

Predicting willingness to pay for digital waste services using class-balanced machine learning

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ABSTRACT

As urban waste generation continues to increase, digital waste management applications offer a promising solution, yet their scalability is often constrained by low user adoption and uncertain willingness to pay (WTP). This study proposes a supervised machine learning (ML) framework to predict individual WTP for digital waste services using survey data from 400 residents of Gorontalo City, Indonesia, where fewer than 60% of households receive reliable waste collection. A random forest (RF) classifier with class-balancing and F2 score optimization was developed to prioritize recall of potential payers. The model achieved strong performance (F2 score: 0.81) and revealed occupation, app usability perception, and cost tolerance as top predictors. Feature importance analysis, correlation assessment, and boxplot visualization further clarified the behavioral and socio-economic drivers underlying payment decisions. By emphasizing recall over precision, the framework minimizes the risk of excluding willing participants and supports inclusive service planning. Beyond the local case study, the proposed approach applies to other cities with similar waste management constraints and emerging digital service ecosystems, offering a transferable decision-support tool for data-driven pricing, outreach, and policy design.

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1. INTRODUCTION

Solid waste has emerged as one of the fastest-growing environmental challenges globally. According to the Global Waste Management Outlook, municipal solid waste is projected to rise from 2.24 billion tons in 2016 to nearly 3.5 billion tons by 2050 if left unaddressed [1]. In Indonesia, the situation is similarly critical: waste generation reached approximately 67.8 million tons in 2020, yet only 60% of urban households benefit from regular collection services, and just 55% of waste is appropriately processed [2]. This discrepancy between waste generation and management capacity has contributed to environmental degradation, public health risks, and rising greenhouse gas emissions, particularly in rapidly urbanizing regions.

Recent advances in digital technology, particularly the widespread adoption of smartphones and the development of internet of things (IoT) infrastructure, have enabled a new class of smart waste management solutions. These include mobile applications that facilitate bin monitoring, schedule optimization, and behavior-based incentives such as gamified recycling [3], [4]. However, despite their technical promise, many of these platforms suffer from low adoption and high churn, often because they fail to integrate seamlessly into users' daily routines or fail to communicate tangible benefits [5]. This phenomenon of

“digital waste” underscores the importance of not only understanding adoption drivers but also forecasting individuals’ willingness to pay (WTP) for premium digital waste-management services

In Southeast Asia, several recent studies have advanced the empirical understanding of WTP for enhanced waste services. For instance, Khuc and Tran [6] proposed the contingent valuation machine learning (CVML) framework, which combines unsupervised clustering with supervised prediction to estimate continuous WTP values for environmental improvements in Vietnam. While innovative, their framework does not predict binary adoption decisions for specific digital services, nor does it address class imbalance—a common issue in predicting rare events like actual payers [7]. Similarly, Ananno *et al.* [8] employed Tobit regression to evaluate determinants of WTP for e-waste recycling in Bangladesh. Although they identify attitudinal and socio-demographic predictors, the study remains limited to traditional econometric approaches without leveraging supervised machine learning (ML) or predictive performance optimization. Meanwhile, Suryawan and Lee [9] examine citizens’ WTP for adaptive municipal solid-waste management in Indonesia using a mixed logit model to capture preference heterogeneity and estimate average WTP for service improvements. Like the prior studies, it delivers valuable aggregate insights but stops short of predicting individual subscription behavior, and it offers no mechanism for balancing or optimizing predictions for the underrepresented group of actual payers.

Against this backdrop, this study introduces a novel ML-based framework to forecast individual-level WTP for a digital waste-management application, contextualized within Gorontalo City, Indonesia—a city where over 4,000 tons of waste are generated daily, yet only half of residents receive reliable collection services [10]. This study addresses key methodological gaps by i) applying a class-balanced random forest (RF) classifier to correct for the imbalance between willing and non-willing payers, ii) using the F2 score as the primary optimization metric to emphasize recall of true payers, and iii) interpreting feature importance to identify the most influential socio-demographic and behavioral factors.

2. METHOD

This study proposes a ML-based framework to predict individual WTP for a digital waste management application in Gorontalo City. The methodological pipeline involved five key stages: survey-based data collection, multi-stage preprocessing, model development, evaluation, and interpretability analysis. Each step was designed to ensure reproducibility, predictive robustness, and theoretical alignment with WTP research. The survey instrument captured input across four conceptual domains, which reflect the key factors identified in prior literature as influencing both adoption and WTP: i) ease of use, as framed by the technology acceptance model [11], referring to the perceived usability of waste services and digital tools; ii) socio-demographic characteristics, such as age, gender, education, and occupation, were included because these factors shape individuals’ access to information, which influences acceptance and willingness to engage with smart waste management systems [12]; iii) behavioral and attitudinal factors, including recycling habits and environmental concern [13]; and iv) cost considerations, encompassing acceptable subscription price ranges and perceived value [14]. These domains not only structure the input features used in the model but also support interpretability and policy relevance in the context of urban waste management.

To ensure the dataset was analytically robust and model-ready, this study implemented a rigorous, multi-stage preprocessing pipeline that goes beyond the more simplistic workflows common in prior WTP studies [6], [8], [9]. First, this study conducted a structural sweep to remove any rows or columns comprised entirely of missing values, avoiding the skew these can introduce in downstream computations. For numeric fields, particularly respondents’ age, we employed a targeted regular expression parser to extract valid integer values and applied mean imputation after IQR-based outlier filtering to minimize distortion caused by extreme values [15], [16].

Categorical variables were handled with nuanced encoding [17]. Binary variables, such as whether respondents found current services adequate, were mapped to 0 and 1. Cost ranges, which are inherently ordinal, were recoded onto a 5-point gradient to retain the low-to-high scale of payment tolerance. Nominal variables such as gender, education, occupation, sorting behavior, and interest in using the application were label-encoded individually rather than combined into grouped list structures [18]. This resulted in a fully flattened, column-wise matrix, enhancing compatibility with ML models and enabling transparent, interpretable feature-level analysis. This level of detail distinguishes our preprocessing workflow from earlier research that often relied on bundled or simplified data transformations.

For model development, this study employed an RF classifier, selected for its robustness in handling mixed data types, non-linear feature interactions, and its ability to yield interpretable feature importance metrics [19]. To address the inherent class imbalance, where non-payers typically outnumber individuals willing to pay, this study applied the `class_weight = “balanced”` parameter. This adjustment ensures that minority classes (i.e., the “willing to pay” group) are appropriately weighted during model training,

preventing bias toward the majority class. This step was essential for improving the model's recall, ensuring that individuals likely to pay for improved waste services were not underrepresented in the predictions.

Model performance was assessed on a held-out test set using four evaluation metrics: accuracy, precision, recall, and the F2 score. Accuracy provided a general overview of model correctness, precision measured the reliability of positive predictions, recall captured the coverage of true positives (i.e., actual payers), and the F2 score emphasized recall over precision through a recall-weighted harmonic mean [20]. This study selected the F2 score as the primary optimization metric because failing to identify individuals who are genuinely willing to pay carries greater consequences than incorrectly classifying non-payers in the context of public service outreach.

Hyperparameter tuning was performed using GridSearchCV, common hyperparameters tuned include the number of trees (`n_estimators`), tree depth (`max_depth`), and minimum samples per node. GridSearchCV optimization consistently improved model accuracy compared to non-tuned models. For instance, in breast cancer classification, accuracy increased from 0.9480 to 0.9545 [21]. All configurations were evaluated using the F2 score as the guiding metric. This prioritization aligns with real-world deployment objectives [22], [23], where ensuring no potential subscriber is overlooked is more critical than eliminating occasional over-predictions.

To enhance the interpretability of the model outputs and strengthen the connection between predictive results and policy implications, this study conducted a multi-step interpretability analysis following model training and evaluation. First, this study extracted feature importance scores from the optimized RF classifier to identify the most influential predictors driving WTP decisions. This step revealed which features the model relied on most during decision-making, providing insight into how various user traits contributed to the final predictions. To further validate and complement this result, we performed a correlation analysis, quantifying the linear associations between individual features and the WTP outcome. This helped confirm which predictors were not only algorithmically important but also statistically aligned with the target behavior. Finally, to explore how key features behave across WTP classes, this study employed boxplot visualizations for the most prominent variables to allow us to examine their distributional patterns and behavioral differences between those willing and not willing to pay. Together, these interpretability steps reinforced the robustness and transparency of our model, transforming raw predictions into actionable insights that can guide digital waste service design, targeted pricing, and user segmentation strategies.

3. RESULTS AND DISCUSSION

Table 1 presents a sample of the fully flattened and analysis-ready feature matrix produced after preprocessing. Each variable occupies a single column, clearly indicating how values were imputed, encoded, and scaled. This approach contrasts with earlier studies that often provided limited detail regarding missing value handling or combined multiple attributes within a single table cell. This comprehensive preprocessing strategy, which includes outlier-filtered imputation, scale-aware encoding, and clear feature flattening [16], [17] ensures that subsequent modeling steps, including class-balanced RF classification and F2-driven hyperparameter tuning, are built upon a transparent and reliable data foundation. Such rigor improves predictive performance while also enhancing the reproducibility and interpretability of the results.

Table 1. Sample of the preprocessed data

ID	Age	Gender	Education	Occupation	Ease of use	App interest	Cost category	Sorting behavior	WTP
110	68	1	1	50	1	2	2	3	1
270	15	1	0	50	0	2	1	2	1
226	53	0	3	50	0	1	2	3	1
310	82	1	3	50	1	3	1	1	1
39	15	1	2	50	1	0	1	1	1

Once the dataset is fully flattened and each feature occupies its own column, our next step is to partition the data into training and testing sets. This study perform a stratified 70:30 split [24], which preserves the original proportion of respondents who are willing (and not willing) to pay. This split ensures that the model can learn from a substantial portion of the data while being evaluated on unseen data to assess its generalization capabilities. Aligned with Joseph and Vakayil [25], the stratified split was employed to ensure that the target variable WTP was evenly represented in both the training and testing sets. This step was crucial for maintaining the class balance between the “willing to pay” and “not willing to pay” groups, which is especially important when working with classification models like RF.

Following the data split, an RF classifier was initialized with the `class_weight` parameter set to “balanced”. This configuration compensated for the minority class by penalizing misclassification of willing payers more heavily during training, thereby preventing bias toward the majority class. Samad *et al.* [26] have done this in a manner to detect phishing uniform resource locators (URLs), thus, we train this baseline model on the 70% training data and generate initial predictions on the 30% holdout to establish a benchmark for accuracy, precision, recall, and the F2 score—the latter chosen because recall (identifying every potential payer) is more critical than precision in our context.

To address the class imbalance inherent in the dataset, Ivanov *et al.* [27] introduced the use of the “`class_weight = 'balanced'`” parameter in Python, which can improve classification accuracy and metrics. In this study, where respondents unwilling to pay outnumber those willing, we trained two RF classifiers: one with the default configuration and one with `class_weight = 'balanced'`. The latter explicitly penalizes misclassification of the minority class (willing payers), increasing its visibility during training. Comparative results (Table 2) on a stratified holdout set confirmed the benefit of this approach. The balanced model achieved higher accuracy (63.5% vs. 61.5%), improved precision (73.2% vs. 71.2%), and a better F2 score (0.758 vs. 0.754), while maintaining identical recall (76.5%). These gains, particularly in the F2 metric that prioritizes recall, demonstrate that class balancing improves the model’s ability to correctly identify potential subscribers without substantially sacrificing precision. This finding validates the decision to prioritize recall-heavy optimization for real-world deployments, where missing a potential payer is costlier than falsely identifying a non-payer.

Table 2. Comparison of RF models with and without class balancing

Metric	Without balancing	With balancing
Accuracy	0.6145833333333334	0.6354166666666666
Precision	0.7123287671232876	0.7323943661971831
Recall	0.7647058823529411	0.7647058823529411
F2 score	0.7536231884057971	0.7580174927113702

Subsequently, Table 3 presents the performance of the RF classifier before and after hyperparameter tuning, providing valuable insights into the effectiveness of the adjustments made. In the initial baseline model, before any hyperparameter tuning, the accuracy was found to be 66.7%. This means that roughly two-thirds of the predictions were correct. While this level of accuracy is reasonable, it indicates that the model could be further improved, particularly in terms of distinguishing between the classes. The precision score was 74.7%, indicating that when the model predicted an individual was “willing to pay”, it was correct 74.7% of the time. This precision value suggests that the model has a solid ability to predict true positives, but it also implies there could still be some false positives—individuals predicted to be willing to pay who were not actually willing. On the other hand, the recall was quite high at 83.1%, meaning the model was successful in identifying a large proportion of the actual willing to pay individuals. This suggests that the model is good at capturing most of the people who are willing to pay, though it comes at the cost of some false positives (lower precision). The F2 score, which emphasizes recall more than precision, was 81.3%, reflecting a model that is focused on capturing as many true positive cases as possible.

Table 3. Performance of the RF classifier before and after hyperparameter tuning

Model configuration	Accuracy	Precision	Recall	F2 score
Baseline RF	0.66666	0.74747	0.83146	0.81318
After tuning	0.65833	0.74	0.83146	0.8114

After performing hyperparameter tuning using GridSearchCV, the model's parameters were adjusted. The `max_depth` was set to 10, which helps prevent overfitting by limiting how deep the trees can grow. The `min_samples_leaf` and `min_samples_split` was also adjusted to allow for more flexibility in how the trees split and grow. Additionally, the number of trees in the forest was increased to 200, according to Liu *et al.* [28] increasing the number of trees in an RF enhances model robustness by reducing variance and overfitting. After tuning, the model's performance showed a slight decrease in accuracy, which dropped to 65.8%. This drop suggests that while the model became more stable and less prone to overfitting, it may have lost some of its ability to correctly predict all instances. The precision also dropped slightly to 74.0%, reflecting a small reduction in the model's ability to correctly predict the willing to pay individuals without over-predicting. However, the recall remained unchanged at 83.1%, meaning the model was just as effective at identifying the willing to pay individuals as it was before tuning. The F2 score followed suit, slightly

decreasing to 81.1%, but still indicating strong performance in identifying individuals willing to pay for better waste management.

Despite the minor decreases in accuracy, precision, and F2 score, the model's ability to recall true positives remained strong. This suggests that the hyperparameter tuning had a positive effect on the model's ability to generalize and avoid overfitting [22], [29] without undermining the model's primary objective of identifying willing payers. The feature importance analysis further supported these findings, showing that occupation and interest in using a waste management app were the most influential features in predicting WTP. A key contribution of this study from prior work is the deliberate choice to optimize the RF classifier based on the F2 score, a recall-oriented metric rarely prioritized in existing WTP prediction models. Whereas earlier studies have tended to focus on average WTP estimates or aggregate-level behavioral trends, this study targets individual-level classification with an explicit design bias toward minimizing false negatives. The use of F2 optimized learning ensures that the model maximizes the identification of potential payers, who are most critical to the financial viability of a digital waste management service, while still maintaining acceptable precision. This approach addresses a methodological gap noted in previous research, which often overlooks the practical importance of recall in subscription-based service planning.

4. MODEL INTERPRETABILITY

The feature importance analysis revealed some interesting insights into the factors driving the WTP for improved waste management services. As illustrated in Figure 1, occupation, which falls under the socio-demographic group, emerged as the most influential feature. With an importance score of 0.351, occupation plays a critical role in determining an individual's likelihood to pay for waste management services. This is likely because occupation is closely associated with income and financial stability, particularly for rural and low-income households [30]. Both of which are key determinants of one's ability to invest in such services. Similar to Motta and Farias [31] found that individuals in higher-paying or more stable occupations are more likely to support and pay [31] for enhanced waste management systems.

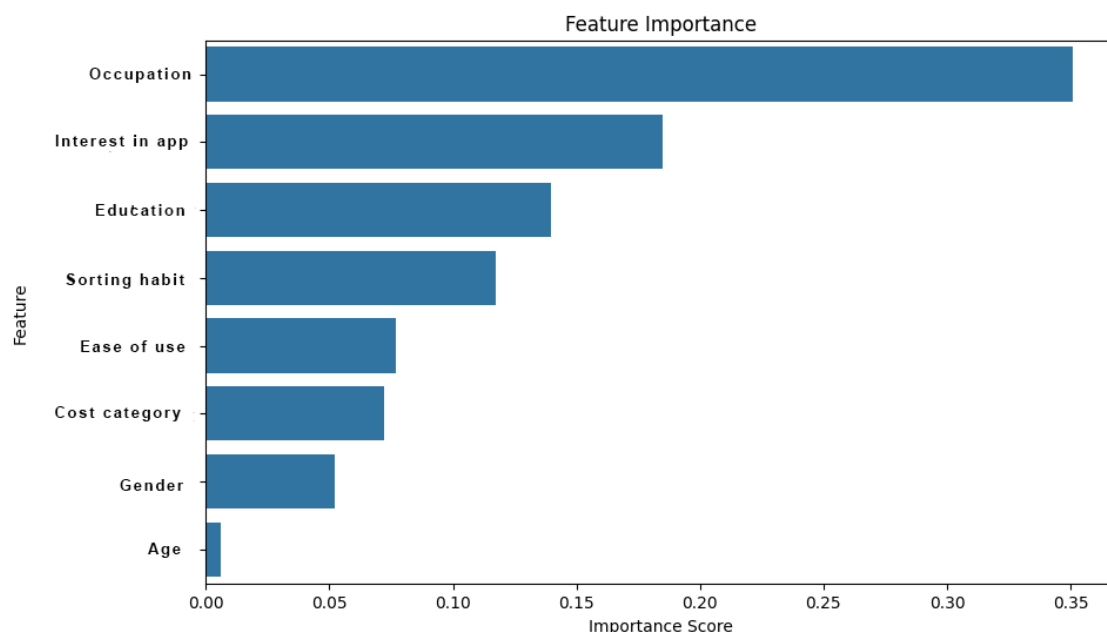


Figure 1. Feature importance scores derived from the RF model

On the other hand, the feature with the lowest importance is age, also from the socio-demographic group, with an importance score of 0.006. This suggests that age does not significantly influence a person's WTP for waste management services, contradicts with Omotayo evidence from South Africa's household survey [32]. Despite its inclusion in the model, age seems to have minimal impact compared to other features in the same group, like occupation, education, or gender.

To further validate and interpret the predictive patterns captured by the RF model, we conducted a Pearson correlation analysis between each feature and the target variable, WTP. It has been used effectively

for feature selection in various domains, including failure mode detection in reinforced concrete bridge columns [33], heart failure prediction [34], and liver disease detection [35]. This additional step allowed us to examine the linear relationships underlying the model's inputs. Notably, the two strongest positively correlated features were cost category ($r = 0.18$) and ease of use ($r = 0.07$), both of which also ranked highly in the RF's feature importance. This alignment reinforces the model's reliability in identifying key drivers of WTP. Conversely, features such as occupation, while showing a weak negative correlation ($r = -0.12$), emerged as one of the top predictors in the model. This discrepancy underscores the strength of the RF algorithm in capturing complex, nonlinear interactions that linear correlation methods may overlook, aligned with Orlenko and Moore [36]. Rather than presenting conflicting results, the correlation analysis in Figure 2 complements the feature importance findings by offering both a confirmatory lens and an explanation for why a ML approach was essential for uncovering subtler behavioral and demographic influences on digital waste service adoption.

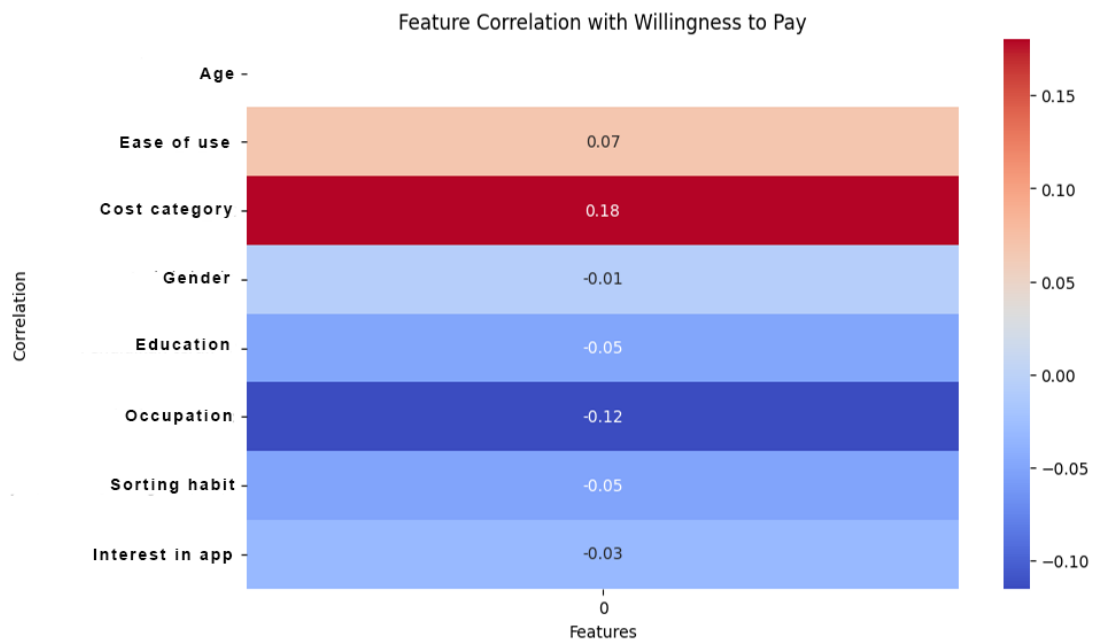


Figure 2. Positive correlation between ease of use, cost category, and WTP

Building on the previous analyses, where both feature importance from the RF model and linear correlations with the WTP outcome were evaluated, this study identified three features that consistently stood out across both methods: occupation, ease of use, and cost category. Occupation emerged as the most influential feature in the model's feature importance analysis, while ease of use and cost category recorded the strongest positive correlations with WTP, despite their lower ranking in model-based importance. To further examine how these variables behave across the binary WTP classes and to capture their distributional characteristics, this study employed boxplot visualizations. Unlike aggregate statistics, boxplots provide a visual breakdown of how feature values vary within and between classes, enabling us to observe medians, variability, and potential outliers [37]. This step offers an intuitive and detailed view into whether specific values or ranges of a feature are associated with higher or lower WTP tendencies, thereby strengthening the interpretability of our predictive findings. Their behavior is illustrated in Figure 3.

In the first boxplot (Figure 3(a)), occupation shows a distinguishable pattern: individuals classified as more willing to pay ($WTP = 1$) tend to have higher occupation codes. Although there is overlap, the median and interquartile range are noticeably higher for this group, supporting the hypothesis that job type is a strong predictor of digital payment behavior. This is consistent with the model's reliance on occupation as a primary split factor and suggests that income stability and formal employment may drive both awareness and ability to pay for improved waste services. Similar to Suryawan and Lee [9], found that citizens with incomes above the minimum wage and those living outside slums are more likely to support adaptive municipal solid waste management services. This highlights a socioeconomic divide in WTP, where formal employment correlates with higher support for service improvements. Policymakers should consider tiered pricing models or targeted subsidies to ensure affordability for lower-income groups [38].

The second plot analyzes ease of use (Figure 3(b)), based on users' perception of the current waste collection system's adequacy. The analysis of ease of use indicates that individuals who perceive the current waste collection system as adequate are slightly more inclined to pay for service improvements. Similarly, research revealed that the use of mobile applications for recycling education can increase intention to recycle, with performance expectancy, facilitating conditions, hedonic motivation, and habit being significant factors in app adoption [39]. Although the visual difference between WTP groups is modest, the upward shift in median ease-of-use scores suggests that users with positive experiences are more open to digital enhancements, viewing them as added value rather than added burden. While not a top predictor, its positive correlation supports its role as a secondary yet meaningful factor in WTP. Policy efforts should focus on maintaining and communicating the reliability of existing services, while gradually introducing digital tools in a user-friendly way [40]. Pilot programs could target areas with higher satisfaction levels to build momentum and demonstrate success. Additionally, training sessions or simplified interfaces could help ensure that digital upgrades are perceived as intuitive and supportive, especially for users with lower digital literacy [41].

Lastly, the cost category plot reveals limited but telling variation (Figure 3(c)). While most responses cluster in the lower cost brackets, the modest increase among the WTP group indicates that even small differences in acceptable cost can signal a significantly higher willingness to contribute. This confirms cost as the strongest predictor of WTP, emphasizing the importance of pricing strategies that align with users' value perceptions [42]. Policymakers should consider setting price points just below identified sensitivity thresholds to maximize participation, while clearly communicating the benefits tied to each pricing tier [43]. Offering flexible payment plans or bundling services with visible quality improvements may further strengthen user buy-in and enhance perceived value [44]. Together, the interpretability analyses provide a comprehensive understanding of the behavioral and socio-economic factors shaping WTP. By integrating feature importance, correlation analysis, and distributional visualization, this study offers actionable insights that support targeted outreach, pricing strategies, and user segmentation in digital waste management services.

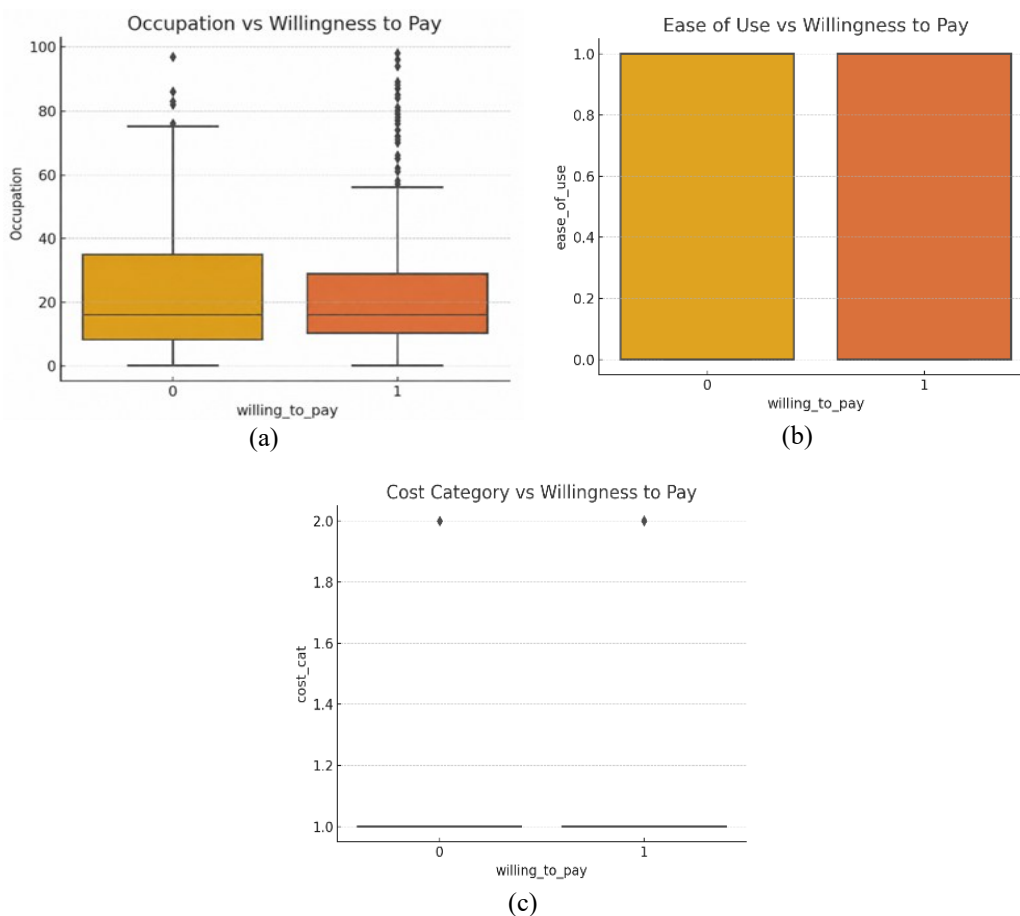


Figure 3. Boxplot comparison of top features across WTP groups: (a) occupation vs. willingness to pay, (b) ease of use vs. willingness to pay, and (c) cost category vs. willingness to pay

5. CONCLUSION

This study responds directly to the challenge identified in the Introduction regarding low adoption and uncertain WTP for digital waste management services in urban areas with limited-service coverage. By developing a class-balanced RF model optimized using the F2 score, this research demonstrates that individual-level WTP can be reliably predicted while prioritizing the identification of potential payers who are most relevant for public service planning. The results confirm that socio-economic stability, perceived ease of use of existing services, and cost tolerance are key determinants of payment decisions, reinforcing the importance of aligning digital solutions with both behavioral and economic realities. Through the integration of recall-oriented evaluation and interpretable ML, this study offers a practical and data-driven approach to support targeted pricing, outreach strategies, and service design. Although grounded in the case of Gorontalo City, the proposed framework is methodologically transferable and can be replicated in other cities that face similar constraints, such as partial waste service coverage, limited infrastructure, and emerging digital waste management initiatives, thereby supporting scalable and inclusive urban waste management planning. Future work may extend this framework through longitudinal analysis, geographic segmentation, and integration of behavioral or usage data, as well as real-world pilot deployment to strengthen its role as a decision-support tool for sustainable and inclusive urban waste management.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [RTRLB], upon reasonable request.

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