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Summary

Although much research has been done on the circular economy, only a few studies have utilized discrete choice experiments to estimate consumers' preferences toward circularity in their purchase decisions. I employ a discrete choice experiment to measure Stavanger residents' preferences for or against circularity when purchasing a mobile phone. I did not find a general preference for circularity in mobile phones. However, I found evidence that consumers are more inclined to choose circulated products when product circularity is highlighted. No preference was found for partially circulated phones over fully circulated ones. I did find evidence that attribute framing influences consumers' purchase choices regarding circulated products.

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1. Introduction

The concept of the circular economy is critical as we strive to reconcile the escalating demands of a consumption-oriented society with the growing pressure for sustainability. Emphasizing keeping resources in use for as long as possible, extracting the maximum value from them while in use, and recovering and regenerating products and materials at the end of each service life is the cornerstone of a circular economy. It is a transformative approach that seeks to advance economic growth without proportionally increasing the utilization of resources by creating a closed-loop system where materials are continuously reused, recycled, and repurposed, thereby reducing the need for new resource extraction and waste production, and promoting a more sustainable and resilient economy. (Stahel, 2016; Elisha O.D, 2020).

Our goals to move towards sustainable development, reduce emissions, and meet ambitious climate targets necessitate more than just systemic changes at the industrial and policy level. They require active participation from consumers, who must make informed choices about the products they purchase and use. However, transitioning from a linear to a circular economy model requires a fundamental shift in mindset, both from businesses, policymakers, and consumers alike.

Political initiatives like the European Commission's Eco-label have played a role in this transition, as part of the larger Circular Economy Action Plan. The Action Plan sets a roadmap for a shift towards a circular economy. At the same time, the EU Eco-label, despite its voluntary nature and somewhat limited adoption, guides consumers towards more sustainable choices by highlighting products with reduced environmental impact (European Commission, 2020; Simon, 2022).

The academic world has engaged extensively with the concept of the circular economy and tools such as the EU's and other eco-labels. Research areas range from exploring consumer barriers to engagement, investigating the label's market penetration challenges, and gauging its influence on consumer decision-making (Testa et al., 2015; Thøgersen et al., 2010; Horne, 2009; Lin et al., 2017; Prieto-Sandoval et al., 2020; Rubik et al., 2007). Of significance is the evidence suggesting that well-trusted eco-labels can surpass brand loyalty, pushing consumers towards less familiar but environmentally friendly products (Testa et al., 2015). This observation paves a potential avenue for businesses aiming to distinguish themselves in a competitive market.

Similarly, it is essential to remember that the consumer is vital in this transition. Adopting circular products is not as straightforward as one might think. Consumers often encounter higher price points for eco-labeled products, which can act as a deterrent, even for the environmentally conscious (Yokessa & Marette, 2019). Moreover, the perception of recycled or regenerated products is often mixed, with misconceptions about their quality and durability (Hamzaoui-Essoussi & Linton, 2014). Consequently, understanding consumer preferences and behaviors is crucial to drive the successful implementation of a circular economy. Through initiatives like education, efficient labeling, and incentivization, we can help consumers make choices that are beneficial for them and the broader goal of a circular economy.

This thesis will focus on the consumer preference and price aspects of the circular economy, particularly in the context of mobile phone purchases. My goal for this research was to see if Stavanger residents would be willing to pay a premium for partially or fully circulated products and the viability of introducing a CE-product label showcasing a hypothetical "Circular Economy Score." Additionally, I am interested in studying the effects of message framing on survey responses and whether changes in the way attributes are presented can significantly influence consumers preferences.

The study utilizes a Discrete Choice Experiment (DCE), which I have distributed to the residents of Stavanger, with a particular emphasis on students of the University of Stavanger, via an online survey. The stated preference (SP) method is used for this study, as the Circular Economy Score is a hypothetical product attribute, thereby lacking real-world data for a revealed preference study. This approach enables us to inquire about consumer preferences and willingness to pay (WTP) for products with varying prices and attributes while isolating the effects of the Circular Economy Score on consumer behavior. Since we wanted to see if the framing of the circularity attribute would influence the respondents' stated preferences, we included two versions of the survey with different framings. Respondents were assigned one version randomly, with no information about the opposite version to not influence their responses.

2. Literature review

2.1 DCEs on consumers' circular purchase decisions

A limited number of discrete choice experiments (DCEs) have examined the influence of circular economy (CE) content on consumer purchasing decisions. Only three articles have been published, all derived from the same study (Boyer et al., 2021a; Hunka et al., 2020; Boyer et al., 2021b). The results revealed a distinct preference for products partially composed of CE materials over those entirely new or reused.

Boyer et al. (2021a) conducted a DCE to quantify consumer reactions to a hypothetical CE product label, which included a multi-level Circular Economy Score. The study utilized an online survey with 800 UK respondents. The findings demonstrated a low- and medium-level circularity preference in products like mobile phones and robotic vacuum cleaners. However, as CE levels increase, this preference diminishes and sometimes reduces the respondents' willingness to pay (WTP). This observation implies that while consumers value circular economy attributes and are often willing to pay a premium, they prefer new or remanufactured products over fully circulated, second-hand, or refurbished ones. Similar conclusions were reached by Hunka et al. (2020) who analyzed the same dataset from the UK-based study. Their research found that consumers favor partially circular electronics over entirely new or entirely reused products. Such products can effectively compete with brand-new items at similar prices, indicating market demand for CE products, especially those that are partly reused.

Interestingly, Boyer et al. (2021a) also found product-specific variations in consumer responses. Consumers were divided in the case of mobile phones, with approximately half favoring new devices and the other half preferring reused ones. However, there was a marked preference for reused devices over new ones for robotic vacuum cleaners. The authors attributed this to the personalized nature of mobile phones and the fragility of some components (screen, battery, camera), issues not relevant to vacuum cleaners, underscoring how non-CE-related attributes influence consumer response to a CE labeling system.

Boyer et al. (2021b) reiterated these findings and identified three customer segments with differing responses to a product's CE score. The segments varied in their valued attributes during hypothetical purchase decisions, with one group interested in circular products regardless of price, a more significant segment interested in circularity but highly price-conscious, and a final group showing a strong preference against circularity in mobile phones. Interestingly, no such segment existed for robotic vacuum cleaners, suggesting that non-CE-related attributes significantly impact some consumers' WTP for circularity.

Given the scarcity of DCEs in this area and that existing studies are all based on the same dataset, there is a clear need for more research. To fully grasp how circular content influences consumers' purchasing decisions, further DCEs should be conducted across different contexts and industries. While the available research offers valuable insights, there is significant potential for exploration.

2.2 Related DCEs

Although there is a scarcity of DCEs focusing specifically on consumers' preferences regarding CE content in consumer products, several discrete choice experiments have been conducted on related topics, such as consumer inclination towards sustainably sourced and recycled materials.

Potoglou et al. (2020) conducted a two-choice experiment involving six countries - Japan, India, Germany, the US, the UK, and Sweden - with a dataset of 6033 respondents to quantify consumers' preferences for sustainable materials in cars and mobile phones. Interestingly, while there was no overarching preference for sustainably sourced materials, significant differences were observed in responses across different countries. Apart from the US, respondents from all other countries demonstrated an increased WTP for cars made from ethically sourced, organic materials, with marginal WTP ranging from €1,951 in Germany to €4,524 in the UK. For mobile phones, respondents from the UK and Sweden strongly preferred sustainable materials, while other countries' respondents leaned toward conventional materials. The divergence in responses might suggest variations in cultural values concerning the products in question, sustainability, or sustainably sourced materials. This hypothesis is supported by Dinh et al. (2021), who used a DCE involving Vietnamese and Japanese student respondents to understand and compare the tradeoffs young consumers are willing to make for green attributes in their purchase decisions. The study found a stark contrast between the two countries, with Vietnamese respondents consistently demonstrating a higher appreciation for green attributes than their Japanese counterparts.

Further highlighting the role of consumers' familiarity with CE concepts, Stein et al. (2020) found that consumers more familiar with CE concepts tend to be more concerned with circularity. The findings underscore the potential benefits of educating customers about CE before they make their purchase decisions, with the authors recommending further research on the viability of third-party CE certification.

A positive WTP for recycled and sustainable fashion products was indicated by Italian and Spanish respondents, as found in a DCE by Testa et al. (2015). The WTP was, however, not significantly influenced by brand awareness, indicating that consumers are less influenced by brand power when purchasing circular economy products, potentially because "up-cycled" fashion products are perceived as inherently high-quality.

Lieder et al.'s 2018 study involving washing machines in Stockholm, Sweden, showcased a positive correlation between greenhouse gas reduction and consumer disposition to choose more recycled and sustainability-aligned choices when presented with different payment schemes. This and previous DCEs suggest that educating consumers about CE increases WTP for circularity and positively influences their purchase decisions.

However, these studies also reveal that cultural differences have a significant impact, and while inhabitants of some countries respond very positively to circularity, other countries exhibit less or even negative appreciation (Dinh et al., 2021; Lieder et al., 2018).

These previous DCEs underline the necessity of conducting similar studies in regions planning to integrate circularity into their policy or business strategies. Given the variations across different cultures, ensuring that the insights derived are relevant and applicable to the specific region of interest is crucial.

3.0 Theory

3.1 Circular Economy Score

There are many different definitions of the circular economy. However, one of the most satisfactory is the definition proposed by Kirchherr et al. (2017). This definition refers to an economic system that shifts away from disposing of materials at the end of its lifespan. Instead, it prioritizes reducing, reusing, recycling, and recovering materials throughout production, distribution, and consumption. I seek to quantify consumers' willingness to pay for circularity using a discrete choice experiment, and for that purpose, I require a means to quantify circularity as an attribute. I accomplish this by adopting Linder et al. (2017)'s metric for quantifying product-level circularity.

$$c = \frac{Economic\ value\ of\ circulated\ parts}{Economic\ value\ of\ all\ parts}$$

In the equation above, *c* denotes the Circular Economy Score for one product based on the economic value of the circulated parts as a fraction of the economic value of all the parts within the product. This allows us to display circularity as a percentage, with a 75 percent circular product being one for which the economic value of its circulated parts accounts for 75 percent of the value of the whole product. Basing circularity on the value of circulated parts versus the value of all parts, rather than resale value, is sensible, considering the value of a whole product usually is greater than the sum of its parts.

Although Linder et al. (2017) go much deeper into the different methods used for calculating economic value, that will not be necessary for my project.

This approach facilitates using an intuitive metric of circularity for respondents to differentiate between the circular contents of products. Consequently, survey respondents who answer the "New Material Score" version receive scores that are the exact opposite of their Circular Economy Score, facilitating an easy conversion to the Circular Economy Score while framing the attribute with the opposite connotation.

3.2 Prospect theory and Message framing

Prospect theory explains that since investors are risk averse while also being opportunity-seeking, they value risk differently if they stand to gain versus lose utility. In prospect theory, the term "risk" pertains to the degree of uncertainty surrounding possible outcomes.

When presented with two choices, one risky and one safer choice, wherein the risk involved relates to the amount of gain the investor might acquire, investors are generally risk averse, choosing the safer option despite the riskier option having a higher expected utility. However, when presented with risky and safe choices wherein the investor stands to incur a loss, investors are risk-seeking, choosing the option with lower expected utility but with the possibility of eliminating most of the loss. Prospect theory explains this behavior in that consumers' total utility depletes more when experiencing loss than it increases when they experience an equivalent gain (Kahneman & Tversky, 1979).

For this experiment, I wish to investigate how these effects may affect respondents' choices when presented with the same options but presented in opposing ways. More specifically, asking respondents equivalent questions but presented as the opportunity to gain circularity or lose new, virgin material. Following prospect theory, I expect respondents to have higher preferences in favor of circularity when presented with different product offers with a variety of "Circular Economy Scores," which is my measure for circularity, as circularity is then presented as a “good” to “obtain.” Contrastingly, I expect consumers tasked with choosing their most desirable products presented with a “new material score” to display a lower preference towards circularity. This follows from the assumption that consumers are loss-avoidant. If new or virgin materials are promoted as a quality attribute of the product, reducing this feature may unfavorably influence consumer preferences. Regardless, the product composition remains the same in all alternatives for both respondent samples since products may only contain circulated materials, virgin materials, or a combination of both. While I do not anticipate that respondents presented with a “new material score” will necessarily show negative preferences toward circularity (given that those conscious of sustainability should maintain their preferences), I do predict that respondents exposed to the “Circular Economy Score” version of the survey will demonstrate a stronger preference for recycled materials.

The subject of message framing has been explored through numerous studies in the past, but the findings have been inconsistent, with some researchers’ findings fully supporting the theory and others only partially supporting it (Levin & Gaeth, 1988; Meyerowitz & Chaiken, 1987; Evangeli et al., 2013). Some researchers question the theory’s validity altogether (Van’t Riet et al., 2016). Nevertheless, my goal is to explore how different message frames may impact respondents’ decision-making and to determine whether these findings can inform the marketing of Circular Economy products.

3.3 Consumer behavior theory

According to the Consumer Behavior Theory, consumers base their choices on their needs, wants, preferences, and attitudes. In addition to intrinsic attributes like price, quality, and features, extrinsic factors such as branding and labeling influence consumer behavior. Product labeling is significant, as it can provide information about a product's characteristics, origin, and sustainability and influence consumer behavior (Katola, 1968; Hoffmann et al., 2020).

When establishing a link between Circular Economy (CE) alignment and consumer utility, it is crucial to consider the relationship between the general consumption of goods and services and an individual's overall well-being. I assume that individuals derive utility from consuming goods and services and aim to maximize their utility while being subject to a budget constraint, recognizing that individuals are constrained by their limited income (Barten et al., 1982). Different commodities have different characteristics, which give utility to the consumer. Commodities have multiple characteristics so that consumers may rank them differently in terms of value (Lancaster, 1966).

In the context of my study, I will ask Norwegian respondents to choose which of several products, each containing a variety of characteristics, would provide them with the most utility. I can utilize this information to determine how CE characteristics benefit Norwegian consumers.

3.4 Discrete Choice Experiments

Discrete choice experiments are a survey-based, stated preference (SP) method of measuring utility when preference data is unavailable. By presenting respondents with various choice sets with two or more alternatives and querying them on which of the proposed alternatives they deem most attractive, we can quantify which attributes respondents consider more valuable or holding a greater level of utility. This approach allows us to understand the relative importance of different attributes and to quantify the tradeoffs consumers are willing to make to obtain more of a given attribute and may give important insight into situations wherein revealed preference (RP) Data is not available.

While researchers have undergone extensive research on the circular economy for the last decade, only some have employed Discrete Choice Experiments (DCE) to acquire insight into consumers' attitudes relating to CE attributes in their purchase decisions. The results of DCEs are fascinating, as DCEs can emulate a real purchase scenario in which the individual respondents have the choice between several different alternative products. The results may then inform the design of circular economy-related products, services, and policies and develop effective strategies for communicating "good" circular choices to consumers. My DCE tasks respondents with making a discrete choice between two different mobile phones possessing various configurations of attributes. Some may, for instance, contain a high battery capacity and a low price but low levels of circularity. Others may be completely circular, with a perfect battery, but compensated with a high purchase price. With enough choice sets and adequate respondents, I aim to use this information to determine an approximate average WTP for CE content for the DCE respondents.

3.5 Hypotheses

Upon a review of relevant academic literature and consideration of applicable theory, I have formulated a set of hypotheses for how I expect consumers' preferences for circularity to vary:

(1) Consumers have a positive preference for Circularity when purchasing mobile phones.

(2) Consumers prefer circular products less when the circularity attribute is framed as the loss of new material than when the attribute is framed as the gain of circularity.

(3) Consumers prefer partially circulated mobile phones and are willing to pay more for them than fully circulated ones.

4.Method

4.1 The Discrete Choice Experiment

A substantial body of research has been conducted on the impact of product labels on consumer decision-making, as well as discrete choice experiments (DCEs) exploring consumers' preferences for sustainable, green, or refurbished products. However, only a limited number of studies employing DCEs have been published on consumers' willingness to pay (WTP) for circularity in the context of purchasing decisions. Notably, the studies by Boyer et al. (2021a; 2021b) and Hunka et al. (2020) all relied on the findings from a single UK survey. Given the potential insights that could be gained from conducting a similar DCE in Norway and the overall scarcity of DCEs on this subject, I aim to adapt this survey for a Norwegian audience. In contrast to the original survey, which incorporated a comparison of respondents' WTP for circularity in two distinct products (mobile phones and robot vacuum cleaners), I have decided to narrow the scope and focus exclusively on mobile phones, given the constraints of my respondent pool. Regarding suitable attributes and attribute levels for this thesis, I naturally included the same attributes as those found in the original survey while making some alterations. The attributes and levels of the original survey are shown in the image below, adapted from Hunka et al. (2020).

Attribute	Levels	Attribute	Levels
Circular economy score	0% circular, everything is new	**Warranty**	Extended to 3 years
	25% circular, recycled parts		2 years
	50% circular, refurbished parts		6 months
	75% circular, most of the products is refurbished		No warranty
	100% circular, everything is refurbished		
Easy to fix	Device can be taken apart and easily repaired at home	**Reseller type**	Authorised dealer
	Critical parts (e.g., battery and display) can be replaced at home		Third-party shop
	Device is sealed and only software/firmware updates are available		Shop on eBay
Appearance	Looks used (scratches, etc.)	**Price (Variant 1)**	259
	Looks brand new		379
			499
			629
Battery life	As new	**Price (Variant 2)**	Random prices were drawn from 259 to 629 range, rounded up to end with a 9
	80% of new		
	50% of new		

Table 1: Original attribute levels

Since I am limited to a smaller and more narrow pool of respondents with a significant representation of students, I removed some attributes that I deemed redundant, as listed below.

Reseller type: I have determined that the “Reseller type” attribute is redundant for my survey, as my respondent pool comprises many local university students. Based on informal discussions with a sample of students, they generally do not exhibit solid preferences or possess significant experience with different types of resellers. The students interviewed demonstrated limited familiarity with the distinctions between authorized and unauthorized resellers and were often unaware of which specific retailers belong to each category. Moreover, my preliminary findings suggest that the reseller type is unlikely to substantially impact respondents’ willingness to pay (WTP) for circularity. By omitting this attribute, I aim to streamline my survey and concentrate on more relevant factors influencing students’ purchase decisions.

Easy to fix: In a survey examining circularity in mobile phones and purchase decisions, I believe the “Easy to fix” attribute may hold less relevance for a sample of local university students. When writing, the most popular phones listed by a leading mobile phone retailer

(Telia, 2023) all have screens and batteries that can be replaced at mobile repair shops, as confirmed through targeted searches for each phone model. As such, the attribute level "Device is sealed, and only software/firmware updates are available" seems unrealistic for a premium mobile phone. Additionally, I argue that students are more likely to prioritize price, performance, or sustainability over a device's repairability.

Appearance: The appearance of a product, particularly smartphones, often plays a significant role in consumers' purchasing decisions. Aesthetics are the first impression that attracts or deters potential buyers. As such, I fear that the attribute of appearance can dominate, drawing attention away from other essential attributes. In discussions with students, many outright rejected purchasing a worn, scratched phone. This tendency reinforces my decision to omit the appearance attribute from my analysis.

Focusing on other aspects of the smartphone, like hardware specifications, software capabilities, battery life, and durability, allows us to provide a more balanced perspective. This approach will enable students and other potential buyers to make informed decisions based on the product's overall value rather than overwhelmingly based on its appearance.

I also changed some of the remaining attributes in my survey to improve the overall quality and validity of the results. The rationale behind these changes is explained below:

Battery life: This attribute may vary significantly among different models, and although respondents were instructed that all phones in the survey were identical except for the presented attributes, I decided to present battery life using more practical, tangible values in the form of hours. Consequently, the choice cards now feature battery life options of 6, 8, or 10 hours under intensive use. By employing specific hour values, I can more accurately convey the expected battery life of each option to respondents, ultimately improving the quality of the survey responses.

Price: In my updated survey, I made significant changes to the price attribute compared to the original UK survey. The original survey presented prices as either £259, £379, £499, or £629 and included a second variant with randomly drawn prices ranging from £259 to £629. In my revised version, I opted for fixed price points of 4500 NOK, 7000 NOK, 9500 NOK, and 12 000 NOK, and I removed the second variant with randomly drawn prices. The new prices were obtained by identifying popular premium smartphone models available in Norway by examining the prices of the top-selling models of last year, according to the largest retailers. The prices of these popular models were then compared to establish a range of prices representative of the premium smartphone segment in the country.

Circular economy score: The circular economy score attribute remains the same in my survey, with the caveat that half of the respondents are instead presented with the reverse-coded "New material score" (NMS) attribute. The NMS is the exact mirror of the circular economy score. It informs the respondent about the proportion of products made from entirely new, never-recycled, virgin materials. Consequently, a high level of utility assigned to the NMS by a respondent signifies an equivalent negative utility placed on the CES and vice-versa. Referencing the segment of this paper about message framing, I expect respondents who are presented with the NMS cards to exhibit a lower preference for circularity than those presented with the CES.

After finalizing the levels and attributes for my study, a model was created to generate an efficient experimental design, concentrating on identifying the main effects. To maintain realistic scenarios, a single constraint was introduced: 0% circular, or completely new phones, were only allowed the highest battery capacity, which is 10 hours. This constraint was implemented as it is unrealistic for an entirely new phone not to have the highest possible battery capacity.

	Phone 1	Phone 2
Battery life (intensive use):	6 hours	10 hours
Warranty:	6 months	2 years
Circular Economy score (CES)	100%	0%
Price:	7000 NOK	9500 NOK

Table 2: Example choice card

A total of sixteen choice cards were ultimately developed. An example of a choice card can be seen above. The CES and NMS versions of the DCE are identical, with the sole exception being the attributes related to the New Material/Circular economy score.

4.2 Survey Distribution

To obtain a substantial number of responses from university students for my survey, we employed a dual-method strategy for distributing the survey: distributing fliers throughout the University of Stavanger campus and sharing anonymous links on social media platforms. The fliers were handed out evenly across the University campus and, as such, should capture a wide variety of students and personalities. However, social media dissemination could introduce some bias. The survey's reach is limited to the authors' social media connections and those who opted to share the survey further, potentially reducing the robustness of my data. The online survey distribution may also favor friends and family, as they are more inclined to participate. As the survey was entirely anonymous, I cannot verify this.

The survey was done with a different duo of master students working on a thesis about digital advertisements and consumer purchase decisions. As such, the survey included questions relating to digital marketing and its influence on the respondent's purchase decisions and the DCE. The information given to respondents about the survey in advance was sparse within both distribution methods, as we wished not to attract an overrepresentation of respondents with strong opinions on the matter. Respondents were, therefore, only told the survey topic: "Digital advertisement and sustainable product preferences."

The survey was comprised of five sections. First, a brief introduction sets the stage. Then, respondents identified their top three social issues. The third part explored attitudes toward digital marketing and presented ad scenarios. For the key part of the survey, the Discrete Choice Experiment (DCE), respondents were randomly assigned one of two versions, featuring either a circular economy score (CES) or a new-material score (NMS). The CES represents the proportion of reused, refurbished, and otherwise circular material in a product, while the NMS pertains to the proportion of new, non-circular material. A total of 20 choice sets were created, with 10 for CES and 10 for NMS, and respondents were required to answer all sets relevant to their survey version. Choice sets were numbered to minimize survey dropouts due to fatigue, as ten sets could be perceived as overwhelming. By displaying the remaining number of sets, I aimed to alleviate potential weariness. However, numbering meant we needed to keep the choice cards consistent, meaning all respondents would encounter the choice sets in the same sequence. This could introduce bias, as the order might influence respondents' choices. Whichever version of the survey respondents received; they were then asked to rate several phone attributes on a scale from 1-5 on their importance in a purchase decision. These included the attributes from the DCE, processing capabilities, memory, appearance, and service and insurance. The debrief included demographic questions, opinions on sustainability, and the role of social media on purchase decisions. Overall, the survey aimed to gather data on the influence on consumer behavior of various factors, particularly sustainability, Circular Economy, and digital marketing. An example of the survey is displayed in the Appendix section of this thesis.

4.3 Willingness-to-Pay (WTP) Calculation

Calculating Willingness to Pay (WTP) provides valuable insight into the economic value that respondents place on the different attributes of a product or service. In the context of my discrete choice analysis, I aimed to estimate the WTP for different levels of product circularity to assess whether and to which degree the circularity attribute might affect consumers' inclination towards circular products.

I calculate WTP by taking the ratio of the coefficients of the non-monetary attribute (in my case, circularity) and the price attribute in my multinomial logit model. This ratio translates the utility impact of the attribute into monetary terms, providing an estimate of how much respondents would be willing to pay for a unit increase in that attribute. In my case, since circularity only exists at certain levels in my data and is thus treated as a factor rather than a numeric variable, WTP will provide an estimate of how much respondents would be willing to pay to rather have 25, 75, and 100 percent circularity than 0. Formally, the WTP for an attribute *i* is calculated as $WTP_k = -\frac{\beta k}{\beta p}$ where β_k is the coefficient for attribute k and β_p is the coefficient for price. *(Train, 2009)*

To quantify the uncertainty around my WTP estimates, I applied the Delta method, a statistical technique used to obtain the variance and confidence intervals of a function of random variables, given the variances and covariances of those variables. In my context, it allows us to calculate the standard errors for my WTP estimates, considering the sampling variability of my model coefficients. This further allows us to produce p-values to assess the statistical significance of these estimates.

The Delta method relies on the assumption of asymptotic normality, i.e., the distribution of the estimates approaches a normal distribution as the sample size increases. It involves calculating the gradient of the transformation function (in my case, the WTP calculation) and using this to approximate the variance of the transformed variable.

The first step is to write down the function for calculating WTP.

$$g(\beta) = -\beta\kappa\ /\beta\rho$$

In this formula, β_k is the coefficient for a non-price attribute k, and β_p is the coefficient for price. This ratio represents the marginal rate of substitution between the attribute and price, that is, how much more someone is willing to pay for a unit increase in the attribute.

I then calculate the gradient of this function at the estimated coefficients, $\hat{\beta}_k$ and $\hat{\beta}_P$. The gradient is a vector of the first derivatives of $g(\beta)$ with respect to $\hat{\beta}_k$ and $\hat{\beta}_P$.

$$g'(\hat{\beta}) = \left(-\frac{1}{\beta\rho,}\frac{\hat{\beta}_k}{\hat{\beta}^2{}_P}\right)$$

The variance of $g(\beta)$ is then calculated as:

$$Var\left[g(\ \hat{\beta})\right] = g'(\hat{\beta})^T \hat{V} g'(\hat{\beta})$$

Where V is the variance-covariance matrix of the estimated coefficients, obtained from the output of the model specification in R. Finally, the standard error is the square root of the variance.

$$SE\left[g(\hat{\beta})\right] = \sqrt{}Var[g(\hat{\beta})]$$

(Hole, 2007).

In R, this can be done using the deltaMethod function from the car package, which implements the necessary calculations *(Fox & Weisberg, 2019).* From this procedure, I obtain the standard error of the WTP, which can then be used to calculate a Z-score, a measure of how many standard deviations an element is from the mean. In this context, the Z-score of the WTP estimate is calculated as follows:

$$Z = \frac{WTP-0}{SE[WTP]}\ .$$

The P-value is then calculated as: $p = 2(1 - \Phi(|\ Z\ |))$*,*

In which Φ is the cumulative distribution of the standard normal distribution. I do this calculation in R using the “pnorm” function. *(R core team, 2023)*

By employing the Delta method and calculating p-values, I can provide not only estimates of WTP but also a measure of the uncertainty around these estimates, improving the reliability of my results.

5.0 Econometric model

5.1 Multinomial Logit

The study utilizes discrete choice models such as the Multinomial Logit (MNL) model. The MNL model is grounded on the Random Utility Model (RUM), a fundamental framework for discrete choice analysis, first introduced by McFadden (1974). The core idea of the RUM is to represent the utility U that individual n derives from choosing alternative j as the sum of a deterministic and a random component.

$$U_{jn}=V(X_{jn};\beta)+\varepsilon_{jn},$$

Here, X_{jn} represents the attributes of alternative *j* for individual *n*, β is a vector of unknown parameters, *V* is the systematic utility function (the component of utility directly influenced by the attributes of the alternatives) and ε_{jn} is the random component of the utility (a part of utility that cannot be directly observed).

Within the RUM framework, we know that the individual *n* will choose the alternative *I* that provides them with the highest utility. The choice probability P_{in} is the probability that alternative *i* provides the highest utility to individual *n* given, however its form depends on the assumptions we make about the distribution of the random component ε_{jn}.

After specifying the choice-probability P_{in} however, we can utilize it in the following log-likelihood function.

$$LL(\beta)=\sum_{n=1}^{N}\sum_{i=1}^{J_n} y_{in} ln(P_{in})$$

LL(β) is the log likelihood function I want to maximize to estimate (β), y_{in} is a variable that indicates choice, being 1 if individual *n* chose alternative *I* and 0 otherwise, and P_{in} represents the specified form of the choice probability.

The multinomial Logit Model by McFadden (1974) determines the probability P_{in} that an individual will choose alternative *i* over all other alternatives *j* in the choice set C_n of J_n alternatives available.

It is obtained from the RUM by making specific assumptions about the distribution of the random components of the utility. Given the RUM framework and MNL assumptions, the Choice probability P_{in} that individual n choses alternative *i* from a set of alternatives is given by this formula:

$$P_{in} = \frac{e^{V(Xin;\beta)}}{\sum_{j=1}^{Jn} e^{V(Xjn;\beta)}}$$

The log-likelihood function for the MNL model is then obtained by substituting the MNL choice probability formula into the general RUM log-likelihood function.

$$LL(\beta) = \sum_{n=1}^{N} \sum_{i=1}^{J_n} y_{in} ln\left(\frac{e^{V(Xin;\beta)}}{\sum_{j=1}^{J_n} e^{V(Xjn;\beta)}}\right)$$

This log likelihood model is identical to the RUM log-likelihood model, however the term in the natural logarithm is the specified choice probability of individual *n* to choose alternative *I* under the MNL model. (Pryanishnikov & Zigova, 2003).

The goal of the MNL model is to estimate the value of β that maximizes the likelihood of observing the choices made by individuals in the sample.

To estimate the parameters β that maximize the likelihood function, I utilize the 'mlogit' package in R. This package estimates the MNL model using a method known as maximum likelihood estimation, common statistical method for estimating the parameters of a probability distribution by maximizing a likelihood function. (Myung, 2003) The 'mlogit' package simplifies the process by internally handling the computation of choice probabilities and the log-likelihood function (Croissant, 2020).

5.2 Independence of Irrelevant Alternatives

The Independence of Irrelevant Alternatives (IIA) is an essential assumption for MNL models. The assumption holds that the likelihood of one alternative being chosen over another is independent of other alternatives in the choice set (McFadden et al., 1977). To assess the validity of the IIA assumption in my MNL model, I employed the Hausman-McFadden test, which is available in R through the hmftest function in the mlogit R package (Croissant, 2020). This test is specifically designed to assess the IIA assumption in MNL models (Hausman & McFadden, 1984).

This test's premise involves comparing parameter estimates derived from two different models. The first model is a complete model that includes all possible choice alternatives. The second model, however, is restricted and includes only a subset of the alternatives from the complete model. If the IIA assumption is valid, removing specific alternatives from the model should not change the relative probabilities of the remaining alternatives. The odds of choosing one alternative over another should remain the same, regardless of other alternatives. In the context of the Hausman-McFadden test, the null hypothesis is that the IIA assumption holds, while the alternative hypothesis suggests that the IIA assumption has been violated.

6.0 Results

One hundred fifty-six participants initially agreed to participate in the survey, with a final amount of 135 completions. This results in a comparatively low dropout rate of approximately 13%. Of the 135 completions, 28 participants engaged through the QR code provided on the fliers we distributed, while the remaining respondents participated via an online link. The survey was designed to be engaging and user-friendly, likely contributing to the higher completion rate.

The average survey duration was around twelve and a half minutes. To ensure that the analysis focused on typical respondent behavior, extreme cases were identified where respondents reported spending an unusually long time on the survey, exceeding one hour. These cases were considered non-representative of active engagement with the survey and were subsequently removed from the average. Even with twelve and a half minutes completion time, the dropout rate remained low, suggesting that the survey duration was not a deterrent for most participants.

Notably, out of the twenty individuals who started but did not complete the survey, only three had made any selections in the choice sets. Most dropouts, 17 in total, decided not to continue even before reaching the choice sets. 11 of these dropped out before reaching the final social-media-related question, and 6 completed the social-media-related part of the survey but still needed to begin the circularity part.

I attribute why some respondents chose to drop out to the natural variance in participant commitment. Some respondents might have been interrupted, lost interest, or found they did not have sufficient time to complete the survey. It is also possible that some of the survey questions or the DCE segment may have been perceived as too challenging or not relevant enough to some participants, causing them to discontinue.

The low dropout rate is satisfactory, however, which could be partly due to the minimal amount of text that respondents had to read and my efforts to ensure that questions were easy to comprehend. As I aimed to measure the variations in responses based on different framing within the alternative block, and I wished to minimize any influence from my explanations of the questions and concepts, all text blocks were kept brief and to the point. This made it easier and less tiresome for participants to complete the survey, contributing to the reduced dropout rate.

6.1 Demographics

		Entire sample	CES	NMS
Observations	People Percentage	135	73 53.67%	62 45.59%
Age	<20 20-29 30-39 40-49 50-59 >60	0.74% 41.18% 36.76% 6.62% 11.76% 2.94%	0% 45.21% 34.25% 4.11% 15.07% 1.37%	1.64% 34.43% 40.98% 9.84% 8.20% 4.92%
Gender	Female Male Prefer not to say	56.68% 41.18% 2.21%	63.01% 35.62% 1.37%	49.18% 47.53% 3.28%
Employment	Employed full time Employed part time Other Student (with or without employment)	31.61% 19.85% 4.41% 44.12%	27.40% 19.18% 5.48% 47.95%	36.07% 19.67% 3.28% 40.98%
Affordability level	Very low Low Moderate High Very high	7.35% 19.85% 23.53% 31.62% 17.65%	6.85% 19.18% 27.40% 28.77% 17.81%	8.20% 21.31% 19.67% 32.79% 18.03%
Choice frequency	Option 1 Option 2 I would choose neither	42.32% 45.48% 12.12%	42.55% 47.83% 9.62%	42.03% 42.54% 15.42%

Table 3: Demographics

Table 1 above presents the descriptive summary for the entire sample and the two framing groups, CES and NMS.

We observe a clear majority of respondents under 40 in my sample, which aligns with our distribution methods that specifically targeted students. The proportion of respondents categorized as under-40s is similar in both survey versions, with 80.46% in the CES survey and 77.05% in the NMS survey falling into this age group. Regarding gender distribution, my survey shows a bias towards women, constituting 56.68% of the responses, compared to 41.18% for men. This gender disparity is driven mainly by the CES version of the survey, where women out represent men by 27.39%. In contrast, the NMS survey exhibits a more balanced gender representation, with women and men being nearly equally represented at 49.18% and 47.53%.

Regarding other demographic imbalances relevant to my project, there is a slightly higher representation of students among CES-version respondents, accounting for 47.95% compared to 40.98% among NMS-version respondents. Additionally, NMS respondents have an 8.67% lead in the proportion of full-time employed respondents. As for my affordability index, the differences are relatively modest. CES respondents show a 7.63% higher proportion of respondents in the moderate-affordability category. In comparison, NMS respondents have 3.48% more responses in the very-low and low affordability categories and 4.24% higher responses in the very-high and high affordability groups.

Moving to the lower end of the ratings, the appearance and, service & insurance attributes, excluding the CES/NMS attribute, received the lowest scores from both groups. Appearance scored 3.39 and 3.59 in the NMS and CES surveys, respectively, while Service & Insurance scored 3.41 and 3.39. These results indicate that both attributes hold roughly equal importance for respondents from both segments. However, the within-group preferences vary greatly, as the variances for the attributes are between 1 and 1.30 for both respondent segments.

6.2 Importance ratings

After concluding the Discrete Choice Experiment (DCE), I asked respondents to perform another task. This task involved rating mobile phone features based on their perceived importance. I provided a scale of 1 to 5, where 1 indicated minimal importance and five represented maximum importance.

The group of features was extensive, including the ones I utilized in my DCE and those identified in the study by Hunka et al. (2020). Although these additional features were not part of my initial experiment, I included them to gain a broader perspective of what attributes respondents consider significant in their mobile phones.

The results of this task can be found in Table 3 below. This table provides a clear visual of how each feature was rated by the respondents, offering the mean value of each attribute's ratings and the variance to understand respondents' level of consensus.

The results of this task can be found in Table 3 below. It includes the average rating for each attribute and the variance, providing insight into the respondents' consensus level.

	NMS		CES	
	Avg. Rating	Variance	Avg. Rating	Variance
Battery life	4.49	0.55	4.34	0.69
Warranty	3.52	1.56	3.30	1.14
NMS/CES	3.00	1.12	2.71	1.15
Price	4.13	0.90	4.38	0.73
Processing capabilities	4.08	0.93	4.00	0.83
Memory	4.03	0.90	4.16	0.63
Appearance	3.39	1.35	3.59	1.30
Service & Insurance	3.51	1.37	3.49	1.06

Table 4: Importance ratings

From the data presented above, it is clear that battery life is a top priority for respondents across both surveys. It takes the lead in the NMS survey with an impressive average rating of 4.49 and is also a front-runner in the CES survey, earning a solid average rating of 4.34. The low variances of 0.55 in the NMS survey and 0.69 in the CES survey further underline the consensus on the importance of battery life. These variances are among the smallest compared to all other attributes in both surveys, indicating a general agreement among respondents about battery life's vital significance in their mobile phone purchase decisions. The NMS/CES attribute stands out as a particularly intriguing aspect to consider. Given the distinct framing techniques utilized in the two survey versions, I expected a higher importance rating for this attribute in the CES survey, as I hypothesized that the circularity framing would positively sway respondents' perspectives. However, the CES survey responses assigned an average rating of 2.71 to this attribute, suggesting it is less than moderately important. It is also worth noting that this CES/NMS rating is the lowest of all the attribute ratings across both surveys, suggesting that it is, in fact, the least important attribute for respondents when considering a phone purchase. As such, the rating of 2.71, indicating somewhere between low- and moderate importance, might, be overstated. The notably high variance of 1.15 in the CES ratings further compounds this complexity. This high variance suggests a considerable divergence in opinion among the CES respondents regarding the importance of the NMS/CES attribute when choosing a mobile phone.

The NMS survey presents slightly higher ratings for this attribute, landing precisely at 3.00, which suggests a "moderate" level of importance. In the context of the survey question, this attribute was labeled as "Material Origin (New Material Score)." Despite the higher rating compared to its CES counterpart, it is unclear from these important ratings how respondents perceive the NMS score compared to the CES. Specifically, the survey question does not directly ask respondents whether a higher NMS score positively influences their purchase decisions. It merely asks how vital the NMS score is to them when considering a purchase. As a result, it is uncertain whether a higher score suggests a positive or negative influence on their buying decision. This ambiguity points to the complexity of interpreting these ratings and underlines the need for further investigation.

Like the CES score, the NMS score also has a relatively high variance, at 1.12. This could be due to differing interpretations of the question among respondents. However, it is equally possible that this high variance reflects the different values held by the respondents, mirroring the situation I observed with the CES score.

The attributes of price, processing capabilities, and memory all obtained ratings between 4.00 and 4.38 across the NMS and CES segments. However, there is a slight variance in their respective preferences. CES respondents tended to emphasize the price and memory of a mobile phone. On the other hand, those in the NMS segment value processing power more. Additionally, there is a slight difference in the spread of responses between the two groups. The NMS respondents showed more variability in their responses, with an average variance of 0.91 for these attributes, as opposed to a lower average variance of 0.73 observed among the CES respondents.

6.3 Model estimation results

I utilized a multinomial logistic model with the “mlogit” package in R, written by Croissant (2020), for my main model estimation.

Conducting the Hausman-Mcfadden test on my data returned a p-value of 0.3593 for the full dataset, 0.6769 for the CES data, and 0.47 for the NMS sample data. These p-values are more significant than the conventional significance level of 0.05. We, therefore, do not have enough evidence to reject the null hypothesis. This means that we cannot conclude that the

IIA assumption is violated in our model. As such, the use of the MNL model is deemed appropriate for our data, given the validity of the IIA assumption.
After ensuring that the model fits correctly and that the IIA assumption holds, the following are the estimated model coefficients for the full sample and the subsets that include only CES and NMS respondents, respectively.

	Dependent variable:		
	CES	**FULL**	**NMS**
(Intercept):2	0.249***	0.102	-0.059
	(0.094)	(0.067)	(0.106)
(Intercept):3	-0.552*	-0.886***	-1.282***
	(0.325)	(0.236)	(0.362)
Price	-0.0002***	-0.0002***	-0.0002***
	(0.00002)	(0.00002)	(0.00002)
Warranty	0.280***	0.321***	0.408***
	(0.076)	(0.055)	(0.085)
Circularity	0.007***	0.0004	-0.008***
	(0.001)	(0.001)	(0.002)
Battery	0.215***	0.183***	0.171***
	(0.031)	(0.023)	(0.036)
Observations	738	1,328	590
R^2	0.157	0.128	0.142
Log Likelihood	-585.567	-1,134.136	-514.170
LR Test (df = 6)	218.641***	331.657***	170.791***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 5: Main model summary

The intercept for each alternative represents the log-odds of choosing that alternative when all explanatory variables are equal to zero, meaning the inherent preferences respondents might have toward specific alternatives. As we observe above, the intercept for Alternative 2 is positive for the full sample and the CES subsample and negative only for the NMS subsample. It is only statistically significant for the CES subsample, for which it is significant at the 1 percent level, meaning that CES sample respondents had an intrinsic preference towards Alternative 2 regardless of its associated attributes. The intercept term for alternative

3, the “neither” option, is negative and statistically significant at the 1 percent level for both the full sample and the NMS subsample, while statistically significant only at the 10 percent level for the CES sample. As expected, the price attribute is negative and statistically significant at the 1 percent level for all subsamples.

The Circularity attribute, our analysis’s main attribute of interest, shows differing results among all three samples. In the full sample, the attribute is positive but insignificant; in the CES subsample, it is positive and significant at the 1 percent level, and in the NMS sample, it is negative and significant at the 1 percent level. This displays a clear but divided preference for and against Circularity among the two respondent groups.

6.4 Dummy-coded model results

To see respondents’ preferences for different levels of circularity, I modified my existing survey data set to include dummy variables for the different circularity levels in my survey data. This allows us to isolate the effects of each circularity level on choice probability. I did this because, in my specific data, circularity may only take on one of four possible values: 0, 25, 75, and 100. Although these are numerical values, they are categories in the context of the data because we lack information about the attribute at values between these points. By transforming “Circularity” into dummy variables, I allow the model to capture the different impacts that different levels of circularity might have on the probability of making a particular choice, which would not be possible if circularity was kept as a single categorical variable.

	Dependent variable:
	Choice
(Intercept):2	0.099
	(0.067)
(Intercept):3	-1.093***
	(0.384)
Price	-0.0002***
	(0.00002)
Warranty	0.282***
	(0.062)
Circularity_25	-0.224
	(0.236)
Circularity_75	0.077
	(0.211)
Circularity_100	-0.152
	(0.192)
Battery	0.158***
	(0.032)
Observations	1,328
R^2	0.129
Log Likelihood	-1,132.727
LR Test	334.475*** (df = 8)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 6: Summary Full sample dummy-coded

Our results above align with the IIA assumption, with a p-value of the Hausman-Mcfadden test of 0.9792. The results presented in the table above show that the intercept term for alternative 2 is positive yet not statistically significant. For alternative 3, the intercept term is negative while highly significant at the one percent level. As such, we can infer that respondents have an innate preference for choosing a product over purchasing neither. As expected, the estimated coefficients of the Price attribute are negative and significant at the one percent level.

Similarly, the coefficients for Warranty and Battery are significant and positive, which is intuitive since both attributes are invariably good from a consumer perspective. The circularity attribute coefficients are positive at 75 percent and negative at 25 and 100 percent. However, the coefficients are insignificant at all levels and do not allow us to make any judgments about the effects of circularity on the total respondent sample.

After subsetting the data and confirming that the IIA assumption still holds for the model trained on both new datasets (CES: p=0.918, NMS: p=0.9616), I present the summary statistics for the CES and NMS respondent groups, respectively.

CES		NMS	
	Dependent variable:		*Dependent variable:*
	Choice		Choice
(Intercept):2	0.240**	(Intercept):2	-0.054
	(0.094)		(0.106)
(Intercept):3	-0.833	(Intercept):3	-1.306**
	(0.532)		(0.574)
Price	-0.0002***	Price	-0.0002***
	(0.00003)		(0.00003)
Warranty	0.215**	Warranty	0.393***
	(0.089)		(0.093)
Circularity_25	-0.152	Circularity_25	-0.300
	(0.336)		(0.347)
Circularity_75	0.594*	Circularity_75	-0.498
	(0.305)		(0.312)
Circularity_100	0.432	Circularity_100	-0.934***
	(0.270)		(0.291)
Battery	0.181***	Battery	0.158***
	(0.045)		(0.048)
Observations	738	Observations	590
R^2	0.159	R^2	0.143
Log Likelihood	-584.337	Log Likelihood	-513.639
LR Test	221.100*** (df = 8)	LR Test	171.852*** (df = 8)
Note:	*p<0.1; **p<0.05; ***p<0.01	*Note:*	*p<0.1; **p<0.05; ***p<0.01

Table 7: Summary dummy-coded CES & NMS

From the results above, the intercept term for Alternative 2 is positive and significant in the case of the CES respondent sample, implying that CES respondents, to some degree, prefer picking Alternative 2 over Alternative 1 regardless of attribute levels. The intercept term for alternative 3 is no longer significant, meaning we cannot infer whether CES respondents specifically prefer choosing among the available options or neither option, regardless of attribute levels. For the NMS subsample, the significance of the intercepts is inverted. NMS respondents show significant aversion to the “neither”-alternative but no significant aversion or inclination towards alternative 2. Price, Battery, and Warranty follow the same patterns as in the full sample for both subsamples and are significant at the five percent level or higher in all cases. For the CES sample, only the circularity level of 75 percent is significant at any level, and even then, it is only significant at the 10 percent level, which is higher than our target of a 5 percent significance level. The coefficients are, however, positive in this instance, so they could be interpreted as 75 percent circularity having a positive impact on respondents’ choices if we are to accept the 10 percent significance. For the NMS survey respondents, a circularity level of 100 percent is the sole circularity level to show statistical significance, this time at a satisfactory 5 percent significance level, and we can interpret our results to show that fully circulated products are less attractive than brand new products among NMS respondents.

6.5 Effect of circularity attribute on choice probability

To further my understanding of the relationship between the circular economy score and respondents' decision-making processes, I wished to explore the effects of changes in this attribute when considered in isolation. For this, I took inspiration from the experiment of Boyer et al. (2021), in which they compared the preferences of circular offers in mobile phones and robotic vacuum cleaners. Instead of utilizing the Sawtooth software, however, we continued to utilize the 'mlogit' package in R. This tool has great utility as it allows us to estimate MNL models from my discrete-choice data and apply them to new, unseen scenarios, which affords us the capabilities I need to perform a similar comparison. First, to ensure that intrinsic preferences did not skew my results, I excluded intercepts from my model, i.e., I set the intercept terms to the value 0. After training on the original dataset, the model shows respondent preferences for one alternative, regardless of attribute differences. In a genuine choice scenario, these apparent preferences among the two product alternatives should not exist and are likely a byproduct of the data collection process. By excluding intercepts, I estimate the effects of the predictor variables relative to a baseline of zero utility rather than relative to the utility of the first alternative. I ensure that it reflects only the influence of the variables of interest and does not include any inherent biases towards one alternative. If we do not remove the intercepts, the choice probability of the alternatives is not equal in the scenario wherein both alternatives have identical attribute levels, which is an essential prerequisite when making such a comparison. However, the drawback of this approach is that by removing the intercept terms, we are not only setting a new intercept term for Alternative 2 to 0, but we are also setting a new intercept term for Alternative 3 to 0, the interaction term for which signifies respondents inherent preference to choose or not choose among the two alternatives.

Since the comparison graph will be based on the coefficients of a new model without intercept terms, the associated coefficients and significance levels are presented below.
All three models align with the IIA assumption (Full sample: p=0.1965, CES: p= 0.4778, NMS: p= 0.1179).

	Dependent variable:		
	CES	**FULL**	**NMS**
Price	-0.0002^{***}	-0.0002^{***}	-0.0002^{***}
	(0.00003)	(0.00002)	(0.00003)
Warranty	0.285^{***}	0.366^{***}	0.491^{***}
	(0.077)	(0.054)	(0.082)
Circularity_25	0.324	0.338^{**}	0.296
	(0.205)	(0.145)	(0.217)
Circularity_75	0.940^{***}	0.499^{***}	-0.024
	(0.221)	(0.151)	(0.220)
Circularity_100	0.753^{***}	0.263^{**}	-0.477^{**}
	(0.171)	(0.127)	(0.206)
Battery	0.246^{***}	0.242^{***}	0.248^{***}
	(0.023)	(0.017)	(0.027)
Observations	738	1,328	590
Log Likelihood	-589.932	-1,138.913	-516.272
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 8: Model summaries, no intercept term

The circularity coefficients for the CES sample are highly significant and positive at 75 and 100 percent circularity. In comparison, the full sample's coefficients are positive and significant at the 5 percent level or higher in all cases. The coefficients are solely significant at the 100 percent level for the NMS respondent sample.

I then trained the model on my dataset, both the full dataset and the subset, to include only CES and NMS data, respectively. This allows us to apply the learned patterns and relationships from the training dataset to make predictions on new scenarios for which I do not have any responses, and subsetting the data allows us the interpret the differences in responses based on which framing of circularity respondents received.
After that, I sought to eliminate potential noise from other variables and focus solely on the impacts of differing Circular Economy Scores by creating new datasets with only two identical options apart from the circularity levels. Both alternatives were set to have fixed

Battery, Warranty, and Price, with Warranty and Battery set to their most attractive levels and Price set to the middle-low value of 7 000. For Alternative 1, the circularity attribute varied, corresponding to the specific values present in the choice cards, being 0, 25, 75, and 100 percent circularity. Alternative 2, on the other hand, remained constant at a circularity level of 0 percent, essentially representing a brand-new product, free from any circularity elements. Since I wanted to compare the choice probability of a product with varying degrees of circularity with a non-circular product, I removed Alternative 3, the “neither” option, leaving us with a two-choice comparison.

Finally, the results of my experiments are displayed in the three graphs below, with the y-axis representing the predicted probability of either alternative being chosen and the x-axis representing the circularity attribute of alternative 1, as alternative 2 has a fixed circularity attribute in every comparison.

Figure 1: Choice probability Full sample

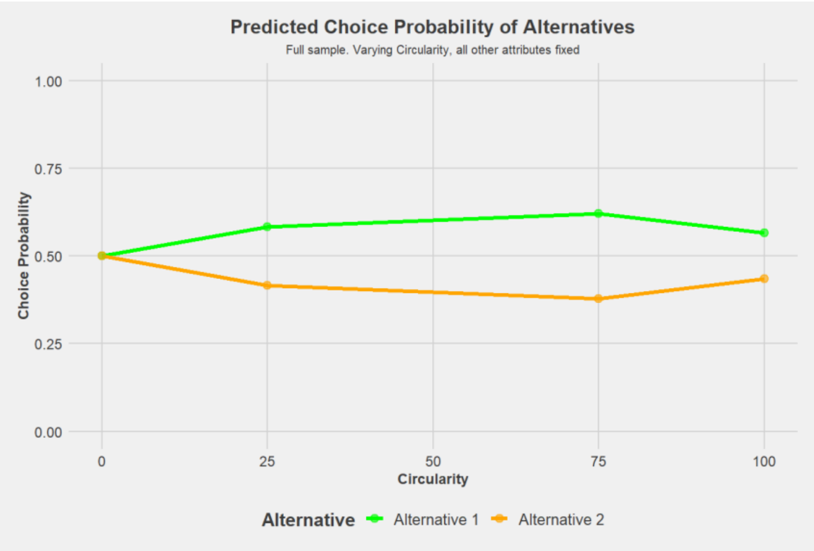


Figure 2: Choice probability NMS sample

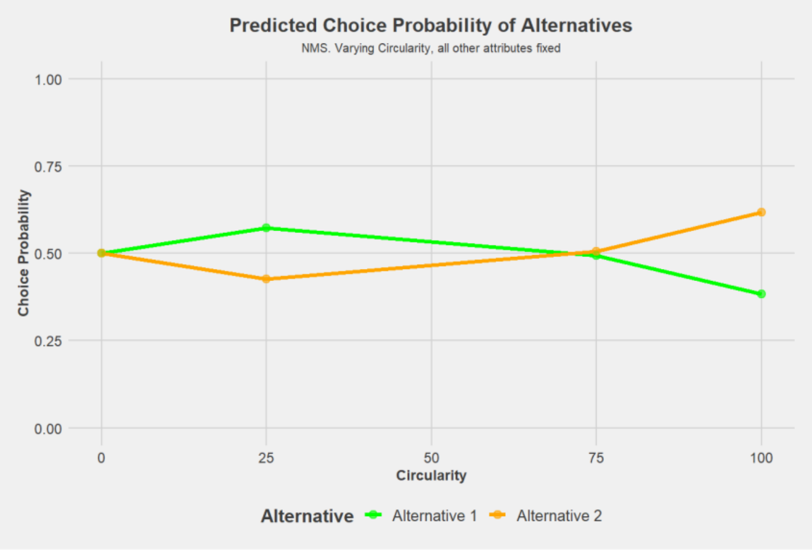
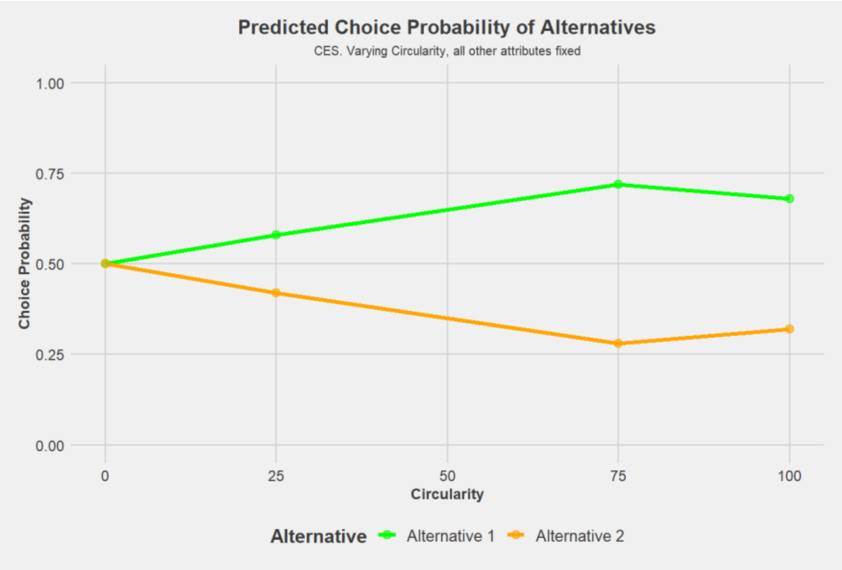


Figure 3: Choice probability CES sample



In a scenario where all attributes apart from circularity remain fixed and identical across products, figure 1 shows that products with some degree of circularity consistently hold a competitive edge over brand-new, non-circulated products. This advantage is observed across all levels of circularity. Products with a circularity measure of 75 percent emerged as the most preferred, surpassing the appeal of fully circular (100 percent) products, which are, nonetheless, still highly favored.

This can be further examined in the graphs of Figures 2 and 3, specifically in the results of NMS respondents. For this subset of my sample, the impact of varying levels of circularity presents a more nuanced picture. I observe that products with a low level of circularity (25 percent) are more attractive than their brand-new counterparts.

However, as the level of circularity escalates to 75 percent, the choice probability for circulated products is almost equal yet slightly lower than that of brand-new products, albeit the difference is minimal. In contrast, fully circulated products, with a Circular Economy Score of 100 percent, are less preferred than brand-new products.

CES respondents display similar patterns as the full sample, with a stronger inclination. In every case, circularity is favored over brand-new products, with products having 75 percent circularity being the most preferred choice.

6.6 Willingness to pay for circularity

To test our hypotheses on whether Norwegian consumers are willing to pay extra for circulated products and to gauge whether this depends on the framing of the circularity attribute, I estimated the mean WTP for the full sample and the two sub-groups, as presented in Table 9 below. These tests were run on the model that included dummy coding of the variables and intercepts to obtain robust results while also giving different WTP estimates for each level of circularity.

Willingness to Pay (WTP) and p-values

Results of different samples

Sample	WTP for Circularity 25	p-value	WTP for Circularity 75	p-value	WTP for Circularity 100	p-value
Experiment 1: Full sample (n = 135)	-1115.3176	[1]	385.3819	[1]	756.4163	[1]
xperiment 2: NMS (n = 62)	-1385.5370	[1]	-2299.9410	[1]	-4311.8660	[1] **
Experiment 3: CES (n = 73)	-738.4545	[1]	2885.2561	[1] .	2096.6332	[1] .

[1] Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 9: Willingness to Pay

The WTP estimates show what respondents are willing to pay to obtain each level of circularity in their purchase decisions, compared to the base level of 0 percent circulated, brand-new products. In our full sample, the WTP estimates show a noticeable disparity across different levels of circularity. For a product with 25 percent circularity, a negative value of NOK 1115 for 25 percent circularity indicates that consumers would need to be compensated for choosing a product with this low level of circularity rather than a brand-new product.

However, as we increase the circularity of the product, the WTP shifts towards the positive side. For a product with 75 percent circularity, the WTP is NOK 385, suggesting that consumers are willing to pay extra for this increased circularity. The trend continues for products with 100 percent circularity, where the WTP further increases to NOK 756.

NMS respondents, on average, would require financial compensation to opt for products featuring any level of circularity. For a product with 25 percent circularity, respondents would need to be compensated by NOK 1385. As the circularity level increases to 75 percent, the required compensation rises to NOK 2299 and then increases dramatically to NOK 4311 for a fully circulated product. Among CES respondents, we observe a shift in WTP as circularity increases. CES respondents exhibit a negative WTP for a product with 25 percent circularity, amounting to NOK 737. However, we observe a swing in attitudes when the circularity level rises to 75 percent. The WTP turns positive, reaching NOK 2885. Interestingly, while the WTP remains positive for fully circular products, there is a slight decrease compared to the 75 percent circularity level at NOK 2096.

Only the finding that NMS respondents demand NOK 4311 in compensation for choosing the highest circulated product is highly significant at the 1 percent level, with the values of NOK 2885 and 2096 for the circularity levels of 75 and 100 respectively, in the CES sample being significant at the 10 percent level.

For the NMS respondents, the demand for a substantial compensation of NOK 4311 for opting for the fully circulated product stands out with a high degree of statistical significance at the 1 percent level. On the other hand, for CES respondents, their willingness to pay for 75- and 100 percent circularity, corresponding to values of NOK 2885 and NOK 2096, respectively, demonstrate statistical significance but only at the 10% level.

7. Discussion

The main model's estimated coefficients for the Circularity attribute were positive and significant for the CES subsample, negative and significant for the NMS subsample, and positive but insignificant for the full sample. These findings do, to some extent, prove that consumers who are made aware of the circularity attribute in their products have a positive inclination towards circular products in a choice situation. However, they fail to provide evidence of a general preference for circularity as the full sample did not show significant results. As such, we fail to provide evidence for hypothesis 1. However, we can support hypothesis 2.

From the dummy coded model estimation, the estimated coefficients for the circularity attributes were negative at 25 and 100 percent circularity levels while positive at 75. Although they were not statistically significant for the full sample, nor were they sufficiently significant for the CES subsample for us to draw definitive conclusions. There was, however, a significant and negative coefficient towards the 100 percent circularity level among NMS subsample respondents, while the coefficients remained negative and insignificant at all other levels. The WTP analysis brought similar patterns but indicated a drop in preference for circularity at the 25 percent levels for the full sample while strengthening the argument that NMS respondents have a preference against fully circulated products since this was the only category to hold significant WTP estimates, of negative NOK 4311. My findings indicate that respondents who choose mobile phones based on the New Material Score rather than the Circular Economy Score prefer fully circulated products. However, since we have no other reference, we cannot conclude regarding hypothesis 3 from these results alone.

The coefficients from the model without intercepts are positive and significant in all cases for the full sample, positive and significant for the levels of 75 and 100 percent circularity for the CES subsample, and negative and significant for the NMS subsample at 100 percent circularity. While removing the intercept term for Alternative 2 is justified since the two product alternatives are identical in all aspects besides the given attributes, removing the intercept term for Alternative 3 might have influenced the coefficients in unintended ways since it represents respondents' preference to purchase neither product. All of the model coefficients for the full sample are, however, significant, and the comparison between Alternatives 1 and 2, when only including the circularity attribute as a differentiator, does appear to show a concave relationship between choice probability and circularity for both the full sample and the subsamples. However, these results must be interpreted with some caution. While they indicate that fully circulated mobile phones are less preferred than those partially circulated, the nuances of individual preferences are unlikely to be fully captured in this analysis due to removing the intercepts.

We, therefore, have some support for hypothesis 3. However, we fail to prove it decisively.

8. Limitations

The most important limitation of this project was the distribution of our survey. We collected only 135 full responses, with less than half coming from students. Given the non-random nature of our distribution method, we cannot assert that we have a representative sample. This applies to students of the University of Stavanger and residents in general regarding their views on circularity in mobile phones. For someone wishing to redo this experiment, I recommend strictly posting the survey on university-related forums to get a representative sample of near exclusively university students.

Another limitation is the levels of the Circularity attribute. We chose a 10-question iteration of the choice experiment to maximize the information extracted by each respondent. However, our iteration did not have any instance of the circularity level of 50 in any choice set. This meant that we could only estimate the coefficients of a 50-circularity attribute level with extrapolation, which would have increased the uncertainty of our results. For future studies, it would be beneficial to include a wider variety of Circularity levels in the survey design, which could provide a more comprehensive view of respondents' preferences.

Another limitation is related to the inclination of respondents to choose an option. For the full sample, the "neither" alternative being negative and significant shows that respondents would instead choose between the two options, even when the attribute levels would imply that they might, in reality, prefer not to engage in a purchase. This inclination may be due to respondents' desire to fully engage with the survey, bearing in mind that they are not committing to a purchase decision. Consequently, they might feel more inclined to select the less than satisfactory but preferable product among the two alternatives. For future studies, it could be beneficial to emphasize that opting for the "neither" alternative is a valid response to a survey question. Alternatively, redefining the "neither" option as an alternative that includes average values across all attributes could help mitigate this bias. This could give more nuanced insights into respondents' true preferences and more accurately estimate their real-world choices.

9. Conclusion

My goal with this study was to answer whether consumers prefer or are against Circular content in mobile phones and whether there is a stronger preference for partially circulated mobile phones than fully circulated. I also wanted to improve research on consumers' relationships with circularity by employing a less commonly used method with the discrete choice experiment. Finally, I wanted to employ different framings of the Circularity attribute, to see whether the presentation of the attribute would have a sizeable effect on respondents' choices. The results offered some interesting insights, although many definitive conclusions could not be drawn due to non-significant results.

I did not find evidence of a general preference among consumers for either circular or non-circular products, independent of how these options were presented. However, I found evidence that consumers choose circular content when presented with a circularity label. While these findings are interesting, they do not suggest a universal or general consumer preference for circular products. However, they suggest that respondents are positively influenced by labeled circularity contents and are likelier to choose circular products when adequately labeled. Conversely, consumers presented with a negative framing of the circularity attribute display an aversion to circular products, which underlines the effects of message framing on respondents' choices.

I observed evidence suggesting that fully circular mobile phones might be less appealing to consumers than their partially circular alternatives, regardless of how they were framed. However, this evidence did not have the level of robustness required to assert it as a definitive fact, pointing to the need for further investigation.

Respondents who answered the "New material score" version of the survey rather than the "Circular Economy score" displayed an aversion to fully circulated products. On average, these respondents were willing to pay an additional NOK 4311 for a brand-new product composed entirely of virgin material rather than opting for a product made entirely from circulated materials. This aligns with my findings, suggesting that consumers exhibit a negative inclination against circularity when it is portrayed as a loss of virgin material.

My findings align with earlier discrete choice experiments on consumers' preferences for circularity when purchasing mobile phones. Consumers are inclined to choose circular when the circularity content is presented to them (Boyer et al., 2021a; Hunka et al., 2020; Boyer et al., 2021b). Unlike Hunka et al. (2020). We could not prove diminishing preferences for fully circulated products compared to partially circulated ones (Boyer et al., 2021a; Hunka et al., 2020). We were, however, able to provide evidence in line with other DCEs on related topics that increasing awareness of the circular contents of a product increases consumers' preferences for circulated products (Stein et al., 2020; Lieder et al., 2018). We also provided evidence that attribute framing plays a role in respondents' stated preferences (Levin & Gaeth, 1988; Meyerowitz & Chaiken, 1987; Evangeli et al., 2013; Van't Riet et al., 2016). Our findings suggest that a circular economy product label could benefit Norway and inspire consumers to make choices more aligned with the circular economy concept and our climate targets. For future research, it would be interesting to determine which levels of circularity are most inviting for consumers, as it could provide insights into the optimal level of circularity that meets the demands of the circular economy best, while also satisfying consumer preferences.

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11. Appendix
Example of survey

Your input is important!

Thank you for participating in this survey conducted by researchers at the University of Stavanger Business School.

The survey is about people's digital advertisement experiences and preferences for product characteristics.

We are only interested in your experiences and hearing opinions. ***There are no right or wrong answers.*** It will take less than 10 minutes to complete the survey.

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Trym Ferdinand Folgerø Dybwad, Aksha Fernando, Leila Asgarkhani
Master student researchers

Acknowledgement and participation agreement

Your participation in this survey is completely voluntary and anonymous. No information that can identify you as as person will be collected. Your answers will be combined with those of other participants to generate combined statistical analysis. You are free to end your participation and exit the survey at any time by closing your browser.

By entering the survey you confirm that you have read and understood the above information.

I DO NOT AGREE TO PARTICIPATE IN THIS SURVEY (EXIT)	I AGREE TO PARTICIPATE IN THIS SURVEY (ENTER)

Which social issues should have the highest priority in public policy and budget allocations? [*Choose the three most important ones for you.*]

Climate	Crime	Equality
Immigration	Economy	Health
Public transport	Culture	Sports
Agriculture	Environmental protection	Defence
Education	Elderly care	Other (please specify):

To what extent do you agree with the following statement: ***I do research online (Google, social media, etc.) before making product purchasing decisions.***

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

To what extent do you agree with the following statement: ***I am willing to buy the products recommended by my friends on social media.***

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

To what extent do you agree with the following statement: ***When I want to buy something, I will take suggestions from social media influencers.***

Strongly agree	Somewhat agree	Neither agree nor disagree
Somewhat disagree	Strongly disagree	

Suppose you come across the following sponsored advertisement for a reusable drinking cup as you scroll through Instagram (or some other social media app).

How likely are you to click on the ad in order to learn more about this product?

Extremely unlikely										Extremely likely
0	1	2	3	4	5	6	7	8	9	10

To what extent does the ad make you think about sustainability issues?

Not at all influential										Extremely influential
0	1	2	3	4	5	6	7	8	9	10

Suppose you come across the following sponsored advertisement for mobile phones as you scroll through Facebook (or some other social media app).

How likely are you to click on the ad in order to learn more about this product?

Extremely unlikely — Extremely likely

0	1	2	3	4	5	6	7	8	9	10

To what extent does the ad make you think about sustainability issues?

Not at all influential — Extremely influential

0	1	2	3	4	5	6	7	8	9	10

More about your preferences for mobile phones

Below you will see several choice cards for new versus refurbished mobile phones. The mobile phones differ in four explicit characteristics:

(1) Battery life
(2) Warranty
(3) New-material score
(4) Price

As you go through the choice cards and express your preferences, we would like you to focus only on these four characteristics. Assume the mobile phones are otherwise the same (i.e., they have the same processing capabilities, memory, appearance, service & insurance features, etc).

Next, we provide some more information about the *new material* score.

The New-Material Score (NMS)

The new-material score (NMS) informs consumers about the proportion of a product that is made from new, non-recycled materials. Some products are entirely composed of new materials, while others are made from a mixture of new and recycled or refurbished components. The NMS can range from 0% to 100%.

NMS = 0% - The whole product is recycled/refurbished
NMS = 25% - Most of the product is recycled/refurbished.
NMS = 50% - Half the product is recycled/refurbished
NMS = 75% - The product contains recycled/refurbished materials.
NMS = 100% - Everything in the product comes from new materials.

(1/10) Between these two products, which one would you purchase?

	Phone 1	Phone 2
Battery life (intensive use):	6 hours	10 hours
Warranty:	6 months	2 years
New material score (NMS)	0%	100%
Price:	7000 NOK	9500 NOK

Phone 1

Phone 2

I would not purchase either phone

(2/10) Between these two products, which one would you purchase?

	Phone 1	Phone 2
Battery life (intensive use):	10 hours	6 hours
Warranty:	1 year	1 year
New material score (NMS)	25%	25%
Price:	9500 NOK	7000 NOK

Phone 1

Phone 2

I would not purchase either phone

(3/10) Between these two products, which one would you purchase?

	Phone 1	Phone 2
Battery life (intensive use):	10 hours	8 hours
Warranty:	6 months	2 years
New material score (NMS)	75%	0%
Price:	12 000 NOK	4500 NOK

Phone 1

Phone 2

I would not purchase either phone

(4/10) Between these two products, which one would you purchase?

	Phone 1	Phone 2
Battery life (intensive use):	10 hours	6 hours
Warranty:	6 months	1 year
New material score (NMS)	100%	0%
Price:	4500 NOK	12 000 NOK

Phone 1

Phone 2

I would not purchase either phone

(5/10) Between these two products, which one would you purchase?

	Phone 1	Phone 2
Battery life (intensive use):	6 hours	10 hours
Warranty:	1 year	6 months
New material score (NMS)	75%	25%
Price:	12 000 NOK	4500 NOK

Phone 1

Phone 2

I would not purchase either phone

(6/10) Between these two products, which one would you purchase?

	Phone 1	Phone 2
Battery life (intensive use):	8 hours	10 hours
Warranty:	2 years	6 months
New material score (NMS)	25%	75%
Price:	4500 NOK	12 000 NOK

Phone 1

Phone 2

I would not purchase either phone

(7/10) Between these two products, which one would you purchase?

	Phone 1	Phone 2
Battery life (intensive use):	6 hours	8 hours
Warranty:	6 months	2 years
New material score (NMS)	25%	25%
Price:	4500 NOK	9500 NOK

Phone 1

Phone 2

I would not purchase either phone

(8/10) Between these two products, which one would you purchase?

	Phone 1	Phone 2
Battery life (intensive use):	10 hours	6 hours
Warranty:	1 year	1 year
New material score (NMS)	0%	75%
Price:	7000 NOK	4500 NOK

Phone 1

Phone 2

I would not purchase either phone

(9/10) Between these two products, which one would you purchase?

	Phone 1	Phone 2
Battery life (intensive use):	8 hours	10 hours
Warranty:	2 years	6 months
New material score (NMS)	75%	0%
Price:	7000 NOK	7000 NOK

Phone 1

Phone 2

I would not purchase either phone

(10/10) Between these two products, which one would you purchase?

	Phone 1	Phone 2
Battery life (intensive use):	8 hours	8 hours
Warranty:	2 years	6 months
New material score (NMS)	0%	75%
Price:	9500 NOK	7000 NOK

Phone 1

Phone 2

I would not purchase either phone

Please rate the importance of the following attributes when considering the purchase of a mobile phone. For each attribute, indicate how much it would influence your decision.
(1-Very unimportant, 5-Very important)

1 2 3 4 5

Battery life

Warranty

Material origin (new material score)

Price

Processing cabablilities

Memory

Appearance

Service and insurance

To what extent do you agree with the following statement:
Information available on social media helps me decide whether to buy sustainable products/brands.

Strongly agree | Somewhat agree | Neither agree nor disagree | Somewhat disagree | Strongly disagree

How important is it for you to represent your commitment to sustainability on social media platforms?

Extremely important | Very important | Moderately important | Slightly important | Not at all important

Which digital channels usually influence your opinion towards *Sustainable* buying decisions?

Social Media | Websites/Blogs | E-mail | Others

To what extent do you agree with the following statements about your shopping behavior?
(1-Strongly disagree, 5-Strongly agree)

1 2 3 4 5

When shopping, I deliberately check products for environmentally harmful ingredients

I deliberately choose products with environmentally friendly packaging.

I'll prefer to buy sustainable products even if they are more expensive than others.

I check environmental and fair trade label before buying the products.

To what extent do you agree with the following statements about environmental and sustainability issues?
(1-Strongly disagree, 5-Strongly agree)

1 2 3 4 5

I believe that sustainable purchasing by me will help in reducing wasteful use of natural resources.

I am very knowledgeable about environmental and social issues.

I know where I can find products that create less wastage.

I have knowledge about the sustainability symbols used on product packages.

I feel good about myself when I am involved in sustainable purchasing.

Humans are seriously abusing the environment.

The Earth has plenty of natural resources if we just learn how to develop them.

The balance of nature is strong enough to cope with the impacts of modern industrial nations.

The so-called "ecological crisis" facing humankind has been greatly exaggerated.

Human ingenuity will ensure that we do not make the Earth unlivable.

What is your gender?

Male | Female | Prefer not to say

What is your age?

<20 | 20-29 | 30-39 | 40-49 | 50-59 | 60<

Considering your current financial situation, how easy or challenging would it be for you to buy a new mobile phone today?

- Extremely easy
- Somewhat easy
- Neither easy nor challenging
- Somewhat challenging
- Extremely challenging

What is your employment situation?

- Employed full time
- Employed part time
- Student (with or without employment)
- Other

We thank you for your time spent taking this survey.
Your response has been recorded.