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Interpretable Ensemble Learning for Online Public Acces Catalog Technology Acceptance Prediction

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ABSTRACT

The Online Public Access Catalog (OPAC) is a digital system that enables users to search for library references through an online interface using keywords. OPAC has been implemented to enhance IAIN Kediri library services. However, its usage has never been evaluated, resulting in limited understanding of user acceptance levels. This study aims to predict the acceptance of OPAC and identify the most influential variables using interpretable ensemble learning methods. This research used cross sectional design with data collected via a survey involving 400 IAIN Kediri students who had experience using the OPAC system. The study integrates the Technology Acceptance Model (TAM) with the Value-Based Adoption Model (VAM) framework. Predictor variables consist of Perceived Usefulness, Perceived Ease of Use, Intention, Technicality, and Enjoyment. The target variable was Actual Use. The measurement scale uses a Likert scale of 1 to 5. The instrument has been tested for validity and reliability. Ensemble learning algorithms used include Random Forest, AdaBoost, XGBoost, Lightgbm, and Catboost, with SHAP applied for model interpretability. Among the models tested, XGBoost achieved the highest predictive accuracy. SHAP analysis revealed that Enjoyment was the most significant factor influencing OPAC acceptance. These results demonstrate the effectiveness of interpretable ensemble models in predicting technology acceptance and suggest their potential as an alternative to data analysis methods. OPAC development can be done by improving the user interface and developing applications on Android.

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A. INTRODUCTION

The digital era demands continuous improvement quality in library services, especially integration of online system that enhance accessibility and responsiveness. Libraries are now expected to offer real-time and accurate information regarding their collections, enabling users to retrieve references quickly and efficiently. The Online Public Access Catalog (OPAC) was a technology that is comprehensively able to answer the challenges and meet expectations of library users in digital era (Nirwana et al., 2021). This technology has several advantages such as high efficiency, reliability, maintainability, and usability (Adjei et al., 2024). Previous research prove that OPAC enhance user satisfaction by optimizing time and cost of user (Afridar et al., 2022; Ardyawin & Afrina, 2023). Therefore, almost all libraries use OPAC to manage their collections.

IAIN Kediri Library has adopted OPAC for increasing library quality services. The entire collection of books, journals, and other academic references has been integrated into the OPAC. This integration enhances the efficiency of accessing reference within the library, which in turn contributes to optimal time utilization and increased academic productivity for student and lectures (Nwobu & George, 2024). Although digital systems can improve the quality of services, adopting this system will pose its own challenges in its implementation especially user acceptance of the technology. Acceptance of technology can be influenced by several multidimensional factors such as sociodemographic, environmental, and cultural (Alqudah et al., 2021; Suyanto, 2022). IAIN Kediri has significant socio-demographic diversity. The background of students comes from various types of educational institutions, both religious and general. This diversity has the potential to provide differences in the level of acceptance of OPAC.

Furthermore, the utilization of the OPAC in IAIN Kediri, has not been systematically evaluated by institution since its implementation several years ago. This has an impact on suboptimal development because there is no accurate source of information regarding the acceptance of this technology by users. Previous research has explained that technology prediction is one of the key factors in the successful implementation of a technology (Chung et al., 2023). This situation requires comprehensive evaluation measures to be taken regarding OPAC in supporting services. Comprehensive evaluation and prediction of OPAC services can refer to the conceptual framework of technology acceptance. Technology Acceptance Model (TAM) is the most widely used framework for measuring and predicting technology acceptance (Santini et al., 2025).

TAM has the advantage able to measure technology acceptance down to the individual level based on functional factor (Wang et al., 2023). Previous studies have adopted the Technology Acceptance Model (TAM) as a conceptual basis for evaluating and measuring user acceptance of technology (Fernanda et al., 2022; Rahayu & Sayekti, 2023). Integrating TAM with Value Adoption Model (VAM) will provide a more comprehensive because it not only measures acceptance based on its function but also on the value given by users to the technology (Widyarini, 2022). Research related to the integration of TAM and VAM was very limited, thus opening a research gap to measure OPAC acceptance using both frameworks to obtain more comprehensive results.

Significant research gap was also found in data analysis methods used. Majority research used multiple linear regression analysis, structural equation models (SEM) for evaluating and technology acceptance prediction (Hidayah & Fernanda, 2021; Setiya Putra, 2023). However, both data analysis methods has limitations when implemented on real data. This method requires that the data must be normally distributed and there must be no multicollinearity between the predictor variables. These limitations can significantly reduce flexibility and accuracy of the analysis. Therefore, a more flexible and accurate analysis method is needed to handle real data. The Interpretable ensemble learning method is a flexible method, has good accuracy for prediction, and does not require any assumptions (Chung et al., 2023).

Interpretable ensemble learning is an integration of ensemble learning techniques with interpretation techniques in machine learning. This integration aims to obtain good accuracy and still have a comprehensive interpretation about data. Ensemble learning works by combining multiple machine learning models to get predictions from a single model. Combining the results of multiple models will produce better accuracy than using just one model (Akano & James, 2022; Laftah & Al-Saedi, 2024). The Shapley Additive Explanations (SHAP) method is an interpretation method for ensemble learning by calculating the contribution of each predictor based on game theory (Lamane et al., 2024). The lack of research focusing on the application of interpretable ensemble learning to predict OPAC acceptance in library services based on the integration of TAM and VAM, provides an opportunity to explore interpretable ensemble learning for OPAC technology prediction.

This research aims to predict the level of OPAC acceptance prediction using the Interpretable Ensemble Learning. This research used 5 ensemble models consisting of Random Forest, Adaptive Boosting (Adaboost), Extreme Gradient Bossting (XGboost), LightGradient Boosting (Lightgbm), and Categorical boosting (Catboost). This research also provides new insights regarding the application of ensemble learning as an alternative method in data analysis and provides a comprehensive analytical of OPAC technology acceptance based on Perceived Usefullness, Perceived Ease of Use, Intention, Enjoyment, and Actual Use. It is hoped that this research will provide new insights and provide accurate information that can be used as a basis for developing OPAC.

B. METHODS

This research used cross-sectional design. The research data was collected through a survey using a Google form on IAIN Kediri students. The population of this study is based on the average number of students visiting to library monthly. The information was obtained from the library database. The minimum sample size is calculated using the Slovin formula which is based on the total population information availability factor in the study which refers to the average number of library visits per month. In addition, this study also did not differentiate students based on certain groups, such as regional origin or faculty, so that the Slovin formula can be applied accurately in this study. Total population in this study was 6000. The number of research samples was calculated using the Slovin formula with margin of eror of 5%. Total sample size of this research was 400 samples.

The instrument in this study refers to the TAM and VAM frameworks as the theoretical basis for measuring technology acceptance. The TAM framework includes the variables of Perceived Usefulness, Perceived Ease of Use, Intention, and Actual Use. The VAM framework in this study uses the variables Technicality and Enjoyment. A Likert scale with details of 1: Disagree, 2: Less Agree, 3: Agree, 4: Strongly Agree was used to measure the assessment of respondents. A preliminary survey of 30 respondents was conducted to ensure the validity and reliability of the questionnaire. The questionnaire has met the validity aspect based on the results of the validity test where each indicator has a correlation value above 0.361 and a Cronbach alpha value above 0.6, as shown in Table 1.

Table 1. Research Variable

Variable	**Target/Predictor**	**Number of Question**
Perceived Usefulness	Predictor	3
Perceived Ease of Use	Predictor	5
Intention	Predictor	3
Technicality	Predictor	3
Enjoyment	Predictor	4
Actual Use	Target	3

The research was conducted through 5 stages with the following details.

1. Data collection using Google Form and checking missing value.
   The first stage of this research is data collection through google form. At this stage, the research was assisted by library staff to distribute google form questionnaire to IAIN Kediri students who had used OPAC. The data that has been collected is checked for missing values. This process is carried out to ensure that the data is complete for analysis.
2. Splitting data into training and testing data
   The data was divided into training and testing data with a composition of 80% training data and 20% testing data. Training data is used for modeling, and testing data was used to measure the accuracy of the Random Forest, Adaboost, XGboost, Lightgbm, and Catboost models using the Root Mean Square Error (RMSE) value.
3. Model Development
   Prediction of acceptance of OPAC technology in this study uses 5 ensemble learning methods which are specifically explained as follows.
   a. Random Forest
   Random forest (RF) work by starting by sampling *n* data (sampling with replacement) from the training data and repeating r times to form a new training data set (D_1, D_2,…D_r). The next process was builds decision tree $f_i(x)$ from D_1, D_2,…D_r. The prediction results from RF are a combination of predictions from several decision trees using the majority vote scheme. When the target is numerical varible or regression case, the final prediction is the average of the predictions of all decision tree models with formula (Bulagang et al., 2020) (Cheng et al., 2023).

$$f(x) = \frac{1}{r}\sum_{i=1}^{r} f_i(x) \qquad (1)$$

   RF is able to overcome overfitting events and is not sensitive to outlier data (Cha et al., 2021).
   b. Adaptive Boosting
   Adaptive Boosting (Adaboost) is part of various ensemble learning algorithm that has a procedure for combining many weak learner models into a more accurate model to make predictions (Ding *et al.*, 2022). The working principle of adaboost is done by doing initial weighting on all training data. Modeling is done through iterations and at each iteration, weight updates and loss calculations are carried out. The final model is the weighted median of all existing decision tree models. In the iteration process, adaboost uses weighted empirical loss with the following formula (2).

$$L_D(h; \ell) = \sum_{i=1}^{m} D_i \ell\big(y_i, h(x_i)\big) \qquad (2)$$

   c. XGBoost
   XGboost is a part of boosting algorithm that works by building decision trees sequentially. Predictions from XGBoost are a combination of predictions from all decision trees built (Su et al., 2023). The XGboost formula is as follows:

$$y_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = y_i^{(t-1)} + f_t(x_i), f_k \in F, i \in n \quad (3)$$

t is a decision tree
n : sample
f_t : decision tree t
F : collection of all decision trees

d. LightGBM
Lightgbm has advantages in terms of computational time efficiency compared to other ensemble models. Microsoft developed this model for both classification and regression cases. Lightgbm has 6 components consisting of Histogram-based learning, Leaf-wise Tree Graph, Gradient Based One Side Sampling, 4. Exclusive Feature Bundling, Parallel and GPU Learning, and Regularization (Ramalingam et al., 2024)

e. Catboost.
Catboost was developed by Yandex in 2017 and is a development of the Gradient Boosted Tree introduced by Yandex in 2017. Catboost has a symmetrical tree formation procedure that is different from the trees used in XGBoost and lightgbm. Symmetrical trees provide better accuracy and computation time. Catboost has the advantage of avoiding events that cause overfitting during modelling (Chang et al., 2023) (Geeitha et al., 2024) (He et al., 2024).

4. Model Evaluation
The evaluation of 5 ensemble learning models is based on the smallest Root Mean Square Error (RMSE) value. Several studies on machine learning use RMSE values to see the accuracy of the models built (Miller et al., 2024; Rai et al., 2022). Model with the smallest RMSE was selected as the best model

5. Determine importance variable Shapley Additive exPlanations (SHAP).
The contribution of the variables Perceived_Usefullnes, Perceived_ease_of_use, Intention, Technicaly, Enjoyment to Actual_Use is measured using the Shapley Additive exPlanations (SHAP) method. SHAP from other methods is also displayed to see the consistency of the contribution of the predictor variables when using other ensemble methods. SHAP didasarkan kepada game theory dengan prosedur menghitung rata-rata prediksi dari semua kombinasi dari variabel predictor yang ada (Feretzakis et al., 2024). Previous research on interpretable machine learning, using SHAP to determine the variables that have the highest contribution [26][27][28]. The stages in the study are presented in figure 1.

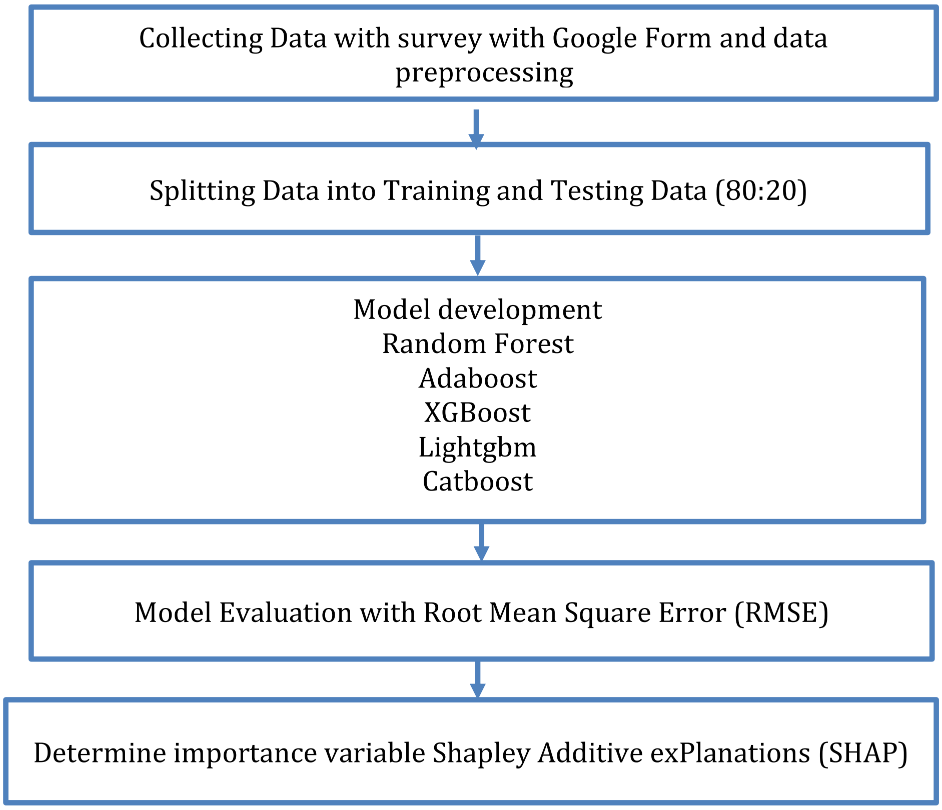

Figure 1. Research Procedure

C. RESULT AND DISCUSSION

1. Descriptive Statistics

The distribution of respondents' answers for the 6 variables in the study is presented in Figure 2. The distribution pattern of respondents varies from a score of 1 to a score of 4. Majority respondents gave an assessment of a score of 3 where this value has the meaning that the respondent have good rating on OPAC. This information is known from the pattern in the histogram which tends to center around a score of 3 on all variables, as shown in Figure 2.

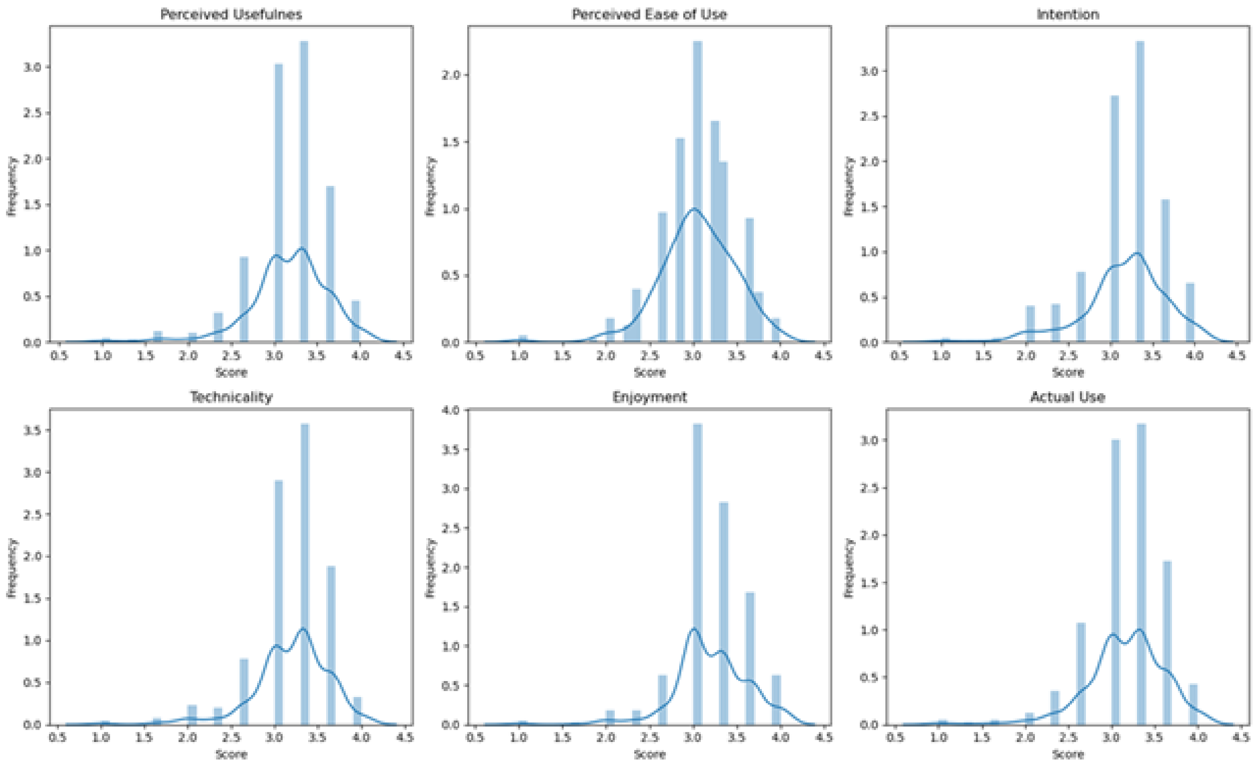

Figure 2. Histogram of six variables

Table 2 provides a more comprehensive interpretation of the data distribution in terms of the average value and standard deviation. The Enjoyment variable received the highest an average value of 3.21. The lowest average values was given by users on the Perceived Ease of Use variable.

Table 2. Mean and standar deviation

Variable	Mean	Standar Deviation
Perceived Usefulness	3,17	0,46
Perceived Ease of Use	3,06	0,43
Intention	3,17	0,50
Technicality	3,20	0,44
Enjoyment	3,21	0,43
Actual Use	3,17	0,45

The correlation analysis in this study aims to provide an overview of the relationship between predictor variables and target variables. The correlation analysis is presented using a heatmap graph presented in Figure 3. The correlation value between the correlation values of the variables Perceived_Usefulness, Perceived_ease_of_use, Intention, Technicality, Enjoyment to Actual_Use are 0.56, 0.52, 0.56, 0.56, and 0.58, respectively. This correlation value classified into the moderate category. heatmap, providing a visualization of the relationship between variables in the study.

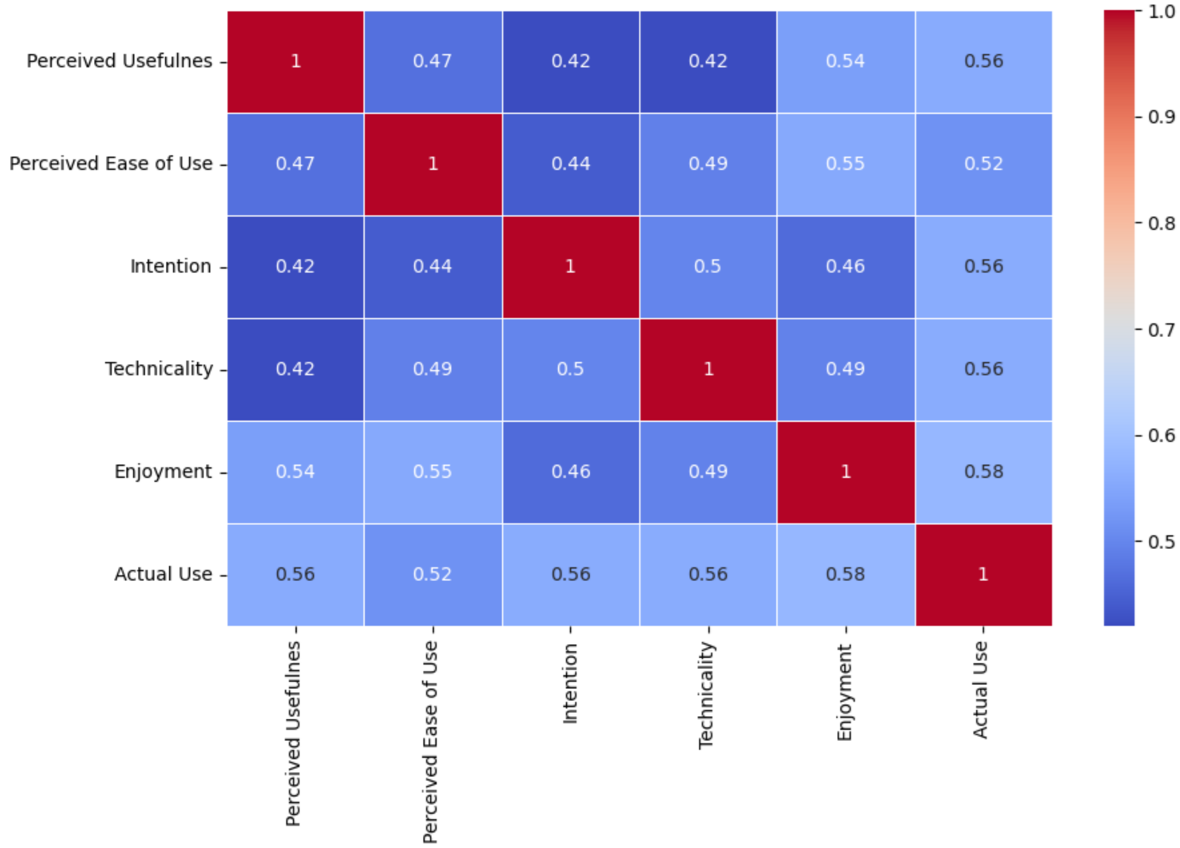

Figure 3. Heatmap correlation between variables

2. Model development and Evaluation

OPAC technology acceptance modeling uses 5 ensemble learning models. Random Forest Regression, Adaboost Regression, XGBoost, Lightgbm, and Catboost was used in this research. The accuracy of the five models was measured using the RMSE. RMSE is one of the parameters used to measure the accuracy of predictions. This value represents the average difference between actual data and predicted data. The smaller the RMSE value, the more accurate the predictions produced. The RMSE value also has the advantage of being easier to interpret than the MSE value.

Table 3. Model Evaluation with RMSE

Ensemble methods	Root Mean Square Error (RMSE)
Random Forest	0.3321
Adaboost	0.3443
XGBoost	0.3303
Lightgbm	0.3522
CatBoost	0.3358

XGBoost has the lowest RMSE value compared to other ensemble learning methods, with a value of 0.3303. The implication of this RMSE value is the level of prediction error of the XGBoost model with actual data of 0.3303. The basic model used is a decision tree. The formation of a decision tree iteratively is done by adjusting the errors of the previous model.

This method also uses L1 and L2 regularization techniques which function to prevent overfitting events in modelling and the model will be more robust when there is outlier data.

3. Determine Importance Variable and Discussion

SHAP Value gives explanation about contribution of each predictor to Actual to Use. The variable that is at the top of the X-axis is the variable with the highest contribution compared to other variables. Based on Figure 4, each ensemble method has different results related to the contribution of each variable. XGboost was the best model with the variable that has the largest contribution is Enjoyment. This result is supported by Adaboost and Lightgbm model.

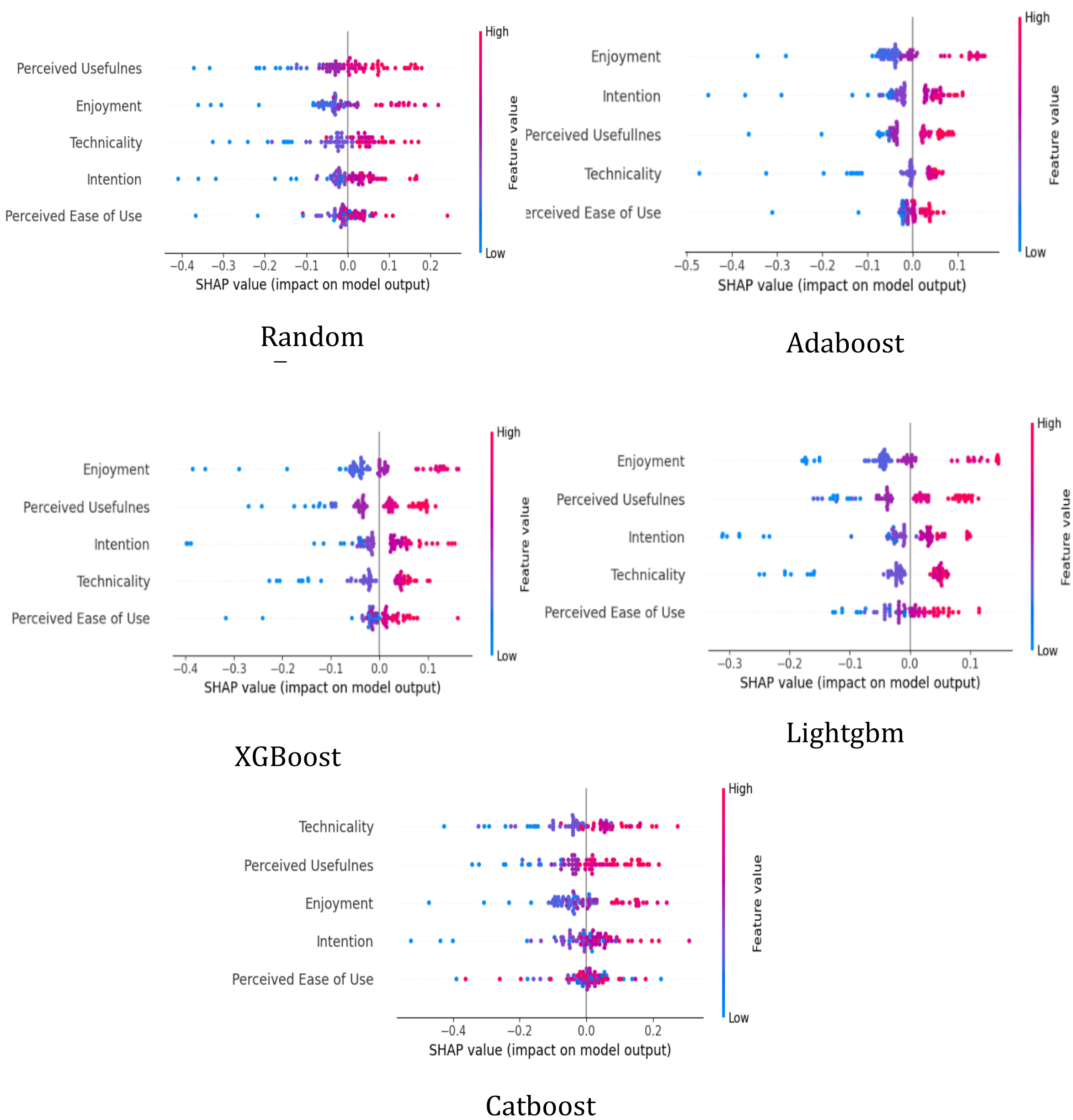

Figure 4. SHAP Value of ensemble learning methods.

The second variable that has the largest contribution was Perceived_Usefullnes. Lightgbm and Catboost methods also produces that Perceived_Usefullnes was the second variable that has the largest contribution. The mean value of SHAP on the enjoyment variable is 0.66. The value provides information that increasing enjoyment of OPAC will increase the prediction of OPAC acceptance by 0.66. This value also represents that 22% of the predicted range of OPAC acceptance can be represented by enjoyment. Based on the evaluation of five ensemble models using RMSE, the XGboost method has the smallest RMSE value and is the best model compared to the other models. This result consistent with the results of studies in several other cases which show that the XGBoost model provides better performance when compared to models such as Deep Neural Network, Lightgbm, catboost, Random Forest (Shahani et al., 2021; Tang, 2024).

XGBoost outperforms other methods because it has better efficiency and uniqueness compared to other methods. Model formation in XGBoost works within the Gradient Boosting framework by integrating several weak classifiers, namely trees, iteratively to produce a stronger classification model (Alizamir et al., 2025). In addition, the advantage of XGBoost lies in the process of combining Decision trees which is carried out iteratively by adding L1 and L2 loss functions so that it can prevent overfitting and able to handle complexity in the data. Decision tree works iteratively by considering prediction errors from previous decision trees so that the resulting Decision tree becomes better (Tarwidi et al., 2023). Previous studies have integrated XGBoost with other methods and consistently produced better accuracy for handling imbalanced data and small data (Imani et al., 2025; Velarde et al., 2024).

The results of the analysis using SHAP resulted in the conclusion that Enjoyment was the variable that has the highest contribution in predicting Actual Use of OPAC. Figure 4 explained that library users who enjoy using OPAC for library services will have an impact on increasing the acceptance of OPAC technology for library services, which is indicated by the increasing Actual Use value of the OPAC. Enjoyment is an indicator of intrinsic motivation which is a positive response from individuals. Enjoyment is a parameter that can be used to measure the level of enjoyment of a product or technology created. In this study, enjoyment is focused on the use of OPAC technology to support library services (Rihidima et al., 2022).

OPAC as a service in the IAIN Kediri library is very relevant to current technological developments. Users give an assessment that the enjoyment of using OPAC is very good. Users feel that searching for information using it is very easy and enjoyable. In addition, the menus available in the IAIN Kediri OPAC provide a pleasant experience. The UI used is very intuitive, and the search features are very easy to understand. IAIN Kediri Library must always innovate to improve the quality of services using OPAC. This innovation can be done by improving more sophisticated search features and providing book recommendations based on user characteristics. For example, students from the Faculty of *Tarbiyah* will get recommendations that are relevant to the field of Education. In addition, OPAC also needs to be developed in the form of an Android application, so that it can increase the level of comfort and satisfaction of users in accessing library services.

D. CONCLUSION AND SUGGESTIONS

The results of the study revealed that the XGBoost method is superior compared to other ensemble learning methods. The importance analysis using SHAP identified the enjoyment variable as the factor with the largest contribution in predicting the acceptance of OPAC technology with mean SHAP of 0.66. This value represents that 22% of the predicted range of OPAC acceptance can be represented by enjoyment. The findings of this study reveal several innovations that must be carried out for the development of OPAC. UI needs to be improved to be more interactive so that the level of satisfaction and enjoyment of users will increase. OPAC must also implement a recommendation system that is able to provide reference recommendations based on characteristics such as faculty of origin or user preferences based on borrowing history. In addition, OPAC must also be developed in an Android application so that it will be easier to access via smartphone.

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