

Article

Leveraging Behavioral Tipping Points to Improve Sustainability Outcomes in Consumer Electronics

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Abstract

Consumer electronics are important for global energy use, material extraction, and toxic exposures. Within consumer behavior, End-of-Current-Use (EoCU) decisions (e.g., to resell, donate, recycle, or throw away) particularly are a planetary health concern, not just a waste management problem. The goal of this work is to inform interventions that nudge users toward more sustainable and data-secure choices. We surveyed 4000 U.S. users on their attitudes, knowledge, and planned EoCU choices, and constructed a Random Forest model to simulate planned behavior as a function of reported knowledge and attitudes. The key result is identification of behavioral “tipping points”, i.e., incremental shifts in knowledge or attitude that produce large changes in sustainable behavior. For example, moving the level of agreement relating to “reselling is worthwhile” from “Neutral” to “Agree” increases the probability of resale by 26%, with stronger agreement yielding minimal further gains, suggesting relatively small changes in perception may thus produce large behavioral changes. The model also identifies trade-offs, with increases in agreeing that resale is worthwhile leading to decreases in giving away (−14%) and recycling (−10%). Economic considerations drive reselling decisions, while environmental concerns drive recycling. Identifying these critical thresholds enables efficient intervention design, as modest attitude changes at transition points may prove more effective than maximizing positive attitudes. These findings challenge assumptions of linearity of behavioral responses, informing circular economy and other policies. They also relate to managing planetary health issues raised by EoCU electronics, such as human and ecological well being, digital equity, and environmental justice. The framework is broadly applicable to identifying behavioral tipping points in other domains, e.g., healthcare, energy efficiency, and data security.



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This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.**Keywords:** Random Forest; electronic waste; End-of-Current-Use; machine learning; consumer behavior; threshold effects; sustainability; circular economy; planetary health

1. Introduction

1.1. End of Current Use of Consumer Electronics and Sustainability

The proliferation of electronic devices has transformed modern life, with 80% of the global population now owning smartphones [1], and the average American household has dozens of network-connected devices. In the U.S., by 2024, 98% of adults owned

a cellphone, and 91% owned a smartphone [2]. Discarded electronics represent one of the fastest-growing waste streams globally, yet only 22% enters documented recycling systems [3].

Electronic devices that a consumer is finished with are often called electronic waste or e-waste. The term “e-waste” itself is misleading, as it implies that all devices leaving a consumer are waste, when, in fact, many are reused [4]. We adopt the more precise term “End of Current Use” (EoCU) to encompass the full range of electronics disposition options available to consumers: storing at home, reselling, donating/giving away, trading in, recycling, or throwing away as trash. Each option carries different implications for both environmental sustainability and data security.

Sustainability and planetary health are intertwined. The Rockefeller Foundation–Lancet Commission on Planetary Health defines the field as the achievement of the highest attainable standard of health, well-being, and equity worldwide pursued through political, economic, and social systems that shape humanity’s future within safe environmental limits [5]. EoCU electronics sit squarely within this framework: Device manufacturing draws down extracted materials and embedded energy, informal recycling exposes vulnerable populations to toxic pollutants, resale markets shape digital access for lower-income consumers, and recoverable personal data poses risks to individual well-being. The disposition decision a consumer makes thus connects human health, ecological systems, and social equity. We situate the present work within planetary health on this basis, and return to these connections in Section 5.

End-of-Current-Use electronics are relevant to the following global sustainability challenges: energy use, waste management, and the digital divide. In terms of energy, while a single device does not account for a large share of consumer energy use, the totality of owned electronic devices does. The annual lifecycle energy use of a typical portfolio of electronics owned by a U.S. consumer in 2007 was around 30% of annual gasoline consumption [6]. EoCU consumer decisions for electronics are important for energy because of the energy intensity of high-tech manufacturing. In contrast with many other energy-consuming products, in which operation dominates energy use, production often represents the majority of lifecycle environmental impacts for electronics [7–9]. For example, 70% of a laptop computer’s lifecycle energy use occurs during production, compared to 30% during operation [10]. The high share of production energy in the lifecycle implies that extending lifespan, e.g., through reselling, is an important energy-saving strategy.

For waste management, the volume of e-waste is substantial and growing. UNITAR reported a global generation of e-waste of 62 million tons in 2022, marking an 82% increase from 2010 [3]. Global e-waste generation is projected to increase by 2.6 million tons per year, leading to an 82 million ton total in 2030 [3]. Around 22% of e-waste generation in 2022 was documented to have been processed in formal recycling systems. Formal recycling systems recover metals such as steel, aluminum, and gold at high yields. Plastics are more difficult to usefully recycle. Much of the remaining 78% of global e-waste is processed by an informal reuse/recycling sector. Informal recycling often involves environmentally destructive processes such as open burning of wire insulation to recover copper and use of open barrels of acid to recover gold from circuit boards [4]. High concentrations of pollutants have been documented at many informal e-waste recycling sites, e.g., in [4,11].

End-of-Current-Use consumer decisions are also important for addressing the digital divide. Markets for used electronics increase access to devices for lower-income populations [4]. Functional devices that are stored, recycled, or thrown away imply a reduced supply to such resell markets.

Parallel to sustainability concerns, EoCU electronics pose significant data security risks. Electronic devices store increasing amounts of personal information, from basic contact

details to financial credentials, health records, and intimate communications. Studies have repeatedly demonstrated that devices entering secondary markets or waste streams often contain recoverable data. MIT researchers examining 158 second-hand hard drives found only 9% had been adequately sanitized, with the remainder containing retrievable personal information including credit card numbers and medical records [12]. More recently, researchers in Ghana recovered sensitive government contracts and financial data from devices in e-waste markets [13]. These security concerns create a problem where fear of data breaches leads many consumers to store devices indefinitely [14], delaying both potential reuse and proper recycling.

Device-locking practices by manufacturers [15] and consumer uncertainty about data erasure further complicate sustainable EoCU management. This confluence of environmental impacts, data security risks, and behavioral challenges underscores the need for comprehensive strategies that address both the technical and human dimensions of electronics disposition.

1.2. Role of Consumer Behavior

Consumer behavior is pivotal in determining the environmental and security outcomes of End-of-Current-Use (EoCU) electronics. When devices reach EoCU, consumers face choices that directly impact sustainability; for example, indefinite storage reduces reuse potential [16], while disposal in household trash locks valuable materials in landfills. It is important to nudge consumers toward more sustainable options—reselling, donating, and recycling—instead of storage or throwing away the product in the trash.

Prior quantitative research has employed various methodologies to understand EoCU disposition behavior, including descriptive statistics [17], logistic regression [18,19], structural equation modeling [20,21], and cluster analysis [18,22]. These studies reveal several key behavioral drivers:

Consumer e-waste disposal behavior is shaped by multiple interconnected factors that vary across different contexts and regions. Convenience and accessibility emerge as primary determinants, with consumers demonstrating higher recycling rates when collection facilities are easily accessible, well-known, and conveniently located [23–25]. Psychological factors play a crucial role in disposition choices, including trust in recycling entities, emotional attachment to devices, and perceived need for backups, often leading to device “hibernation”—indefinite home storage driven by data security concerns and lack of formal recycling channels [19,25–27]. Environmental awareness varies geographically, with developing countries frequently lacking both the knowledge and infrastructure for proper e-waste management, though higher awareness generally correlates with more responsible disposal practices [28]. Economic considerations influence behavior differently across contexts; for example, financial incentives motivate responsible disposal particularly in developing nations, while device malfunction, obsolescence, and repair costs drive disposal decisions, with younger consumers showing a greater tendency to discard rather than repair damaged devices [29,30].

Consumer behavior thus sits at the intersection of environmental and security challenges. These decisions are key to environmental and data security outcomes. From a sustainability perspective, reuse is preferable to recycling, which is preferable to throwing away in the trash. “Poor” decisions are common; for example, consumers often store unused devices indefinitely [16]. While, in some cases, a stored device provides utility as a spare or data backup, often it does not, losing any potential value for reuse. Consumers also often throw electronics away in the regular trash, even when recycling is reasonably convenient [31]. Valuable materials in electronics thus end up in landfills rather than being recovered.

These decisions involve complex trade-offs between convenience, financial value, environmental concern, and data security. Understanding these decision-making processes is essential for developing effective interventions that improve both sustainability and security outcomes.

1.3. Behavioral Tipping Points

Behavioral economics and psychology provide critical insights into the threshold dynamics that underpin human behavior, particularly in environmental contexts. Granovetter's concept of "tipping points" highlights that small changes in conditions can lead to significant shifts in behavior, particularly in the adoption of sustainable practices, where values, incentivization, and varying factors can lead to dramatic behavioral shifts [32]. In environmental contexts, there are critical thresholds where the accumulation of knowledge, convenience, or social pressure can trigger individuals to adopt more sustainable practices such as electronic waste recycling [33]. Threshold effects for EoCU electronics could manifest in various forms. For instance, convenience thresholds suggest that, when recycling options are easily accessible, consumer inertia may be overcome, fostering increased participation in recycling programs. Refs. [32,34] support this notion, revealing that perceived operational convenience is a positive predictor of recycling intentions. Similarly, Ref. [34] emphasizes that easing the logistics surrounding the recycling process can effectively encourage household participation in recycling initiatives. Moreover, knowledge thresholds play a crucial role in influencing recycling behavior. Ref. [33] found that consumers are more likely to engage in e-waste recycling when they are sufficiently informed about the environmental impacts of e-waste or the security consequences associated with improper disposal. Incremental education efforts emphasizing environmental knowledge can help overcome these knowledge gaps and facilitate increased recycling rates. Furthermore, financial thresholds have emerged as significant factors in determining whether consumers opt to recycle e-waste. Factors such as the perceived financial benefits of reselling devices or the costs associated with recycling programs impact consumer decision-making [35]. This economic consideration can lead to the development of tailored incentive programs that reward recycling, thereby leveraging financial thresholds to achieve behavioral changes.

1.4. Machine Learning in Consumer Behavior Prediction

Traditional statistical methods used in consumer behavior research rely on the assumption of linear relationships between predictors and outcomes. This is particularly relevant for regression analysis, where the underlying model structure is frequently based on linear equations. However, this assumption does not hold for many real-world phenomena, where decision-making processes exhibit nonlinear dynamics and threshold effects.

Machine learning approaches have emerged as powerful alternatives to regression methods, showcasing notable advantages in capturing the intricacies of consumer behavior. Among these methodologies, ensemble methods such as Random Forests have garnered significant attention for their ability to combine multiple models to improve prediction accuracy. Random Forests specifically operate by constructing a multitude of decision trees during training and output the mode of the classes for classification tasks or the mean prediction for regression tasks. This approach effectively mitigates the issues of overfitting and variance associated with single models, offering a significant improvement in predictive performance [36–38].

Random Forests, as part of the broader category of ensemble learning, are uniquely suited to addressing the complexities inherent in consumer behavior data. They incorporate randomization in both the selection of data subsets for building trees and the selection of features used in node splits, resulting in an ensemble of trees that can better capture the nonlinearities

and interactions present in the data. Studies have demonstrated that ensemble methods, including Random Forests, outperform traditional linear models across various applications, including healthcare outcomes, market behavior predictions, and more [37,39–41].

Previous applications of Random Forest models in consumer behavior research [42,43] have demonstrated success in capturing nonlinear relationships and complex interactions, for example, [44], where Random Forest is compared with multinomial logit models, [40], where consumer segments are delineated through feature interactions, and [45], where interpretable machine learning is applied to mode choice modeling. The non-parametric nature of Random Forests—where there is no need to specify a prior model structure—enhances their applicability to consumer behavior research. This flexibility allows researchers to explore multi-variate relationships without the constraints of linear assumptions, thus providing deeper insights into consumer preferences and behaviors. Studies have illustrated how Random Forests can effectively delineate complex consumer segments by identifying pivotal interactions between various product features and satisfaction levels [40,46,47]. Furthermore, as consumer data continues to grow in size and complexity, the scalability of ensemble methods like Random Forests becomes an important advantage, allowing seamless integration with big data frameworks [36,42].

2. Focus of the Paper and Contributions

Our research question is as follows: *“Are there tipping points in stated knowledge and attitudes that lead to large changes in likelihood of behavior in End-of-Current-Use decisions for electronics?”* We move beyond the assumption of a linear association between intended behavior and stated attitudes and knowledge. In order to answer this question, we develop a survey and predictive simulation model that has general utility for the decision-making processes in this space. The model simulates consumer disposition decisions relating to an EoCU electronic device (i.e., to resell, donate, recycle, or throw away) using 19 attitude and knowledge variables. The modeling approach used is Random Forest. With each variable measured on a bipolar Likert scale, we can identify nonlinear behavioral tipping points, i.e., “small” changes in response that lead to large changes in behavior. In contrast, a linear response would appear as a regular incremental change in behavior progressing through the Likert scale. The hope is that tipping points are promising areas for future targeted “nudges” to encourage sustainable and data-secure behaviors.

2.1. Behavioral Modeling Methods

Random Forest models have previously been used to simulate behavior (see Section 1.4), but this prior work does not elicit linear/nonlinear changes in behavior as a function of individual determinants (in our case, response to attitude/knowledge prompts). We propose an individual effect function to extract information from Random Forest models to characterize behavioral tipping points. The individual effect function picks an attitude/prompt and a behavior and sets all other explanatory variables to their mean values, and then the probability of the behavior for different values of the attitude prompt is calculated (−2 to +2 Likert scale in our case). Nonlinear behavior in these functions can reveal the threshold level for interventions, where a small change in attitude can lead to large changes in behavior. This approach for identifying tipping points can be applied in a variety of domains, as it has the potential to identify effective interventions.

2.2. Sustainable Electronics Behavior

This work is the first to explore threshold dynamics in consumer decisions relating to EoCU electronics. Previous regression-based studies have examined EoCU behaviors using traditional linear models, including [18]’s multinomial logistic regression on consumer

electronic disposition and [48]’s analysis of e-waste recycling determinants, which examines one disposition in isolation. Both studies assume linear relationships between attitudes and behaviors, which cannot capture threshold dynamics.

Regression is unsuited to identifying tipping points. Likert scale responses for attitudes and knowledge can be treated in regression as a discrete variable (taking, e.g., values of -2 , -1 , 0 , $+1$, $+2$) or as a series of dummy variables. The choice of discrete variable representation, by definition, assumes a linear relationship; thus, it cannot identify a nonlinear tipping point. Using dummy variables allows variation per response but does not protect ordinality, i.e., one expects many responses to increase monotonically, e.g., use of recycling should increase with awareness, but dummy variables do not have the appropriate constraint.

3. Materials and Methods

The study outline is provided below, progressing from data collection through analysis to behavior simulation. Figure 1 provides a visual summary of the flow of the study.

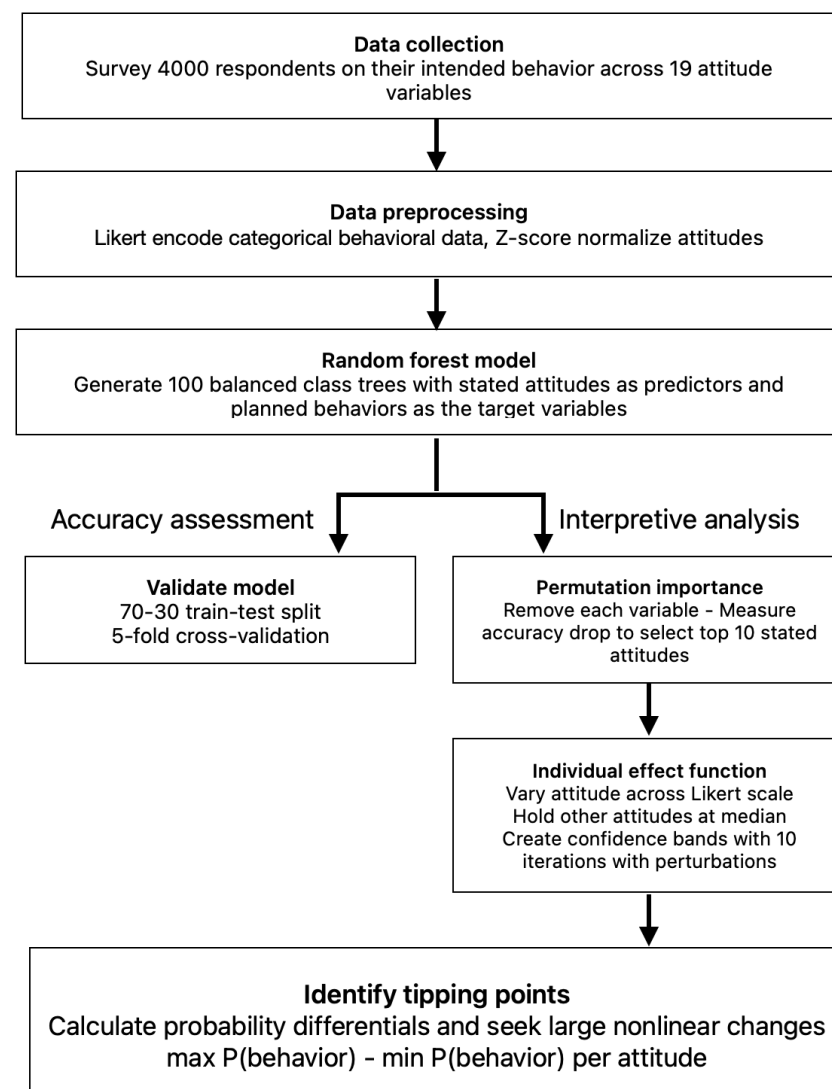


Figure 1. Summary of flow of methodology.

We first developed and deployed a comprehensive survey examining 10 categories of network-connected consumer devices, collecting responses from 4000 U.S. participants (400 per device category) through the Prolific platform. Data is captured via Qualtrics,

assessing both past and intended disposition alongside 19 attitude and knowledge variables measured on 5-point bipolar Likert scales.

Supporting Information S2 provides the full wording, response coding, and behavior questions for all 19 attitude and knowledge variables.

To verify income representativeness, we compared the survey mean income (\$75,137 from bin midpoints) with a U.S. Census mean calculated using the same bin structure (\$81,603), confirming that the sample is representative of the U.S. income distribution. Data quality was maintained through a 16-flag system that detects logical contradictions, attention check failures, and implausible demographic patterns; responses triggering 3 or more flags underwent manual review. Full data-cleaning details are reported in Supplementary Information S1.

Following data collection, we preprocessed the survey responses by encoding categorical behavior variables, standardizing all attitude variables using z-score normalization, and imputing missing values where necessary. We then constructed a Random Forest classifier with 100 decision trees, balanced class weights, and controlled parameters to simulate EoCU disposition behaviors from the standardized attitude features. The analysis phase involved four complementary approaches:

1. Assessment of feature importance using both Gini and permutation metrics to identify which attitudes most strongly influence disposition behavior and to prioritize variables for attitude effects analysis.
2. Validation of the model using out-of-bag error estimation, feature stability analysis across random seeds, and threshold sensitivity testing.
3. Calculation of individual effect functions for shifting an attitude across the Likert scale range while holding other attitudes at median values. The linearity or nonlinearity of this response indicates a tipping point.
4. Development of visualization techniques, including probability curves with confidence bands, importance ranking comparisons, and decision tree pathway illustrations to communicate behavioral tipping points and enable simulation of intervention scenarios.

The survey captures each respondent's final intended disposition action for a specific device. The model simulates user intended disposition among the resell, donate/give away, recycle, and throw away options. Some users indicated intent to store or were uncertain on what to do; these are not included in the model because the objective was to understand which "final" option is chosen among the four. Storing is a qualitatively different decision in that it is a passive default. Including storage alongside active options in a single classifier would conflate a passive non-decision with active choices. A consumer who stores out of inertia shares unobserved characteristics with one who throws a device away, cutting across what would be distinct categories. The present paper models the choice among active disposition options conditional on the consumer having decided to act.

3.1. Survey Development

Following a systematic review of the End-of-Current-Use behavior literature, we designed a comprehensive survey to examine the relationship between disposition behavior and consumer attitudes and knowledge. The survey encompassed 10 categories of network-connected devices: smartphones, tablets, wearables, gaming consoles, augmented reality/virtual reality (AR/VR) devices (e.g., Apple Vision Pro, Cupertino, CA, USA, Meta Quest, Menlo Park, CA, USA), streaming devices (e.g., Apple TV, Cupertino, CA, USA, Roku, San Jose, CA, USA), security devices (e.g., smart doorbells, baby monitors), connected kitchen appliances (e.g., robotic vacuum cleaners, coffee makers), smart TVs, and smart home equipment (e.g., thermostats). Device selection prioritized newer technologies with

high ownership rates, excluding traditional computers, printers, and networking equipment. According to industry data, Internet of Things device ownership varies, e.g., from 96% for smartphones to 31% for smartwatches [49].

The survey distinguishes between stated and revealed preferences by querying both past disposition behavior and intended future actions. Respondents reported on seven disposition options: storing, recycling, reselling, donating to friends/family, trading in through manufacturers/carriers, dropping off at donation centers, or discarding in household trash. For future intentions, respondents could also say that they were uncertain about what they will do.

We assessed attitudes and knowledge through targeted prompts addressing convenience, environmental impact, data security, and economic considerations for each disposition option. For example, respondents rated agreement with statements like “it is convenient to X my device” and “X-ing my device helps protect the environment”. Additional questions explored data security concerns and the perceived importance of personal information stored on devices, following frameworks established in industry research [50].

The survey employed single-item measures with 5-point Likert scales, a methodological choice validated by research demonstrating their effectiveness when constructs are precisely defined [51,52]. Data collection utilized the Prolific platform to recruit 4000 unique U.S. respondents, with 400 responses per device category. Qualtrics controls prevented duplicate participation across device-specific surveys, ensuring response integrity. The sample’s demographic distribution aligns with Consumer Technology Association benchmarks [53], confirming its representativeness of the U.S. population.

3.2. Data Preprocessing

Prior to analysis, we preprocessed the survey data to prepare it for modeling. The categorical intended behavior variable was first cleaned to remove any text repetition artifacts, then encoded using scikit-learn’s Label Encoder, generating numeric labels for each behavior category. All 19 attitude variables were standardized using z-score normalization (mean = 0, standard deviation = 1) to ensure that all features were on comparable scales. The survey design required responses to all attitude prompts, resulting in no missing data for the 19 attitude variables. A mean imputation step was included in the preprocessing code as a defensive measure but was not triggered.

The resulting feature matrix, comprised standardized attitude scores for all respondents, while the target vector contained the encoded behavior choices.

Standardization is a monotonic transformation that does not alter the Random Forest’s split structure or predictions. For the individual effect function, the target attitude is varied across the five raw Likert values which map one to one onto the standardized scale. The non-parametric nature of Random Forests imposes no functional form on this mapping, allowing the model to detect threshold, linear, or non-monotonic patterns directly from the data.

3.3. Random Forest Model Specification

Having established the rationale for employing a Random Forest model, we implemented a classifier designed to predict End-of-Current-Use (EoCU) disposition as a function of 19 stated attitudes and knowledge items, each measured on a bipolar 5-point Likert scale. The model was developed with the following specifications: 100 decision trees, a minimum of five samples per leaf to reduce overfitting, and no maximum depth constraint, allowing trees to grow until the sample size criterion is met. A fixed random state was used to ensure reproducibility, and class weights were automatically balanced to account for any imbalances in behavior category frequencies. This implementation used scikit-learn’s

RandomForestClassifier, where each tree is trained on a bootstrap sample and considered a random subset of features at each decision node.

After excluding storage and uncertainty responses, the four classes were balanced at 198 observations each (792 total). Balanced class weights were therefore redundant and did not alter the predicted probabilities. The baseline probability to correctly predict each class was 25%.

3.4. Attitude Effect Analysis

To quantify how attitudes influenced behavior choices, we developed an approach to analyze attitude effects. In regression models, coefficients quantify the strength of each predictor's effect on the outcome. Random Forest models do not produce coefficients, but we can probe the model to estimate analogous attitude effects, i.e., the change in predicted probability of a behavior resulting from a change in an attitude variable.

The process begins with the selection of the ten most important attitudes based on permutation importance scores derived from the fitted Random Forest model. For each of these key attitudes, we construct a baseline dataset in which all features were set to their median values. We then systematically vary one target attitude across all five points of the Likert scale (ranging from -2 to $+2$) while holding all other attitudes at median, generating behavior predictions at each level. We call this an individual effect function:

$$\begin{aligned} &\text{Individual Effect Function} \\ &(\text{attitude response } j \text{ for behavior } X) = \end{aligned}$$

$$P(X \mid \text{attitude} = j, \text{others at median values}) \quad (1)$$

Plotting the individual effect function as a function of j indicates the linearity/nonlinearity of the behavioral response to the attitude j .

The individual effect function evaluates predictions at a fixed median covariate profile, representing a synthetic respondent, and varies one attitude at a time while holding others fixed. It does not capture joint attitude shifts that may occur in practice (e.g., learning about recycling may simultaneously increase recycling knowledge and recycling convenience perceptions), nor does it reflect the full range of population heterogeneity. The confidence bands capture model sensitivity to small perturbations, not sampling uncertainty. These are standard limitations of partial dependence analyses at fixed profiles.

The individual effect function differs from standard partial dependence plots [54] in three respects: It holds non-target attitudes at a fixed median profile rather than averaging over the observed sample distribution, which preserves threshold effects that population averaging would smooth out. It evaluates the model at the five discrete Likert categories to locate specific adjacent-category transitions rather than producing continuous curves. It simultaneously displays all competing behavioral outcomes, directly revealing trade-offs across disposition options. These properties make the individual effect function suited to identifying behavioral tipping points, which is the objective of this paper.

To account for variability, this process is repeated ten times with slight random perturbations drawn from a normal distribution with mean 0 and standard deviation 0.1, which is roughly one-tenth of a standard deviation from the median. This is sufficient to capture model sensitivity without fundamentally changing the baseline scenario applied to the non-target features. These repeated simulations enable the construction of confidence bands around each estimated effect, thereby capturing uncertainty in the individual effect predictions.

The resulting confidence bands capture variability due to small changes in the covariate profile. They do not quantify sampling uncertainty from the finite survey or

measurement error in Likert responses. Bootstrapping respondents, on the other hand, will not change the location of the steepest adjacent-step transition given the current stable state of the model, as discussed in Section 4.1.

For each attitude–behavior pairing, we calculated the maximum probability differential, i.e., the difference between the highest and lowest predicted probabilities across the Likert scale:

$$\begin{aligned} \text{Probability Differential (attitude response } j \text{ for behavior } X) = \\ \max[P(X)] - \min[P(X)] \\ \text{across Likert values of } j \text{ from } -2 \text{ to } +2 \end{aligned} \quad (2)$$

While permutation importance ranks attitudes by their contribution to overall model accuracy across all behaviors, probability differentials reveal which attitudes most strongly influence each specific behavior. We selected attitudes for detailed presentation based on which produced the largest probability differentials within each disposition category (resell, recycle, give away, throw away). This approach ensured that the threshold effects reported in the results reflect attitudes with demonstrated influence on specific disposition decisions rather than spurious relationships.

3.5. Feature Importance Assessment

To assess feature importance, we used two complementary methods: The first was Gini importance, which reflects the mean decrease in node impurity weighted by the probability of reaching each node averaged across all trees in the ensemble. The second was permutation importance, in which each feature was randomly permuted and the resulting drop in model accuracy was measured. This process was repeated ten times to produce stable estimates. Compared to Gini importance, permutation importance provides a more reliable assessment, particularly when features differ in scale or distribution.

Feature stability was evaluated by comparing Gini and permutation importance rankings, which produced consistent top-10 lists (Table 1). Gini and permutation importance assess variable influence through fundamentally different mechanisms. The consistency of the top-10 rankings across both methods indicates that the importance estimates are not artifacts of split-opportunity bias or predictor correlation.

Table 1. Attitude variables with top 10 values of importance. Importance shows a decrease in model accuracy (proportion correctly classified) when the variable is randomly permuted.

Attitude Variable	Description	Importance
recycle_know_where	Knows where to recycle the device	0.148
resell_worthwhile	Believes reselling is financially worthwhile	0.116
resell_investment	Considered resale value when purchasing	0.091
donate_convenience	Perceives donating as convenient	0.084
resell_convenience	Perceives reselling as convenient	0.064
recycle_trust	Trusts recyclers to handle device properly	0.057
recycle_convenience	Perceives recycling as convenient	0.057
donate_useful	Believes donated devices should be useful	0.051
resell_value	Knows the resale value of the device	0.047
resell_offline	Knows local/offline reselling options	0.045

3.6. Model Validation

Although our primary goal is interpretive rather than predictive, we undertook several model validation steps: Model performance was assessed via a 70/30 stratified

train–test split (held-out accuracy: 44.1%) and 5-fold cross-validation on the full dataset ($44.7\% \pm 3.9\%$). Tipping point stability was assessed by repeating the individual effect function 10 times with random perturbations applied to non-target features, producing the confidence bands reported in the results.

3.7. Visualization and Interpretation

To effectively communicate our findings, we employ several visualization techniques: Probability curves are used to illustrate how the likelihood of each behavior changes as a function of attitude level with confidence bands derived from multiple simulation runs. To highlight the behavioral outcomes most affected by individual attitudes, we employ a color-coding scheme in which blue indicates positive changes and orange indicates negative ones. Bar charts are used to present importance rankings, showing both the Gini and permutation metrics side by side. In addition, individual decision trees from the forest are visualized to illustrate key decision pathways and logic used by the model. All analyses were implemented in Python 3.12 using NumPy, Pandas, scikit-learn, and Matplotlib. The complete analysis pipeline was designed for full reproducibility, with all random seeds fixed and code thoroughly documented to support transparency.

4. Results

In this section, we present findings from our Random Forest analysis examining how consumer attitudes influence four End-of-Current-Use behaviors post-storage for electronic devices: reselling, recycling, giving away, and throwing away. For each behavior, we analyze probability differences across attitude scales, identify critical tipping points, and examine trade-offs with other disposition options. The probability differences shown represent the change in likelihood of each behavior when attitudes shift from their minimum to maximum values on the Likert scale.

4.1. Overall Model Accuracy

Although the primary purpose of our Random Forest model was interpretive rather than predictive, we assessed its classification performance to establish baseline validity. Using a 70/30 train–test split with stratified sampling, the model achieved 44.1% held-out accuracy across four behavior classes (give away, recycle, resell, throw away). This exceeded the 25% baseline expected from random classification by a factor of 1.76, indicating that the attitude variables capture a meaningful signal in disposition decisions. The confusion matrix, full classification report, and calibration curves for each behavior class are reported in Supplementary Information S4.

Permutation importance analysis identified the attitudes most strongly influencing disposition behavior overall (Table 1). Permutation importance measures the decrease in model accuracy when a given attitude variable is randomly permuted, thereby breaking its relationship with the outcome. Higher values indicate that the variable contributes more to the model's predictive ability. For example, when knowledge of recycling location is permuted, model accuracy drops by 14.8%, making it the most influential predictor overall.

Pairwise interactions among the top 10 variables were tested by constructing interaction terms and assessing their importance in augmented Random Forest models. The strongest interactions involved the same variables that ranked highest individually, e.g., “knows where to recycle” and “donation is convenient”, which had an importance score of 0.074. Variables outside the top 10 did not produce meaningful interactions.

From these high-importance attitudes, we selected variables for individual effect functions (1) based on which produced the largest probability differentials (2) for each behavior. This approach ensured that the threshold effects we report reflect attitudes with

demonstrated influence on disposition decisions rather than spurious relationships. The results section presents the effects for the attitudes generating the largest behavioral shifts within each disposition category. The attitude effects analysis presented in Sections 4.2–4.4, quantifies how shifting individual attitudes across the Likert scale influences the probability of each disposition behavior. To account for model variability, we repeated each simulation ten times with slight random perturbations applied to non-target features, generating the confidence bands shown in the figures. The width of these bands reflects uncertainty in the estimated effects; narrower bands indicate more stable predictions across simulation runs.

4.2. Reselling Behavior: Worthwhileness as the Dominant Driver

Reselling behavior exhibited the largest probability swings of any disposition option, with perceived worthwhileness creating notable threshold effects. Figure 2 shows the individual effect function for the prompt “reselling is worthwhile” for the four behaviors. It shows a 26.4% probability differential, the strongest attitude–behavior relationship in our analysis. However, this difference was not uniformly distributed across the attitude scale. Resell probability remained near 17% for consumers who viewed reselling as not worthwhile or were neutral to its impact (Likert values -2 to 0). At the transition from “neutral” (0) to “agree” (1), the probability jumped by 26.4%, with virtually no additional gains from further positive movement. This sharp threshold indicates that simply shifting perception from “neutral” to “somewhat agree” captures most of the potential behavior change.

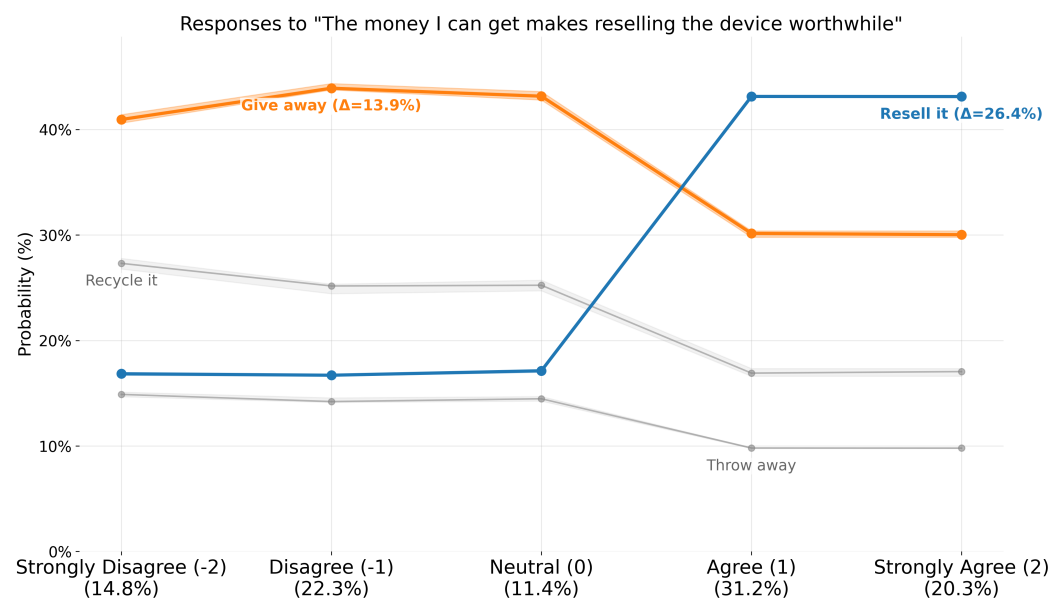


Figure 2. Probability of behavior choice by consumer perception that resale is financially worthwhile: changes in probability for recycle, give away, resell, and throw away attributed to agreeing with statement “The money I can get makes reselling the device worthwhile”. Percentage numbers below the Likert scale category show the share of survey responses for that response. Reselling shows the strongest increase ($\Delta = 26.4\%$) when consumers agree that resale is financially worthwhile, while giving away decreases the most ($\Delta = -13.9\%$).

The financially worthwhile variable visualizes the interaction between different behaviors. It is also one of the top two contributing factors to the change in give-away probability. Give-away behavior decreased substantially as perceptions of resale value increased, dropping from 41% to 30%. This 13.9% point reduction indicates that financial considerations can redirect devices from donation pathways toward market-based disposition. Throw-away behavior showed minimal sensitivity to resale perceptions, suggesting that financial motivations primarily compete with donation rather than disposal behaviors.

Figure 3 shows the individual effect function for the prompt “considering future resale” for the four behaviors. As shown, perceptions of “considering future resale” show similar patterns, with a 16.3% probability difference for resell. Here, the critical transition occurred while moving from “disagree” to “neutral”, suggesting that consumers need not strongly consider future value—merely not dismissing it is sufficient to substantially increase reselling likelihood. This threshold effect has important implications: interventions may not need to convince consumers that their devices are highly valuable, only that they possess non-zero value.

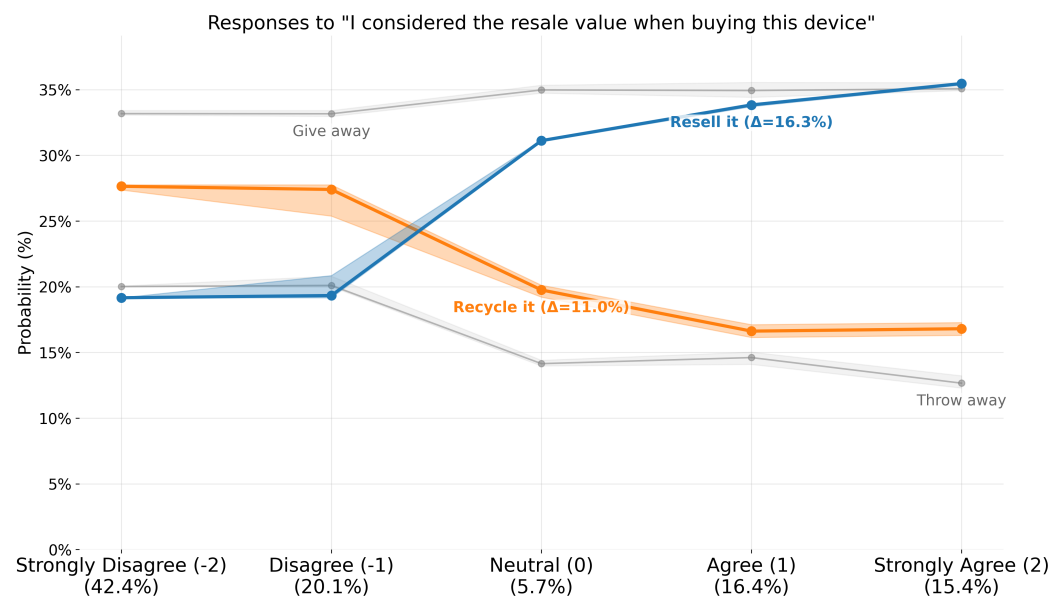


Figure 3. Probability of behavior choice by consumer consideration of future resale value: changes in probability for recycle, give away, resell, and throw away attributed to agreeing with statement “I considered the resale value when buying this device”. Percentage numbers below the Likert scale category show the share of survey responses for that response. Consumers who consider future resale when purchasing show increased reselling probability ($\Delta = 16.3\%$) and decreased recycling probability ($\Delta = -11.0\%$). Give-away and throw-away behaviors show minimal variation across agreement levels.

4.3. Give-Away Behavior: Balanced Influences

Figure 4 shows the individual effect function for the prompt “donation is convenient” for the four behaviors. This shows a positive relationship with a steady upward trajectory as convenience beliefs strengthen. The probability of giving away starts at 27% when consumers strongly disagree that donating is convenient, rising gradually to 37% for those who strongly agree. This 10.3% increase overall represents a moderate but consistent effect across the attitude spectrum, contrasting with the threshold patterns observed in reselling behavior. The convenience relationship suggests that logistical barriers can shape donation decisions. Unlike financial considerations, which create sharp substitution effects, the **gradual** slope for the perceived convenience suggests that each incremental improvement in perceived convenience yields proportional behavioral gains. Reducing friction through better donation infrastructure could systematically increase giving-away rates across the population.

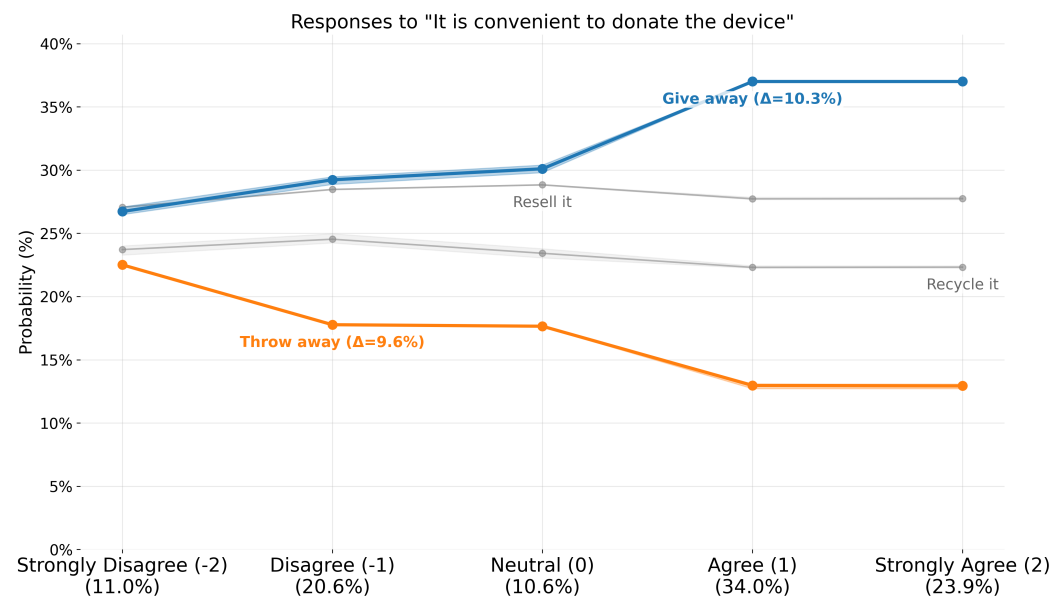


Figure 4. Probability of behavior choice by perceived convenience of donating devices: changes in probability for recycle, give away, resell, and throw away attributed to agreeing with statement “It is convenient to donate the device”. Percentage numbers below the Likert scale category show the share of survey responses for that response. Consumers who find donating convenient show increased probability of giving away devices ($\Delta = 10.3\%$) and decreased probability of throwing away ($\Delta = -9.6\%$). Recycling and reselling behaviors show minimal variation across convenience agreement levels.

Convenience effects also generate notable cross-behavioral impacts, particularly with throw-away behavior. As donation convenience increases, throw-away probability declines from 22% to 12%, creating a 9.7% reduction. This inverse relationship indicates that improving donation accessibility primarily draws consumers away from disposal pathways rather than other reuse options. Recycling and resell behaviors show minimal sensitivity to donation convenience, suggesting that logistical improvements in donation infrastructure specifically compete with waste disposal rather than creating broader behavioral redistribution across all disposition options.

4.4. Recycling Behavior: Knowledge Thresholds

Figure 5 shows the individual effect function for the prompt “I know where to recycle” for the four behaviors. Results for recycling behavior as a function of knowledge show a threshold pattern in the responses. This illustrates how informational barriers can constrain environmentally responsible choices. The blue line shows recycling probability starting at 15% when consumers strongly disagree with the notion that they know where to recycle, modest levels around 17% for those who disagree or remain neutral, and then a sharp jump to 26% once consumers agree they know locations. This 11.6% increase represents a substantial knowledge-driven behavioral shift, with minimal additional gains from moving to strong agreement. The threshold pattern reveals how location knowledge operates as a fundamental enabler for recycling behavior. Unlike the gradual convenience effects observed with donation, recycling location knowledge appears to create a binary decision framework; either consumers have sufficient knowledge to access recycling services or they effectively cannot participate. The sharp transition between neutral and agree positions indicates that basic location awareness captures most of the potential behavioral change, suggesting that simple informational interventions could yield significant results.

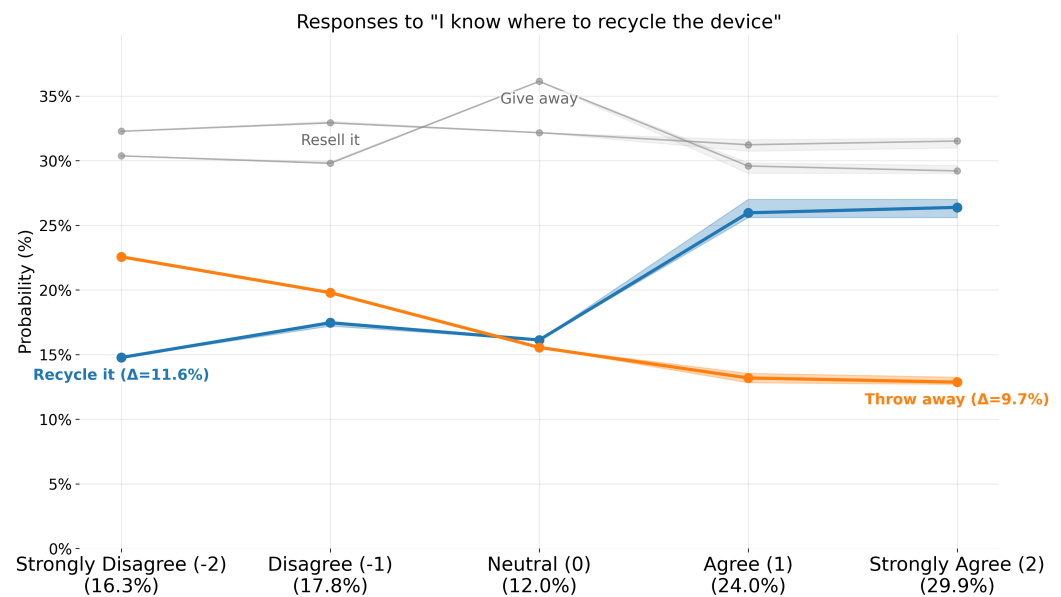


Figure 5. Probability of behavior choice by knowledge of recycling location: changes in probability for recycle, give away, resell, and throw away attributed to agreeing with statement “I know where to recycle the device”. Percentage numbers below the Likert scale category show the share of survey responses for that response. Consumers who know where to recycle show increased recycling probability ($\Delta = 11.6\%$) and decreased throwing away probability ($\Delta = -9.7\%$). Give-away and reselling behaviors show minimal variation across knowledge agreement levels.

Knowledge effects also generate notable cross-behavioral substitutions, particularly with throw-away behavior. The orange line demonstrates that, as recycling location knowledge increases, throw-away probability declines from 22% to 12%, creating a 9.7% reduction. This inverse relationship indicates that recycling knowledge primarily draws consumers away from the least sustainable disposal pathway rather than competing with reuse options. Give-away and resell behaviors show minimal sensitivity to recycling knowledge, suggesting that environmental awareness primarily operates through waste diversion rather than creating broader behavioral redistribution across all disposition alternatives.

We also completed an analysis of “throw away” as a function of “I know the resale value of the device” which is available in Supporting Information S3.

4.5. Implications for Behavior Change

The distinct threshold patterns across behaviors suggest targeted intervention strategies. For reselling, the critical intervention point is shifting value perception from negative to neutral, achievable through simple demonstrations of non-zero value rather than extensive value maximization efforts. For recycling, basic location awareness combined with threshold convenience improvements would capture most potential behavior change. Give-away behavior’s balanced influences suggest multi-faceted approaches may be needed, while the default nature of disposal indicates that any alternative made salient and accessible could reduce waste.

The strong behavioral trade-offs revealed by our analysis challenge single-behavior promotion strategies. Increasing recycling through improved convenience and knowledge may reduce reselling of devices that retain value. Conversely, promoting resale value awareness may divert devices from established recycling programs. These trade-offs suggest that optimal intervention strategies should consider device characteristics and lifecycle stages to promote the most environmentally beneficial pathway rather than generically increasing all sustainable behaviors.

The individual effect function evaluates predictions at a fixed median covariate profile, which may not reflect heterogeneity across respondent subgroups or device categories. The sample size (792 observations across 4 classes) does not support stable within-subgroup estimation. Device-level analysis is reserved for future work with larger per-device samples.

5. Discussion

This study employed Random Forests to examine how consumer attitudes and knowledge influence End-of-Current-Use disposition behaviors for electronic devices. The analysis revealed that these relationships are characterized by threshold effects and behavioral trade-offs that linear models cannot adequately capture.

The results are based on a simulation of intended behavior from stated attitudes. Whether shifting attitudes through interventions produces the behavioral changes the model predicts is a question for future experimental work, including randomized controlled trials. The model focuses on intended behavior because the objective was to identify intervention targets for future decisions. Comparing tipping point locations between intended and past behavior models is a direction for future work.

The model aggregates all 10 device categories to identify common attitudinal patterns. It is likely that attitudes, knowledge, and disposition behavior vary between devices; for example, resale value awareness may be more influential for smartphones than for smart kitchen appliances.

Some attitudes show a nonlinear effect on behavior, i.e., the “tipping point”: Several attitude–behavior relationships exhibited pronounced tipping points where shifting one position in attitude triggered a large behavioral change. The perception that reselling is financially worthwhile demonstrated the most striking threshold effect: resell probability remained stable at approximately 17% across negative and neutral attitudes, then jumped 26.4% upon transition from “Neutral” to “Agree”, with minimal additional gains at stronger agreement levels. Similarly, knowledge of recycling locations showed threshold dynamics, with recycling probability increasing sharply from 17% to 26% at the neutral-to-agree transition. These patterns indicate that critical behavioral transitions occur at moderate rather than extreme attitude positions.

Some attitudes show a close-to-linear effect on behavior: Not all attitude–behavior relationships exhibited threshold dynamics. Perceived convenience of donating showed a gradual, approximately linear relationship with give-away behavior, rising steadily from 27% to 37% across the Likert scale. This pattern suggests that incremental improvements in perceived convenience yield proportional behavioral gains, contrasting with the discrete jumps observed for financial and knowledge variables.

Trade-offs exist: increasing a desired behavior (resell) reduces other desired behaviors (recycle and donate). Thankfully, increasing knowledge of donating and recycling tends only to reduce throwing away in the trash, with only a small effect on reselling and donating.

The analysis revealed systematic trade-offs between sustainable disposition options. Increases in reselling probability correspond to decreases in giving away (−14%) and recycling, indicating that financial value awareness redirects devices from donation pathways toward market-based disposition. However, these trade-offs are largely acceptable from a sustainability perspective, as reselling typically represents the most environmentally beneficial outcome by extending device lifespan and capturing embedded manufacturing energy. Importantly, interventions targeting recycling knowledge and donation convenience primarily reduce throwing away in trash (−9.7% in both cases), with minimal displacement of other sustainable behaviors.

Implications for behavioral nudging: There is potential for information interventions to shift consumer behavior towards more sustainable options. For example, if a consumer

learns the value of reselling, they may do that instead of throwing products away in the trash. This analysis does not explore the effects of nudging, but does reveal which nudges might be effective. We suggest that behavioral tipping points are promising intervention points: a relatively small change in attitude/knowledge yields a large behavioral change.

The identification of behavioral tipping points suggests that targeted interventions at threshold positions may prove more efficient than efforts to maximize positive attitudes across the board. For reselling, the critical intervention point is shifting value perception from negative or neutral to modest agreement, which is achievable through simple demonstrations that devices retain non-zero value rather than extensive value maximization efforts. For recycling, basic location awareness represents the primary barrier; therefore, informational campaigns communicating where to recycle could capture most potential behavioral change. The finding that throw-away behavior functions as a default rather than an active choice suggests that any alternative made salient and accessible could reduce disposal rates.

Implications for behavioral modeling: Multinomial logit models are often used in behavioral modeling, yet our findings highlight methodological limitations: When Likert-scale predictors are used in logit models as continuous variables, the assumption of constant marginal effects average out the threshold dynamics we observe. The 26.4% jump in reselling probability at the neutral-to-agree transition would be smoothed into a modest linear coefficient, obscuring the actionable insight that interventions need only achieve moderate attitude shifts.

Researchers can attempt to accommodate nonlinearity by converting Likert responses to dummy variables, but this approach introduces its own complications: One category must be omitted as a reference group, creating interpretation challenges when the reference category itself influences behavior. Dummy coding also sacrifices the ordinal information inherent in Likert scales and can generate multicollinearity when attitude variables are correlated. The independence of irrelevant alternative assumptions underlying multinomial logit further constrain its ability to capture the substitution patterns we observe, where increased reselling draws primarily from giving away rather than proportionally from all alternatives.

Implications for sustainability: Returning to the sustainability issues discussed in the introduction (energy use, waste management, and the digital divide), the goals are increasing the reselling of functional devices and recycling seriously broken and obsolete ones, with reduced storage at home and throwing away in the trash. Increased reselling contributes to lower lifecycle energy impacts when it replaces the purchase of a new device and often addresses the digital divide when it does not (a low-income consumer can buy a device they could not otherwise afford). Extension of lifespan leads to lower volumes of generated waste, which partially addresses the impacts of informal recycling. Lower amounts of e-waste, however, do not solve the informal recycling problem, which must be addressed with parallel policy efforts, e.g., [55,56].

Implications for planetary health: The connections introduced in Section 1 are borne out in our findings: Reselling extends device lifespan and retains embedded manufacturing energy and extracted materials in use, keeping material in circulation rather than drawing down virgin resources. The trade-offs we identified, i.e., where increased reselling draws from donation, and recycling knowledge draws primarily from trash disposal, indicate that interventions act on a system of competing pathways rather than on isolated behaviors, and that the optimal pathway for planetary health depends on device condition and lifecycle stage. The toxic exposures of informal recycling fall disproportionately on lower-income populations who did not consume the devices, so diverting functional devices toward resale and broken ones toward formal recycling is also a question of environmental justice. Resale markets, in turn, expand device access for lower-income consumers, linking disposition behavior to digital equity. These are the interdependencies of human health,

ecological systems, technology, consumption, and equity. These inform planetary health concerns. We do not measure health or equity outcomes directly; our contribution is to identify the behavioral leverage points through which interventions in this system could plausibly act, leaving the quantification of downstream health and ecological benefits to the future experimental work noted below.

In previous work, we addressed storage and behavior, finding, for example, that addressing data security concerns when reselling or recycling can be an important strategy to help consumers let go of devices [18]. This work reveals a significant potential to encourage reselling and recycling by informing consumers of the value/convenience of these options. The quantification of the sustainability benefits of educational nudges requires additional work, including randomized controlled trials of behavioral interventions.

6. Conclusions

Consumer disposition behaviors for electronic devices are affected by threshold effects and trade-offs, not just gradual linear relationships. Critical tipping points typically occur at neutral rather than extreme attitude positions, indicating that modest, achievable attitude shifts could generate substantial behavior change, i.e., shifting the perception of resale from neutral to modest agreement or communicating where to recycle captures most of the available behavioral change. Because sustainable behaviors compete, intervention design must consider which disposition pathway is optimal for a given device type rather than promoting all alternatives to disposal generically. Positioned within planetary health, this work identifies the behavioral leverage points through which EoCU interventions connect to resource extraction, toxic exposure, environmental justice, and digital equity, providing an empirical foundation for targeted interventions that recognize the nonlinear dynamics of consumer decision-making.

Supplementary Materials: The supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/challe17030024/s1>.

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