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A Sustainable Perspective: Using Machine Learning Approach to Predict the Donation Behavior of Used Smartphones in Indonesia to Extend Smartphone's Usage Life

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ABSTRACT

The growing issue of electronic waste (e-waste) in Indonesia, driven by the short lifecycle of smartphones and limited interest in refurbished devices, highlights the need for sustainable disposal alternatives. This study investigates the factors influencing Indonesians' willingness to donate used smartphones, promoting e-waste reduction and digital access for underprivileged students in rural areas. Analyzing data from 416 respondents, we found that 57% expressed willingness to donate, with key factors including device obsolescence, age, and involvement in social activities. Machine learning models applied to predict donation behavior accurately predicting outcomes 91.67% of the time. The findings reveal the potential of functional but obsolete smartphones to address educational needs, offering a sustainable solution that bridges the digital divide and supports e-waste reduction. These insights guide strategies for social organizations to enhance donation programs, tackling both behavioral and logistical barriers for greater environmental and social impact.

Keywords: Electronic Waste, Circular Economy, Decision Tree, Random Forest, Neural Network

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1. INTRODUCTION

Waste electrical and electronic equipment (also known as WEEE) has become one of the world's biggest concerns as electronic and electrical product development has rapidly increased following the growth of science and technology. E-waste comprises a diverse range of materials, some of which are harmful. If abandoned gadgets are not properly handled, they may create severe environmental and health issues. Modern electronics also need scarce and costly resources, such as crucial raw materials. These may be recycled and reused if the waste is properly controlled (Commission, 2024; Kuehr, 2019). It has also been known that Asia is the world's most significant contributor to electronic waste, with up to 24.9 million metric tons (Mt), which is almost half of the total electronic waste from all over the world (Forti *et al.*, 2020). Indonesia is one of the countries in Asia with enormous consumption of electronic devices. The annual growth rate for electronic waste in Indonesia is around 14.91%. In 2028, electronic waste is predicted to be about 487,416 tons; 442,176 Mt dominated by mobile phones (Santoso *et al.*, 2019).

Indonesia, as the world's fourth most populous nation, is characterized by remarkable socio-cultural and economic diversity. Home to over 17,000 islands, its population encompasses a wide range of ethnicities, languages, and traditions, shaping distinct societal norms and behaviors. This diversity extends to consumption patterns, including electronic devices, where differences in income, education levels, and cultural values influence attitudes toward e-waste and sustainable practices. Smartphone penetration in Indonesia is expanding; it reached 44.44% in 2017 and is expected to reach 67.15% by 2020 (Statista, 2023a). Indonesia has a vast number of smartphone users, with 183.68 million in 2020 (Statista, 2023b). Indonesia is the fourth-largest smartphone market, behind China, India, and the United States. Mairizal *et al.* (2021) and Maheswari *et al.* (2017) discovered that the average period for a smartphone to reach end-of-life in Indonesia was less than three years. In a comparatively short period, a smartphone becomes obsolete or approaches the end of its useful life. Extending the life of electronic items is one strategy that might be utilized to decrease electronic waste. Therefore, reuse, remanufacture, and refurbishment theory could help reduce electronic waste, as these theories use the circular economy concept (Surange *et al.*, 2024; Atasu *et al.*, 2021; Shu-San, 2019).

The most popular methods for disposing of cellphones in an Indonesian community that values collaboration among its members include selling them on the secondhand market, donating them, gifting them to family or friends, or reusing them after repairs (Safa'at *et al.*, 2019). A few smartphones were thus disposed of in the trash (Siringo *et al.*, 2020).

However, previous studies in Indonesia showed that people there are not interested in refurbished smartphones; they prefer new low-end smartphones (Halim *et al.*, 2022). Additionally, while buying new phones, some people left their old phones unused, sold them to the second-hand market, or even gave them to their relatives, but there are only a few people that donated their old phones, which is only about 3.03% (Lestari, 2022).

The COVID-19 pandemic underscored the critical role of smartphones in education, particularly in marginalized communities where online learning became a necessity. However, nearly half of Indonesian students in rural areas lacked access to these essential devices (FSGI, 2020; Zahrawati and Nurhayati, 2021). Beyond the pandemic, smartphones remain crucial tools for education, offering students access to diverse learning resources and improving academic outcomes (Sari *et al.*, 2020). Addressing this digital divide by encouraging smartphone donations aligns with the principles of a circular economy, emphasizing reuse and reduced environmental impact (MacArthur, 2019).

In post-pandemic, used smartphones still play an essential role in education (Haleem *et al.*, 2022); particularly, smartphones have helped overcome the digital divide in low- to middle-income countries like Indonesia. Used smartphones offer low-income students' economical access to educational information, online classes, and e-learning platforms, providing students with free or low-cost apps for language resources, science simulations, and practice quizzes. As mobile internet usage rises, even second-hand smartphones allow students in remote areas to access global information resources and make digital tools more affordable for those students. It empowers self-study, and smartphones provide video tutorials, instructional games, and e-books for independent study. Recycling smartphones for education reduces e-waste and promotes green practices. Expanding educational smartphone donation initiatives can provide devices to students in remote areas. These measures can boost the impact of used smartphones on educational systems and ensure that all students, regardless of income, can succeed in digital learning environments.

Research on the feasibility and potential of extending the useful life of products, particularly reusable smartphones, has drawn significant interest from researchers. Cordella *et al.* (2021) propose ways to enhance the reliability and repairability of products to extend their lifespan. Smartphones are frequently replaced before their expected lifespan due to socio-economic and technical factors. Enhancing the reliability of smartphones can reduce the frequency of early replacements. Nevertheless, in the event of failures, it is necessary to promptly and cost-effectively carry out repairs. This can be achieved by implementing modular design principles, ease of disassembly of crucial components, providing access to spare parts, and repair services. In a study conducted by Coughlan and Fitzpatrick (2020), the feasibility of collecting used ICT (Information and Communication Technology) items for the purpose of reusing them was examined. The study revealed that 28% of computers, smartphones, and tablets obtained from the events satisfied the criteria for being repurposed as reusable items. Reuse occurs when a product is sold or donated to family, friends, charitable organizations, or non-governmental organizations (Sonego *et al.*, 2023). This donation or sale facilitates the extended period of the product's service lifecycle of the product. Reuse also mitigates environmental impacts by delaying the consequences associated with product replacement and disposal. Among the smartphone disposal categories, reuse was the dominant choice compared to storage, formal collection, and informal collection.

Considering the distinct culture and character of societies, as well as different policies in each country, some research focuses on the collection and reuse practices of discarded smartphones and/or ICT waste within the scope of a particular country. Coughlan and Fitzpatrick (2020) explored the feasibility of collecting consumer ICT waste for reuse in Irish workplaces. A series of public collection events were organized, providing individuals with an incentive to return their data-bearing devices (such as laptops, tablets, and smartphones). During these events, free data wiping and destruction services were offered. The gathered devices were dispatched to a certified organization specializing in preparing them for reuse. At this facility, the devices underwent rigorous testing and evaluation to determine their eligibility for reuse, based on both technical and economic considerations. Gurita *et al.* (2018) studied the possibilities for reusing, remanufacturing, and recycling smartphones in Germany. The results show that Germany has a great potential for reuse and remanufacture based on the potential collection amount. However, the existing low rates of collecting WEEE (Waste Electrical and Electronic Equipment), the absence of a quality preselection process, and customers' negative perceptions of remanufactured smartphones make it difficult to achieve the remanufacturing of these products under the current circumstances. Islam *et al.* (2020) conducted a survey to assess the mobile phone disposal behavior of Australian consumers. The majority of respondents, specifically 43.98%, stored their waste mobile phones at home. Approximately 13% of the participants accessed council collection locations to dispose of their phones, whereas around 11% of the customers discarded their phones in regular residential waste collection bins. Approximately 10% of respondents reported selling their used mobile phones to others, while around 9% chose to hand over the phones to a recycling organization. In Bai *et al.* (2018) study, the attitude and behavior of Chinese consumers towards smartphone recycling were explored. Information security is the primary factor influencing consumers' recycling decisions. In addition, buyers are more inclined to purchase from suppliers who provide recycling services. Despite China's notable advancements in enhancing the social environment and raising awareness about phone recycling, many people still choose to keep their discarded smartphones at home.

In many cases, there is a perception that reused smartphones have lower quality compared to brand new ones. In order to increase their acceptability, researchers have investigated methods to improve customers' attitudes towards reuse. Sharifi and Shokouhyar (2021) explored consumers' attitudes toward refurbished mobile phones using a social media analytics approach. The findings suggest that environmental factors have a slightly greater influence on the potential buyer's motivation compared to financial factors. The key factors to consider when presenting a refurbished mobile phone were price, warranty, quality, and the seller's reputation.

Some studies found that smartphone reuse is not limited to reselling products as second-hand, refurbished, or remanufactured smartphones, but also for donations (to family, friends, charities, or non-governmental organizations/NGOs) and repurposing. Li *et al.* (2010) presents a design for reuse model wherein obsolete devices are repurposed to fulfill a category of applications that can be adequately served by older technology that is comparatively less dependable. Particularly, we discover a strong correlation between the reuse of smartphones and primary school educational applications. Zink *et al.* (2014) a case study on repurposing by developing a smartphone application that imitates the features of an in-car parking meter. The LCA research determines that repurposing is a more environmentally favorable end-of-life choice than refurbishing for old smartphones. Sa'diyah *et al.* (2021) explored the effect of using smartphone-based learning media to improve students' critical thinking skills during Covid-19 pandemic. Ali and Shirazi (2022), used machine learning approach to compare the sustainable e-waste management between Swiss and Canadian system.

While numerous studies have explored smartphone reuse through recycling and refurbishment in developed nations such as Germany and Australia, Indonesia presents unique challenges and opportunities due to its distinct cultural, social, and economic landscape. Previous research highlights a preference among Indonesians for new, low-cost devices over refurbished alternatives and identifies limited participation in donation-based smartphone reuse programs. Additionally, Indonesia's religious and cultural norms significantly shape individual behaviors, yet their intersection with technological adoption and sustainability practices still needs to be explored. Indonesia's unique socio-cultural fabric plays a pivotal role. Religious practices, community engagements, and familial values deeply influence individual and collective behaviors, including attitudes toward sustainability. For instance, religious teachings and communal gatherings often emphasize generosity and sharing, which could be leveraged to encourage smartphone donations. At the same time, the country's economic disparities highlight the importance of tailored approaches to address both the environmental impacts of e-waste and the digital divide affecting rural and underserved communities. These gaps underscore the need for tailored approaches considering the interplay of cultural factors and technology in promoting sustainable behaviors.

This study addresses these gaps by examining the behavioral and external factors influencing Indonesians' willingness to donate used smartphones. The study uses machine learning approaches such as decision trees, random forests, and neural networks to identify major predictors of donation behavior, which include socio-cultural, psychological, and economic factors. Machine learning is particularly suited to this investigation because it can uncover complex, non-linear relationships in data, providing both predictive accuracy and actionable insights. By leveraging these methods, the study advances our understanding of culturally specific donation behaviors and offers a practical framework for enhancing smartphone donation programs. This dual focus on behavioral insights and technical innovation positions the research to contribute meaningfully to e-waste management and digital inclusion in Indonesia.

2. METHODS

This section outlines the proposed predicting used smartphones donation behavior in Indonesia methodology in four stages. Initially, it focusses on designing questionnaires, validating, and testing the questionnaires before collecting data through Google-form. Subsequently, the collected data will be pre-processed to ensure its quality for analysis and profiling the respondents of this survey. The core of the approach lies in data modeling using machine learning approaches, i.e., decision tree, random forest, and neural network. Finally, the conclusion and suggestion are derived based on the best performance metric. Figure 1 illustrates the representation of this methodology.

2.1 Designing Questionnaire

The questionnaire is intended to identify the factors that influence donating behavior. Psychologically, the intention to donate consists of two factors, i.e. the internal and the external ones.

2.1.1 Internal Factors Affecting Donation Behavior

Internal factors that affect donation behavior are the motivation that comes from inside the people. A person's willingness to donate is affected by decision-making behavior. Decision-making behavior is influenced by some factors such as personal factors, cultural factors, social factors, and psychological factors (Kashif *et al.*, 2015; Lee and Chang, 2007). These factors are described as follows:

2.2 Personal factors (Carroll *et al.*, 2005)

Personal factors that affect the decision-making behavior in donation activities based on the previous study are:

- Age: The effects of age are significant in donation activities. It is known that an increase in age makes a person's probability of participation in donation increase. This is possible as life experience and time could change one's mindset and behavior.
- Education level: A person's education level also influences the decision-making behavior in donation activities. A person with a higher education level is more likely to donate than the lower one as they get better knowledge and understanding.
- Income: The effects of income are also significant in a person's willingness to donate. A higher income level results in an increase in a person's probability of participating in donation activities.
- Number of children: The number of children also positively influences the probability of participation in donation activities. It is known that a person who has more children has a bigger empathy for other children in need resulting in an increase in their willingness to donate.

2.2.1 Cultural Factors

Culture is the foundation of an individual's behavior. There are some aspects that could be considered as cultural factors, for example:

- Family upbringing (Dou *et al.*, 2014): Family upbringing plays an important role in building an individual's character. Children grow up with different mindsets, characters, preferences, and behaviors due to differences in every family's upbringing. Therefore, children who have been taught to be generous from an early age are more likely to give or take part in donations when they grow up.
- Religious upbringing (Carroll *et al.*, 2005; Zubairi and Siddiqui, 2019): Religion also influences an individual willingness to donate. It is said that a more religious person is more likely to give than others, especially on their religion special occa-

Figure 1. Research outlines.

sions. For example, Christians donate more on Christmas and Muslims donate more on Ramadhan. Therefore, there is an increase in donating behavior for religious people, especially on their religious special occasions.

2.2.2 Social factors

Social factors explain the relationship an individual has with other people. Social relationships usually come from a group of people who interact and stick with each other for a very long time, such as family, friends, organizations, and co-workers (Cheung and Chan, 2000). Social relationships affect a person's donation behavior since the person who interacts and relates with more people usually becomes more aware of social problems and issues. As a result, they are more likely to be actively involved in social activities, such as donations (Wiepking and Breeze, 2012).

2.2.3 Psychological Factors

Psychological factors that have the most impact on donation behavior are emotions. These are the most significant emotions that affect donation behavior (Zubairi and Siddiqui, 2019):

- Empathy: Empathy is known to be the capability to view the outside world from the other person's perspective and the ability to understand another person's feelings as if it is their own feeling (Hojat *et al.*, 2001). Empathy is usually known to be the potential motivation in making donation decisions. People usually donate more when they feel empathy because they can feel what other people are feeling (Hibbert *et al.*, 2007).
- Need for forgiveness: Another emotion that usually drives a person to donate is the need for forgiveness. Forgiveness is known to be the act of forgiving someone or also known as releasing one's anger toward another person. Thus, the need for forgiveness can be defined as a person's need to be forgiven for their actions. People usually donate more to find redemption for their guilt (Rees, 2023).
- Altruism: Altruism is defined as selfless behavior. It is known to be the act of putting another person's needs first. Therefore, altruism could affect a person's willingness to donate as they are willing to do things that bring advantages to others (Kerr *et al.*, 2004).
- Desire to help others: Desire is a strong feeling to want something (Cambridge, 2024). Thus, the desire to help others means a strong feeling to help others. Having a strong feeling to help others will result in an increase of a person's willingness to donate because donation is considered as an activity to help other people in need (Wan *et al.*, 2017).

Therefore, the emotions that affect a person's willingness to donate based on previous study findings are empathy, the need for forgiveness, altruism, and the desire for helping others (Zubairi and Siddiqui, 2019). The study in this paper will focus on factors that affect Indonesian people's willingness to donate based on the previous study findings.

2.2.4 External Factors Affecting Donation Behavior

External factors that affect donation behavior could be defined as the factors that come from an organization to which people are donating. According to a study by Kim and Kim (2021), there are 4 factors that need to be considered that affect people's willingness to donate, especially in an online organization. These factors will be used in this paper to examine the connection between people's donation behavior and the organization's characteristics. These factors are defined as follows:

- Trust: Trust is defined as a complex relationship characterized by two elements, which are cognitive and affective. The cognitive one is based on people's knowledge of the organization, including their activities and capacities. The affective one is based on the connection between a person and the organization that could be developed over time (Heffernan *et al.*, 2018).
- Ease of use: Ease of use is adopting the concept of simplicity. It is known to be the act when people feel the easiness and the simplicity of doing something. Ease of use could be offered by simplifying the flow of the process and making the process easy to understand (Kim and Kim, 2021; Sufyan and Mas'ud, 2022).
- Service Quality: Service Quality is defined as the competency offered by the organization. A service could be defined as a good service when it fulfills the expectations of the consumers. This could be measured by the comfortability and hospitality of the service. This could also be measured by the service time offered by the organization (Jones and Shandiz, 2015).
- Safety: Safety in online organizations is known to be the basis of trust. A person's trust will grow when their safety is ensured. Online organizations are usually known for personal data usage. Therefore, this could increase consumers' concerns about data misuse. When the consumer's data safety is ensured, a person is more likely to use online services (Park and Kim, 2006).

2.3 Data Collecting and Preprocessing.

To ensure the content validity and reliability of the questionnaire, a systematic validation process was conducted. The initial questionnaire design was reviewed by subject matter experts in behavioral science and sustainable technology to align the items with the study's objectives. A pilot test was administered to a smaller sample of 50 respondents, representing the target demographic, to identify ambiguities and ensure clarity. Feedback from this pilot test was used to refine the questionnaire further.

Reliability was assessed using Cronbach's alpha, with a threshold of 0.7 considered acceptable for internal consistency. The overall Cronbach's alpha for the questionnaire was calculated at 0.833, indicating high reliability. Additionally, inter-item correlations were examined to ensure that all questions contributed meaningfully to their respective constructs without redundancy. These steps ensured that the questionnaire was both valid and reliable for capturing the factors influencing donation behavior. The final design has been aligned with the study objectives and provides essential information while concluding the questionnaire design's validation process after minor corrections and modifications. The questionnaires in Google Forms were distributed to Indonesians via Line, WhatsApp, Instagram, and TikTok. The data has been cleaned from redundancy and transformed to enrich the clarity in the preprocessing step.

2.3.1 Data-driven learning process

The data-driven learning process aims to predict the Indonesians willingness to donate the used smartphones. Three classifiers are proposed for finding the factors that influence used smartphones and predicting the respondent's willingness to donate their used smartphones. The three classifiers are tree (single classifier), random forest (ensemble learning) and artificial neural network.

2.3.2 Tree

Decision tree is also known as a classification tree. It is usually used to make a prediction based on the model made from the data. The prediction is to classify an object to define a set of classes according to its attribute value, demographic, or other variables (Rokach and Maimon, 2015). A decision tree contains a root node, internal nodes, and leaf nodes. A root node is the start of a decision tree which contains the largest information to split data based on a specific feature. Internal nodes are the nodes that contain the decision rule which will determine further separation and will be divided into other internal nodes or leaf nodes. Leaf nodes are the final part of a decision tree where a final class prediction is shown in the node (Sá *et al.*, 2011).

The decision tree has drawback as follows: Decision tree overfitting occurs when the tree gets too complex owing to excessive branching. This condition may limit the model's applicability to new data. Untuned decision trees may assign more weight to features with more levels or splits, resulting in inferior insights. It has lack of stability, small changes in the training data might cause significant tree structure changes, making the model less robust (Bramer, 2013).

2.3.3 Random Forest

The random forest method is one of the ensembles learning methods in machine learning. As an ensemble learning method, it can be challenging to interpret the random forest output and the most impactful feature since the model is quite complex. Therefore, the importance of features can be used to help identify the most influential features in every prediction made by the model. Feature importance measures the contribution of each variable to make a good prediction, and it is usually measured by the decrease in impurity on each decision tree in the forest. The variables that cause a greater reduction in the impurity are considered more important (Hwang *et al.*, 2023; Palczewska *et al.*, 2013). The random forest method has been widely used to predict donation behavior, such as donation for typhoon victims, kidney donation, and blood donation (Kurata *et al.*, 2022; He *et al.*, 2021; Selvaraj *et al.*, 2022). Random forest is one of the machine learning methods that is used to improve the decision tree methods. The random forest method contains several decision trees, and each of them will generate a decision. From each decision, one decision will be chosen as the majority decision (Tan *et al.*, 2019). However, random forest methods generate numerous trees and aggregate their outputs, requiring more computer resources than single decision trees. Random forests are more accurate than decision trees, but their ensemble nature makes it challenging to explain predictions. In high-dimensional datasets with many irrelevant features, random forests might overfit despite being ensemble models (Ayyadevara, 2018).

2.3.4 Neural Network

Neural networks are one of the most critical part of machine learning. It is inspired by the work of the human brain which has many neurons and works as a network. It could learn to find a pattern in a dataset, and it also could generalize them. Data processing using neural networks will improve as the neurons establish new connections, it will learn more as the connections between their neurons change (Mehlig, 2021). There are two types of neural networks based on its architecture. The first one is the single-layer neural network which contains only a single input layer and an output node. The second one is known as the multi-layer neural networks which contain multiple computational layers. The most common multi-layer neural network is the feed-forward network assuming that all nodes in each layer are connected to the nodes in the next layer and moving in the forward direction (Aggarwal, 2018). The additional layers are between input and output which is known as the hidden layers because these layers cannot be seen directly either from the input or the output of the models. By using more hidden layers, the neural network could extract higher-order statistics from its input (Haykin, 2009). However, neural networks need lots of labeled data to train. The model may not perform well on smaller datasets. Deep architecture neural networks require a lot of processing power. Neural networks are commonly called "black-box" models because their decision-making processes are hard to understand. With improper regularization and hyperparameter tuning, neural networks might overfit the training data and fail to generalize to new circumstances (Vakalopoulou, 2023).

Those three classifiers are chosen since decision trees are inherently interpretable, making them ideal for understanding the factors influencing willingness to donate smartphones. The visual representation of how different variables affect decisions allows researchers to communicate findings to stakeholders easily. Random forests, an ensemble learning method, combine multiple decision trees to improve accuracy and robustness, mitigating the risk of overfitting associated with individual decision trees. Even though the neural network is categorized as a black box method, it excels at capturing complex, non-linear relationships in data. It makes them suitable for identifying subtle patterns in donation behavior influenced by psychological and social factors.

2.3.5 Performance

A variety of performance metrics have been extensively implemented to determine whether a model is producing accurate predictions. These include the f1 score, confusion matrix, accuracy, recall, and precision, each elaborated upon in the following section.

The confusion matrix, which represents the actual and predicted values of the model across multiple classes, is described as a table (see Table 1).

The confusion matrix is frequently employed to identify error patterns. It is the foundation for calculating other classifier metrics, including accuracy, recall, precision, and F1 score, based on its value in each class (Burkov, 2019). Nevertheless, every classifier serves a unique purpose. The subsequent sections clarify each classification utilized in this study (Arumugam *et al.*, 2022)

Accuracy: To measure the overall correctness of a model's prediction

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Precision focuses only on the positive predictions.

$$Precision=\frac{TP}{TP+FP} \tag{2}$$

Recall calculates the ratio of true positive predictions divided by the sum of all true positive and false negative values and is best used to minimize the number of false negatives.

$$Recall=\frac{TP}{TP+FN} \tag{3}$$

F1 Score calculates the mean of precision and recall and is best used when the classes in the dataset are imbalanced.

$$F1\,score=\frac{(2\ x\ Precision\ x\ Recall)}{(Precision+Recall)} \tag{4}$$

3. RESULTS AND DISCUSSION

3.1 Data Description

In this section we discuss the internal and external factors affecting donation behavior based on the survey. The survey was conducted through Google form across Indonesia and responded by 416 respondents. With 416 data points, the study maintains an acceptable ratio of respondents to features (independent variables). This ratio is sufficient for algorithms like decision trees and random forests to build accurate and reliable models without overfitting (Rajput *et al.*, 2023). Additionally, the models used—decision trees, random forests, and neural networks—can work effectively with moderately sized datasets, particularly in cases like this study where the focus is on behavioral prediction rather than high-dimensional image or text data. The dataset was split into training (80%) and testing (20%) sets, resulting in 332 training and 84 testing samples. This splitting provides a robust foundation for model training while ensuring enough data to validate performance.

The respondent's profile (Table 2) exhibits that most likely equal in gender and occupation. Moreover, the data represents the Indonesian population, which is concentrated in Java (Statista, 2020). The profile domicile shows that Java has the highest percentage of respondents (43.4%), followed by Sumatra, Sulawesi, Kalimantan, and Papua (Statista, 2020). The sample size provides a reasonable cross-section of Indonesia's diverse demographic and geographic population, capturing age, income, education, and cultural norms variations. This diversity level ensures that

Table 1. Confusion Matrix

Classes	Positive (Predicted)	Negative (Predicted)
Positive (Actual)	True Positive (TP)	False Negative (FN)
Negative (Actual)	False Positive (FP)	True Negative (TN)

Table 2. Personal factors: Respondents' profile

Subject	%	Subject	%	Subject	%
Gender		Domicile		Income (in Million Rupiahs)	
Male	51.2	Java	43.3	< 3	18.5
Female	48.8	Sumatra	20.4	3 – 6	27.4
Occupation		Sulawesi	17.1	>6 – 10	25.0
Worker	58.4	Borneo	11.3	>10 – 15	14.9
Student	41.6	Papua	7.9	>15 – 25	8.7
				>25	5.5
Age		Last education		Number of children	
< 22	32.7	Highschool	35.6	No children	60.3
23-28	30.8	Diploma	7.5	1 – 2	31.7
29-34	21.6	Undergraduate	42.1	3 – 4	7.9
>35	14.9	Master or Ph.D	14.9		

the findings reflect the population being studied.

3.2 The Internal Factors Affecting Donation Behavior

Beliefs and religious observance are integral components of Indonesian society, which is founded upon Pancasila, the nation's national philosophy. Therefore, attending religious services and frequency of daily prayer are part of the cultural and social factors in this survey. In addition to this, places of worship serve as venues for charitable contributions and donations. Most respondents (37.7%) participate in religious services once a week, are

Table 3. Cultural and Social factors

Subject	%	Subject	%	Subject	%
Attending religious services		Daily prayer frequency		Number of close friends	
Almost never	7.5	Never pray.	13.7	1 – 3 persons	34.6
Only on special vent	16.6	1 – 2 times	62.5	4 – 8 persons	48.6
Once or twice a month	16.1	3 – 5 times	21.4	9 – 15 persons	13.5
Once a week	37.7	>5 times	2.4	>15 persons	3.4
More than once in a week	22.2				
My family has always taught me the value of sharing.		Engaged in social activities.			
Yes	71.9	Yes	73.6		
No	28.1	No	26.4		

Table 4. Psychological factors: Respondents reason for willing to donate their used smartphones

Subject	%	Subject	%	Subject	%	Subject	%
Empathy		Altruism		The need for forgiveness.		The desire to help.	
I sympathize with the donation beneficiaries.		I am concerned about the wellbeing of the donation beneficiaries.		Donating helps me feel pardoned.		I genuinely wish to assist the recipients.	
Strongly disagree.	10.3	Strongly disagree.	26.7	Strongly disagree.	24.0	Strongly disagree.	13.2
Disagree	32.2	Disagree	19.0	Disagree	28.4	Disagree	28.4
Agree	38.2	Agree	28.6	Agree	26.4	Agree	28.1
Strongly agree.	19.2	Strongly agree.	25.7	Strongly agree.	21.2	Strongly agree.	30.3
I am aware of the recipient's needs.		I'm concerned about the receiver's potential struggles if I choose not to donate.		I believe that giving away belongings offers me a feeling of contentment and tranquility.		I am delighted to facilitate the donation recipients' access to better education.	
Strongly disagree.	24.5	Strongly disagree.	23.3	Strongly disagree.	20.7	Strongly disagree.	21.2
Disagree	20.0	Disagree	23.3	Disagree	30.0	Disagree	21.9
Agree	28.4	Agree	27.6	Agree	24.8	Agree	20.0
Strongly agree.	27.2	Strongly agree.	25.7	Strongly agree.	24.5	Strongly agree.	37.0

taught the importance of sharing by their family (71.9%), pray 1-2 times daily (62.5%), and participate in social activities (73.6%). Most of them (48.6%) have four to eight close friends (see Table 3).

Table 4 shows the psychological statement voted by the respondents. More than 50% of respondents agree or strongly agree that they are willing to donate their used smartphones because of the psychological factors. Only the feeling of contentment and tranquility does not give a strong effect to the willingness to donate, since more than of the respondents disagree or strongly disagree with this statement.

3.3 External Factors

External factors from the organization to which people donate influence donation behavior. Donors (58.8%) trust orphanages and religious groups in Indonesia as a place to donate used smartphones to those in need. Online contribution systems still need to be tested by donors. About 40% of respondents claimed they could contribute anytime (Table 5 shows the detailed).

Table 6 exhibits the donated smartphone condition. Smartphone gifting preferences differ. Most participants donate outmoded smartphones (47.8%) and those still functional and not yet outmoded (45.4%). An outmoded (obsolete) smartphone is a functioning phone without the newest features. For instance, it uses a 3G network and lacks AI. The outdated smartphone may meet donation receivers' WA, searching, zoom, and other needs. The donated cellphones are valued IDR 1,500,001–IDR 3,000,000 (45.1%); IDR 3.000,000–IDR 5.000.000 (46.6%).

3.4 Willingness to Donate

At the end of the survey, the respondents were asked their willingness to donate their used smartphones. More than half of respondents (53%) are willing to donate. This study aims to identify the factors that impact an individual's willingness to donate their used smartphone. Three machine learning models—decision tree, random forest, and neural network—are implemented to forecast those variables in accordance with the survey data.

For model construction purposes the collected data is split into training and testing sets in an 80:20 ratio. The model uses a decision tree, random forest, and neural network machine learning. Each model's hyperparameters will be examined before comparison to other approaches. The grid search is used as a tool to perform hyperparameter tuning. It evaluates the model's performance using 5-fold cross-validation (cv=5) and accuracy value to determine the best hyperparameters for each method. Each model's performance will be assessed using accuracy, recall, precision, and F1 score. Since the data is balanced, as shown by the target value distribution ratio, the evaluation metrics will focus on model correctness.

In the decision tree, we used maximum depth 2 and minimum samples leaf 4; while for the random forest we used number of trees 18, maximum depth 6, maximum

Table 5. The organization and the ideal moment to donate.

Subject	%	Subject	%
To which charitable organization would you want to donate your used smartphone?		When is the ideal moment to donate?	
Social, e.g. orphanage,	31.3	During religious events	23.1
Religious, e.g. church, mosque.	25.5	After natural disaster	37.0
Educational, e.g. university	18.8	Whenever I want	39.9
Online donating platform	3.5		
Any kind of legal organizations.	16.1		

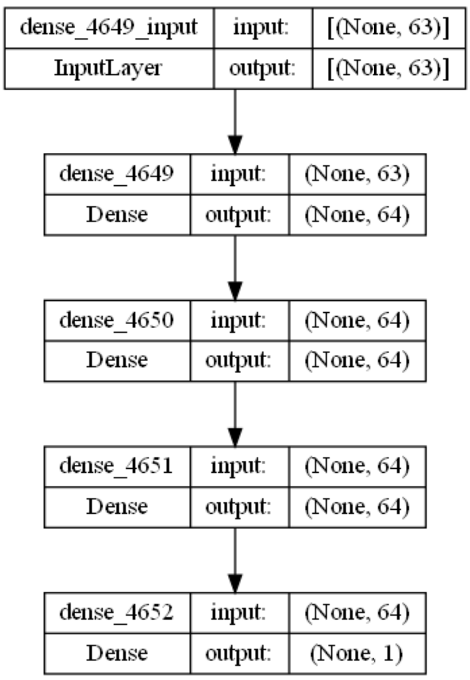
Table 6. The donated smartphone

Subject	%	Subject	%
How obsolete is the smartphone you are willing to donate?		How is the donated smartphone’s performance?	
Already obsolete		In good condition but obsolete	32.0
It is functional and isn’t obsolete.	47.8	Lag issues despite having sufficient hardware.	42.5
It has new tech and features.	45.4	Minor hardware damage does not prevent its use.	25.5
	6.7		
What sort of damaged used smartphone are you ready to donate?		At what price would you be willing to donate your used smartphone? (in million IDR)	
Damage free	19.5		
Defective screen	26.4	< 1.5	45.1
Deceleration response (lagging)	31.5	1.5 – 3.0	46.6
Disruptive sound system	3.8	3.0 – 5.0	7.8
Defective hardware	18.8	5.0 – 70	0.5

features Log 2 and random state 27. The neural network construction is based on the three hidden layers, 64 number of neutrons, 128 batch size, and 10 Epoch. Additionally, we use Adam optimizer, ReLU for hidden layer activation function, and Sigmoid for output layer activation function. The neural network model architecture and the testing accuracy over epochs is depicted in Figure. 2

The three models—decision tree, random forest, and neural network—achieved varying levels of accuracy, precision, recall, and F1 scores. Decision Tree: Accuracy of 83.33%, providing interpretability and clarity regarding the hierarchical importance of predictors. Random Forest: Accuracy of 84.52%, enhancing robustness and generalization through ensemble learning. Neural Network: Achieved the highest accuracy at 91.67%, capturing complex, non-linear relationships among variables (Table 7). Despite the neural network's superior predictive performance, decision trees and random forests were crucial in identifying feature importance and understanding behavioral trends. The neural networks are black boxes, they cannot identify the factors influencing the Indonesians' willingness to donate their used smartphones. Therefore, we employ a random forest as a decision tree to show the most critical factors influencing donation. The random forest in this study has 18 trees with a maximum depth of six. Thus, the feature significance value is essential for understanding the primary factors driving smartphone donation. Figure 3 shows the relevance of the top ten feature of importance of the random forest.

The models discovered numerous significant characteristics impacting respondents' willingness to donate. The feature importance analysis (Figure 3) identified “participation in social activities” as a significant predictor of donation behavior. This finding aligns with social capital theory (Claridge, 2018), which emphasizes the role of interpersonal networks and community engagement in fostering pro-social behaviors, such as altruism and philanthropy. In the Indonesian context, where communal values and collective well-being are deeply embedded in cultural practices, participation in social activities serves as a gateway to increased social awareness and responsibility (Maulana *et al.*, 2021). These activities likely expose individuals to the needs of others, reinforcing a sense of empathy and obligation to contribute. Another key factor, “family sharing values,” reflects the strong influence of familial relationships on decision-



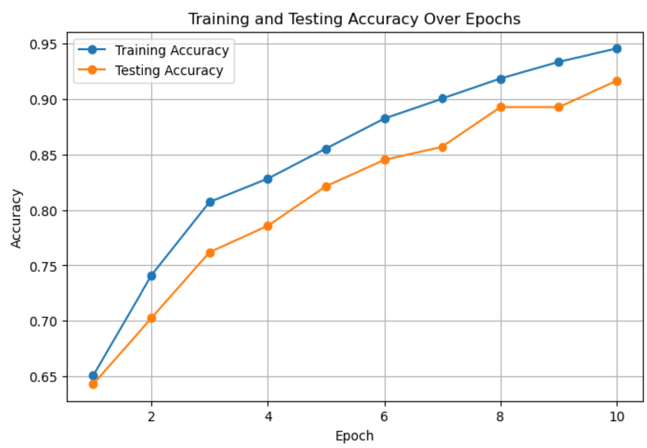


Figure 2. The neural network model architecture (left) and the neural network training and testing accuracy over epochs (right).

Table 7. Performance measures

Model	Accuracy	Precision	Recall	F1 score
Decision tree	83.33	81.67	94.23	87.50
Random forest	84.52	84.21	92.31	88.07
Neural network	91.67	92.45	94.23	93.33

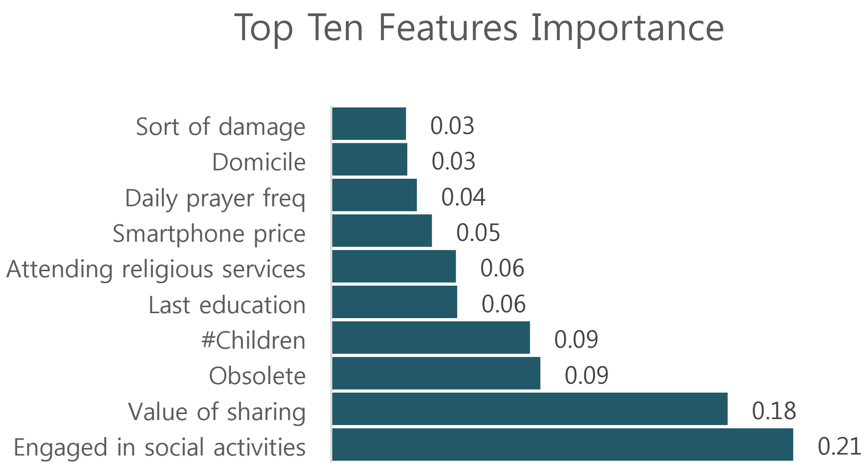


Figure 3. Top ten features of importance.

making in Indonesia. Rooted in collectivist cultural norms, Indonesian families often prioritize shared responsibilities and mutual support, making family teachings about generosity a pivotal driver for donation behaviors (Riany *et al.*, 2017). Similarly, "religious attendance" emerged as an important factor, underscoring the role of faith-based teachings and practices in shaping ethical and charitable actions (Lewis *et al.*, 2013). This aligns with research that highlights the motivational impact of religious doctrines and communal worship on philanthropic tendencies (Grönlund and Pessi, 2015). Obsolescence of smartphones played a critical role, indicating a practical aspect of donation decisions. Respondents were more inclined to donate devices that, while functional, no longer met their technological needs. This suggests that donation behaviors are influenced by a balance of altruism and convenience (Drea *et al.*, 2021; Tantia *et al.*, 2019), where donating obsolete devices provides both social value and an avenue for responsible disposal. These insights underscore the complex interplay between cultural norms, personal values, and practical considerations in shaping donation behaviors. By linking these factors to established behavioral theories and Indonesia's unique socio-cultural context, this study provides a nuanced understanding of the drivers behind smartphone donations, paving the way for more effective and culturally resonant intervention strategies.

Figure 4 presents the decision tree model illustrating the pathways and factors influencing Indonesians' willingness to donate obsolete smartphones. This hierarchical representation reveals the decision-making process based on a series of socio-behavioral, cultural, and practical conditions. The root node of the decision tree highlights smartphone obsolescence as the most significant factor. Respondents were far more likely to consider donating if their smartphones were obsolete (functional but no longer meeting their personal needs). This aligns with practical motivations, where individuals balance convenience (disposal of unused devices) with altruism.

3.4.1 Social and Demographic Factors

The tree further branches into social behaviors and demographic characteristics, which play crucial roles in donation decisions: (1) Social engagement, Individuals who actively participate in social activities (e.g., community events, group interactions) demonstrate a higher willingness to donate. (2) Religious Attendance: Regular attendance at religious services (once a week) emerges as another critical factor. This reflects the influence of Indonesia's strong religious culture, where teachings and community worship emphasize values of charity, generosity, and shared responsibility. (3) Age: Younger respondents (under 22 years old) were more likely to donate, most likely because they were more receptive to new habits and had less commitment to outdated technology.

3.4.2 Economic and Practical

Economic and practical aspects influence decision pathways at multiple nodes: (1) Smartphone Price: Mid-range smartphones (IDR 1,500,001–IDR 3,000,000) emerge as a critical threshold. Respondents with devices in this price range are more likely to donate, perhaps because these devices are functional and valuable enough to help others but no longer desirable to the donor. (2) Device Condition: Respondents who noted lagging problems but affirmed that the smartphone's hardware was in good condition showed greater willingness to donate. This suggests that functional devices, even with minor performance issues, are seen as suitable for donation, reinforcing the importance of practical disposal options for such items. (3) Speaker Damage: Devices with damaged speakers reduce the likelihood of donation, as donors may view these devices as less useful to recipients. This emphasizes the role of perceived usability in donation decisions.

3.4.3 Family and Social Networks

Family values and peer relationships also influence willingness to donate: (1) Close Friends: Respondents with 1–3 close friends showed a stronger willingness to donate when combined with other factors, such as religious attendance and lag issues. Close social networks may encourage charitable behaviors through shared norms or peer influence. (2) Family Sharing Values: While not explicitly visualized, family-based influences (e.g., shared values of generosity) can be inferred as secondary drivers when combined with social engagement and economic thresholds.

3.4.4 Complex Interaction of Factors

The pathways in the decision tree reveal the complex interplay between socio-cultural, economic, and practical considerations: (1) Social engagement and religious attendance act as motivational triggers, reinforcing behaviors rooted in cultural and communal values. (2) Practical considerations, such as the device condition and price, intersect with altruistic motivations, reflecting a balance of empathy and convenience. For example, an individual engaged in social activities, who attends religious services, and owns a functional mid-range smartphone is significantly more likely to donate than someone lacking these attributes.

Figure 4 underscore the importance of cultural and practical factors in shaping donation behavior: Cultural Sensitivity: Strategies promoting smartphone donations must align with Indonesian cultural norms, particularly emphasizing the role of religious teachings and community participation. Campaigns integrated with religious events and social gatherings are likely to resonate more effectively. Targeted Programs: Younger demographics,

```
Start: Is the smartphone obsolete?
├── No
│   └── Engaged in social activities?
│       ├── Yes
│       │   └── Lag issues?
│       │       ├── Yes: Attending religious services once a week?
│       │       │   ├── No: 1-3 Close friends?
│       │       │   │   ├── No: Willing to donate
│       │       │   │   └── Yes: Earnings IDR 3,000,001-IDR 6,000,000?
│       │       │   │       ├── No: Willing to donate
│       │       │   │       └── Yes: Not willing to donate
│       │       │   └── Yes: Willing to donate
│       │       └── No: Smartphone price IDR 1,500,001-IDR 3,000,000?
│       │           ├── No: Not willing to donate
│       │           └── Yes: Willing to donate
│       └── No: Not willing to donate
└── Yes: Age < 22?
    ├── Yes: Smartphone price IDR 1,500,001-IDR 3,000,000?
    │   ├── No: Not willing to donate
    │   └── Yes: Never attending religious services?
    │       ├── Yes: Engaged in social activities?
    │       │   ├── No: Not willing to donate
    │       │   └── Yes: Willing to donate
    │       └── No: Not willing to donate
    └── No: Speaker damage?
        ├── Yes: Not willing to donate
        └── No: Have 1-2 children?
            ├── Yes: Not willing to donate
            └── No: Engaged in social activities?
                ├── No: Not willing to donate
                └── Yes: Smartphone has lag problems, but hardware is in good condition?
                    ├── No: Not willing to donate
                    └── Yes: Willing to donate
```

Figure 4. The text-based flowchart for the 11th tree in the random forest model.

active community members, and owners of mid-range, functional smartphones represent ideal target groups for donation initiatives. Device Usability: Ensuring minor repairs (e.g., addressing lag issues or speaker problems) can make donated devices more appealing and usable for recipients, thereby increasing donor participation.

Therefore, to translate these findings into actionable outcomes, the following strategies are proposed: (1) In line with the participation in social activities, we proposed partnerships with Indonesian NGOs: Working with local NGOs with community trust and reach can boost smartphone donation efforts. NGOs can facilitate donations to underprivileged people while resolving donor concerns about transparency and security. To maximize participation, incorporate smartphone donations into existing social campaigns, such as blood donation or food distribution events. Social media sites like Instagram, TikTok, and WhatsApp should be used to target younger donors. Tech-savvy, socially conscious youth respond well to messages about environmental sustainability and rural education. (2) By the family sharing values, we recommend designing campaigns that appeal to family-oriented values, emphasizing how donating can help other needy families. Promote intergenerational participation in donation programs, encouraging parents and children to donate together. (3) Integration with Religious and Social Events: Donation campaigns can be promoted by aligning them with religious holidays or community festivals that celebrate charity. This strategy emphasizes religious attendance and social activities from the study. (4) By smartphone obsolescence, we proposed incentivized programs: Small discounts, certificates of appreciation, or tax deductions for donated devices can boost participation. Offering similar perks with smartphone shops or communications carriers could expand such schemes (5) Concerning age, we proposed simplifying donation processes: Mobile apps and drop-off points can simplify donation processes. Attracting donors requires clear instructions, accessible locations, and data security. E-Waste Management Awareness Campaigns: Public education campaigns about the environmental benefits of donating old but functional smartphones can change attitudes and encourage sustainable practices. Working with schools and universities to include these messages in curriculums or events may affect behavior. These ideas can help stakeholders improve smartphone donation programs and reduce e-waste and educational inequality in Indonesia.

4. CONCLUSIONS

This research offers valuable insights into Indonesians' willingness to donate used smartphones, emphasizing critical predictors such as religious attendance, family sharing values, and participation in social activities. A poll revealed that 57% of Indonesians are willing to donate their used smartphones. These results demonstrate the intricate interplay of cultural, psychological, and practical factors influencing donation behavior. The research identified smartphone obsolescence as a critical determinant by utilizing machine learning models, underscoring the significance of harmonizing convenience with altruism in donation decisions. The potential to address educational disparities and reduce e-waste is the broader societal impact of these findings, which extends beyond individual behaviors. Donors contribute to digital inclusion for marginalized students and promote environmentally sustainable practices by donating functional yet obsolete smartphones.

Additionally, integrating donation programs with cultural and religious contexts can enhance their effectiveness and reach. For the internal factors, the psychological statement substantially contributes to the willingness to donate, except the feeling of contentment and tranquility does not strongly affect the willingness to donate. As for the external factors, most donors contribute obsolete smartphones (47.8%) and those still functional and not yet outdated (45.4%). An obsolete smartphone is a functioning phone without the newest features. For instance, it uses a 3G network and lacks AI. The outdated smartphone may meet donation receivers' WA, searching, zoom, and other needs. Moreover, social organizations are the favored philanthropic organizations among most respondents (31.3%). In addition, the respondents are willing to donate smartphones with a price of 1.5 - 3.0 million rupiahs (45.1%); IDR 3.000,000 – IDR 5.000.000 (46.6%).

The machine learning finding shows smartphone obsolescence drives donation, followed by age and social involvement. The crucial aspects also demonstrate that social activities, family sharing, and religious attendance significantly impact Indonesians' desire to donate used smartphones. This finding provides alternate solutions for managing waste electrical and electronic equipment, which will benefit Indonesian students, especially those in rural areas who are in need. Combining interpretability with predictive power, the machine learning models provided actionable insights into the behavioral and contextual factors influencing willingness to donate to smartphones. These findings pave the way for targeted interventions to reduce e-waste and support digital inclusion.

While the study is deeply rooted in Indonesia's unique socio-cultural and economic landscape, the underlying principles have broader applicability. The findings can be scaled to regions with similar socio-economic conditions, such as other emerging economies in Southeast Asia, South Asia, or Africa, where cultural values, economic disparities, and digital divides similarly influence behaviours. Future research can modify this framework to these contexts, ensuring strategies align with local norms and priorities. Tailoring projects to reflect the socio-cultural and economic traits of regions helps stakeholders develop sustainable programs addressing worldwide issues of e-waste and digital inequality, promoting significant influence outside of Indonesia.

This study has several limitations that should be acknowledged. First, the reliance on self-reported data introduces the potential for response bias, as participants may overstate socially desirable behaviors or underreport undesirable ones. Second, the findings are specific to Indonesia, where cultural, economic, and social contexts play a significant role in shaping donation behaviors. As such, the generalizability of the results to other countries may be limited without adjustments for local contexts.

Future research could address these limitations by incorporating longitudinal data to track actual donation behaviors over time and expanding the study to include diverse cultural settings. Investigating other forms of e-waste, such as laptops or tablets, to build a comprehensive understanding of donation behaviors across electronic devices and their donation patterns could also provide broader insights into sustainable practices globally. Additionally, investigating the long-term impact of donation campaigns on environmental sustainability and educational outcomes could further inform policy and program design. These avenues will enhance the scalability and applicability of strategies to foster a circular economy while addressing pressing societal needs.

4.1 Data Privacy and Ethical Considerations

Given the sensitive nature of the data collected, including income levels and religious practices, strict measures were implemented to ensure data privacy and ethical compliance. Respondents were informed about the purpose of the study, the voluntary nature of participation, and the confidentiality of their responses. Data collection adhered to ethical guidelines, with personally identifiable information anonymized to prevent any risk of exposure.

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