesmas, consisting of top 20 important features

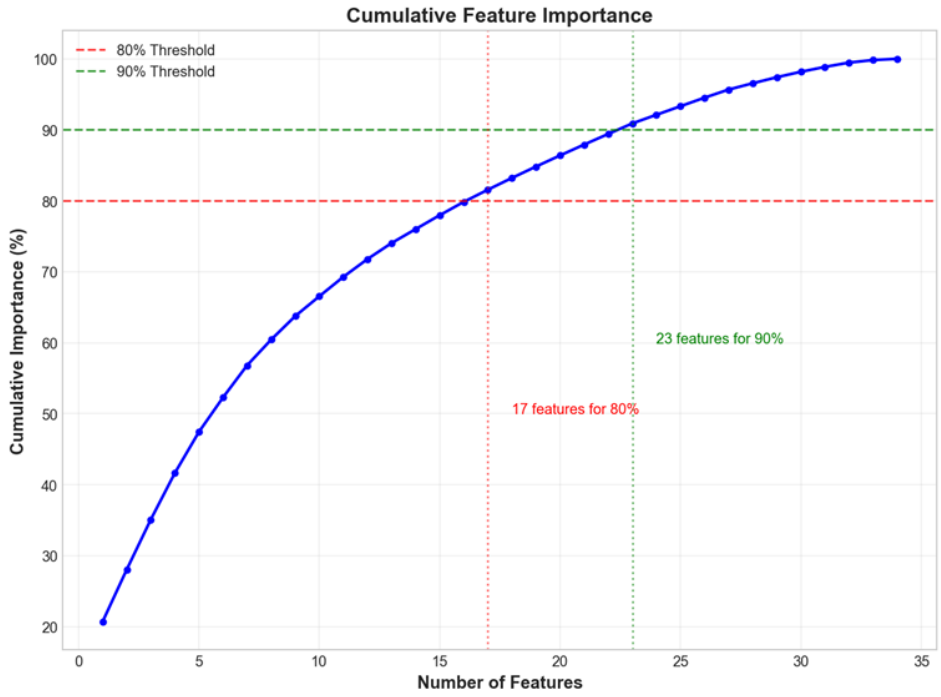


Figure 8. Feature importance analysis from e-Puskesmas, consisting of features selected at thresholds

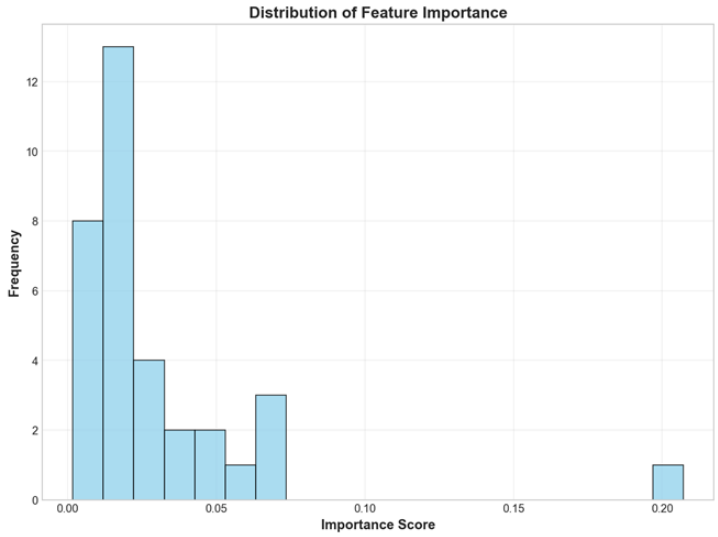


Figure 9. Feature importance analysis from e-Puskesmas, consisting of distribution of feature importance scores

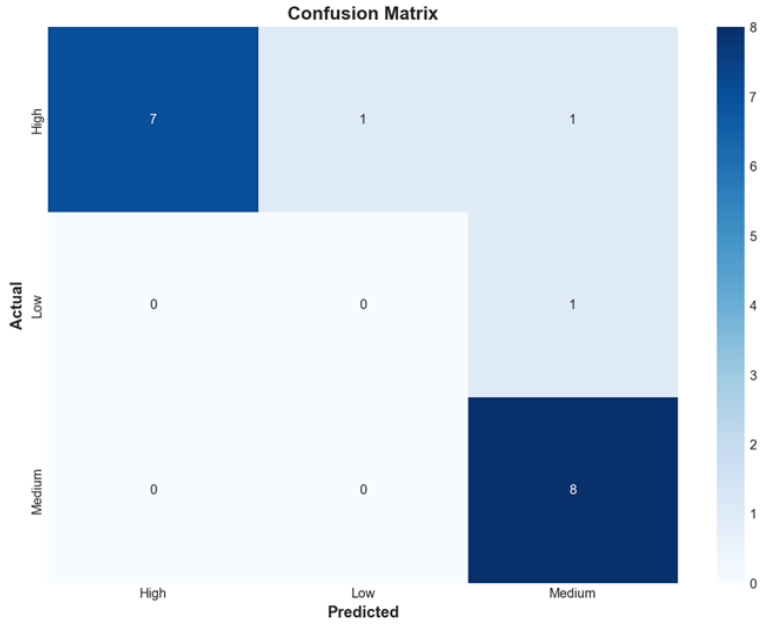


Figure 10. Feature importance analysis from e-Puskesmas, consisting of confusion matrix of classification results

Table 13. Classification results for domains APO12 and DSS02 in COBIT 2019

Classification report	Precision	Recall	F1-score	Support
High	1.00	0.78	0.88	9
Low	0.00	0.00	0.00	1
Medium	0.80	1.00	0.89	8
Accuracy			0.83	18
Macro average	0.60	0.59	0.59	18
Weighted average	0.86	0.83	0.83	18

4. CONCLUSION

This study aims to determine whether e-Puskesmas governance can be predicted rather than merely assessed. Based on data from 58 respondents across 16 Puskesmas in Bekasi, the capability level for the

APO12 domain (risk management) reached level 2 with a score of 83.5%—one level under the target. Meanwhile, the DSS02 domain (managed service requests and incidents) met the level 4 target with a score of 79.4%. Furthermore, feature analysis revealed that risk management exerted a slightly greater influence than service management, with weights of 0.5172 and 0.4828, respectively. The RF model developed in this study was reasonably accurate in predicting medium and high levels (achieving an F1-score of 0.83) but failed to identify low levels due to data imbalance. These findings indicate that while the model can be used to screen for priority health centers, it cannot be relied upon to detect centers with critical issues. However, it is important to emphasize that the findings of this study are limited to the APO12 and DSS02 management objectives and do not represent an overall assessment of the e-Puskesmas IT governance system, which would require evaluation of all 35 COBIT 2019 management objectives and 5 governance objectives. Additionally, the questionnaire data used in this study covered only selected process activities rather than all management practice activities prescribed by COBIT 2019, and used binary (yes/no) responses instead of metric-based measures as recommended by the framework. These limitations must be considered when interpreting the results.

5. FUTURE WORK

In the future, researchers need to increase data collection from Puskesmas with low governance or use the SMOTE technique. Furthermore, future research should expand the assessment to include additional COBIT 2019 domains, utilize metric-based performance measures for each management practice activity, and collect more comprehensive data covering all required activities to achieve a complete capability level assessment. Despite its limitations, this study demonstrates that combining COBIT 2019 with ML is possible and beneficial. This kind of predictive approach, in the proposed opinion, is a new direction for IT governance audits, not only for e-Puskesmas but also for other digital government systems.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to all respondents from the Community Health Centers in Greater Bekasi for their valuable participation. This research was supported by Bina Insani University.

FUNDING INFORMATION

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. No funding was raised or provided for the conduct of this study.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

This study does not involve individual personal data or identifiable human subjects. Therefore, informed consent was not required.

ETHICAL APPROVAL

This study did not involve human participants or animals, and therefore did not require ethical approval. All procedures were conducted in accordance with relevant institutional and national guidelines.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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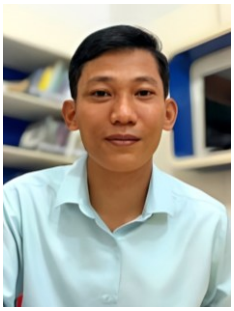

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