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Understanding purchase decision for remanufactured laptops: A utility-based analysis of consumer preferences in an emerging economy

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ABSTRACT

This study investigates the determinants of consumers' purchase decisions for remanufactured laptops in Indonesia, where a limited understanding of remanufacturing continues to hinder adoption of the circular economy. Rather than examining purchase intention, the study model's purchase decision as a trade-off-based decision process reflects consumers' decision-making of remanufactured products. A MaxDiff (Best–Worst Scaling Case 1) discrete choice experiment was conducted involving 434 Indonesian undergraduate students. Preferences were modeled within a random utility theory framework using multinomial logit estimation via maximum likelihood, and consumer heterogeneity was subsequently examined through latent class analysis, revealing four distinct preference segments. The results show that the dominant driver of purchase decision is functionality expectation, followed by perceived consumer effectiveness and perceived safety, indicating that consumers prioritize performance assurance and risk reduction over environmental motivations. Environmental consciousness and social influence have weaker effects, indicating an attitude–behavior gap for sustainable consumption. Furthermore, the latent class analysis identified four heterogeneous consumer segments with varying valuation logics. This suggests practical implications for future strategies to increase the purchase decision of remanufactured electronics in emerging economies through knowledge creation about the customer perceptions, where a greater emphasis on functional reliability, certification, and transparent quality communication may prove more effective than traditional environmental appeals.

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1. INTRODUCTION

Technological innovation is not the only necessity for transitioning to a circular economy—we must also change consumers' perceptions and behavior toward remanufactured goods in terms of how they are perceived [1], [2]. Globally, remanufactured products are becoming increasingly popular in global markets as an environmentally sustainable and cost-effective alternative to new products. That, however, is yet to be fully seen in much of the developing world, from which a country like Indonesia hails. Consumer distrust, inadequate product elucidation, and poorly constructed educational programs regarding the benefits of remanufactured products [3], [4] are major barriers to consumer acceptance.

However, multiple studies emphasize the need for consumer perceptions to develop a market for remanufactured products. For example, Chinen *et al.*

[4] pointed out that consumer orientation and delivery of the right information can massively increase the acceptance of remanufactured. This is significant because, especially in electronic waste, remanufactured products are considered significantly with doubt and more doubts about quality and happy customers. Some authors propose that leaders need to address these quality concerns by using communication technologies, such as blockchain, as a mechanism for building consumer trust with real-time or proximate supply chain information [5].

Among them, Indonesia has an interesting paradox, although most electronics are reused informally here still no clear idea of what a remanufactured product is. Consumers often mistake remanufacturing for second-hand or informal repair, and this leads to resistance even in a market where the price is only marginally higher [6], when the product offers quality comparable to that of new. The absence of differentiation in the minds of consumers represents a real impediment to the ability of the industry to grow formal remanufacturing [7]. Zhang *et al.* [8] discussed how poor consumer perceptions regarding remanufactured products can hinder the development of a robust remanufacturing market. Zhang *et al.* [8] argued that consumers may remain skeptical about considering such products without proper separation and explanations on what remanufacturing actually consists of, often looking to cheaper second-hand alternatives that lack sufficient guarantees.

Consumer electronics especially laptops are a highly visible, relevant, and strategic case for remanufacturing among the many product categories that fall within the circular economy. Sharma et al. highlighted that employing sustainable strategies in high-tech fields (including laptops) transforms industry norms and guides the design, development, delivery, and consumption of products, further facilitating remanufactured goods as a viable business model that creates increasingly contentious economic outcomes [9]. In line with these visions, Centoamore and Pinto [10] explained that maintaining product quality through remanufacturing not only increases the lifetime of products but also keeps functional economic and material assets in reserve for future. Laptops are also highly valuable and technically complex consumer products used in education, work, and everyday life. Their comparatively brief upgrade cycles, consistently stable demand, and considerable replacement costs make them a prime candidate for remanufacturing programs that strive to provide an economical and sustainable proposition [11].

Laptops are utilized by a wide array of markets, including students, educators, office workers, entrepreneurs, and creative professionals, and each depends on mobile computing machines to facilitate their work and productivity [12], [13]. Among these user segments, university students are among the largest and most active consumer groups for laptops [14]. Most of their academics and day-to-day activities rely on digital tools, allowing small academic laptops to be a need rather than a desire. In Indonesia, this segment is highly sensitive to product price [15] and tends to place value over the nonenvironmental attributes of eco-friendly products [16]. Thus, remanufactured laptops properly positioned are highly likely to fulfill their functional needs at a lower price [17].

Although environmental consciousness may not inherently motivate student purchasing behavior [18], this demographic maintains several key advantages that make them a target group for circular economy applications. Students are in the life transition stage, and they are building long-term consumption habits [19]. The decisions they make today will influence not only future market demand but also public acceptance of alternative products such as remanufactured goods [20]. However, one of the major challenges is that many students still do not recognize the technical rigor and quality assurance supporting remanufacturing, instead assuming it resembles informal repair or second-hand [19]. Lack of understanding of how to create price action has been attributed to fear and low willingness to pay [21].

The novelty of this study lies in the integration of three underexplored aspects in RPR. First, unlike previous studies that predominantly focused on general purchase intention and behavioral acceptance using conventional survey-based approaches [16], [22], [23], [24], [25], [26], this study investigates the complexity of consumer purchase decision-making by examining how consumers evaluate and trade off multiple product-related and psychological factors toward remanufactured laptops [24], [26], [27], [28], [29], [30]. Second, this study extends prior literature by adopting a stated preference and purchase decision perspective grounded in random utility theory [31], and CBT [32]. While most previous studies have emphasized behavioral intention constructs, only a few have examined actual consumer valuation and preference structures through decision-oriented approaches, such as WTP and stated preference analysis [21], [25], [27], [31], [32], [33], [34]. Third, this study provides contextual evidence from an emerging country setting, where research on remanufactured products remains relatively limited [35]. Existing studies indicate that consumers in emerging markets tend to exhibit different characteristics, such as higher price sensitivity, lower trust in remanufactured products, and lower sustainability awareness [21], [22], [23], [24], [27], [32]. Consequently, this research aids in reducing the contextual gap in literature while providing an enhanced understanding of how consumers in developing economies respond to and decide whether or not to purchase remanufactured products.

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Thus, this study focused on six major psychological and informational factors that are potentially significant determinants of Indonesian undergraduates' purchase decision toward remanufactured laptops through a trade-off-based analytical perspective. These factors were derived from a systematic literature review (SLR) of previous empirical studies on RP adoption and sustainable consumption behavior. Expectations regarding the functionality, perceived effectiveness of pro-environmental behavior, perceived safety, environmental concern, green knowledge, and informational social influence repeatedly surfaced as dimensions that guide consumer evaluation of remanufactured products.

The major contributions of this research are as follows:

(1) Identification of factors (relative importance) affecting consumer purchase decisions in remanufactured laptops.
This study adds insights to the literature on remanufacturing and sustainable consumption by understanding the psychological, informational, and evaluative aspects of how consumers weigh different factors concerning remanufactured laptops.

(2) MaxDiff analysis is clustered via LCA, allowing for heterogeneity of consumer preferences.
By applying MaxDiff analysis and latent class segmentation, the study delineates how consumer preference structures vary across segments to generate a more nuanced picture of the underlying heterogeneity within consumers' evaluative processes when it comes to remanufactured products.

(3) Progressing utility-based preference analysis in consumer contexts
This study enhances the theoretical interpretation of relative utility importance without directly providing economic willingness-to-pay value estimates by contextualizing consumer preferences within a framework grounded in random utility theory (RUT).

(4) An empirical example from a research context that is often ignored and underexplored
This research adds context-specific empirical direct insight to the currently limited literature on remanufactured product acceptance in emerging economies, a subject of consumer awareness and trust that has been barely touched upon regarding remanufactured electronics.

(5) Recognizing and ranking the preference drivers that influence or support consumer evaluation.
The findings demonstrate that the relative influence of functionality expectation, perceived consumer effectiveness, and perceived safety on consumer purchase decisions is stronger than that of environmental consciousness or informational social influence.

(6) Managerial and Policy Guidelines for Remanufacturing Ecosystem Development.
Provides guidance for communication, quality assurance, and certification strategies for firms and policy makers seeking to achieve a greater level of consumer acceptance of remanufactured laptops.

2. RELATED WORK

2.1. Research positioning

We comprehensively established the research positioning using a systematic literature review, which allowed us to clearly articulate several dimensions, including (a) theoretical foundations and frameworks, (b) problem statement, (c) dependent variables, and (d) methodological approach (Table 1).

The literature review shows that RPRPs vary in developed and developing countries. In developing countries, the main barriers include low customer acceptance and awareness [23], [27], [34], low willingness to pay/purchase decision [21], and complexity of consumption behavior [30], [32]. Such issues are primarily connected to low sustainable awareness, high price sensitivity, weak trust in the quality of remanufactured products, and immature circular economy ecosystems. In contrast, studies covering developed countries dive into more sophisticated issues, such as stated and revealed preferences [26], [31], premium feature preferences [35], and behavioral segmentation, indicating further market maturity and a weaker sustainability orientation.

Driven by these differences, this study outlines three specific complementary research questions: the complexity of adoption behavior, the lack of stated preference studies, and the limited evidence from emerging economies. The second factor is that the consumption behavior of remanufactured products is influenced by multiple factors based on the perception of price, environmental concern, perceived quality, and social attitude [22], [24], [30], [32], [36], [37], which makes it an extremely complex consumption behavior. Second, most previous studies have been based on generalized purchase intention, but research focusing on specific decision-making tasks with stated preference approaches, which help to capture consumer trade-offs and attribute preferences, has been very limited [31], [34]. Third, although consumer characteristics and market conditions in developing economies are very different from those in developed countries, empirical evidence based on emerging countries is still limited [28]. Thus, this study provides contextual evidence from an emerging country's point of view while complementing the understanding of consumer preferences toward remanufactured products.

Previous studies mainly utilized high-level behavioral theories, including complexity theory [21],

Table 1. Summary of research positioning

Author(s)	Year	Fundamental Theory and Framework	Problem statement	Dependent Variables	Methodology
Chen *et al*. [21]	2019	Complexity theory	Low willingness to pay	Willingness to pay and purchase decision	Multivariate Statistics
Singhal *et al*. [23]	2018	Theory of planned behavior	Low Customer Acceptance and Awareness	Purchase intention, behavioral intention, and behavioral attitudes	Multivariate Statistics
Abbasi *et al*. [32]	2022	Stimulus Organism Response theory (SOR)	Complexity of the consumption behavior	Purchase intention, behavioral intention, and behavioral attitudes	Multivariate Statistics; Inferential Statistics; Comparative / Configurational Methods
Kuah *et al*. [27]	2020	Sharing economy theory	Low Customer Acceptance and Awareness	Purchase intention, behavioral intention, and behavioral attitudes	Descriptive Statistics, Inferential Statistics, Multivariate Statistics, Regression and Econometrics
Milios *et al*. [33]	2019	Theory of planned behavior (TPB)	Low Customer Acceptance and Awareness	Purchase intention, behavioral intention, and behavioral attitudes	Regression and Econometrics: Multivariate Statistics
Kabel *et al*. [25]	2020	Theory of planned behavior (TPB	Low Customer Acceptance and Awareness	Purchase intention, behavioral intention, and behavioral attitudes	Multivariate Statistics and Inferential Statistics
Pisitsankkhakarn *et al*. [28]	2020	Theory of planned behavior (TPB)	Lack of study in emerging countries	Purchase intention, behavioral intention, and behavioral attitudes	Multivariate Statistics and Inferential Statistics
Wewer *et al*. [29]	2020	Complexity theory	Low Customer Acceptance and Awareness	Purchase intention, behavioral intention, and behavioral attitudes	Regression and Econometrics: Inferential Statistics
Fraccascia *et al*. [16]	2023	Theory of Consumer Decision-Making Process	Low willingness to pay and low customer acceptance and awareness	Purchase intention, behavioral intention, and behavioral attitudes	Descriptive statistics, inferential statistics, and multivariate statistics
Wang *et al*. [30]	2020	Signaling Theory	Complexity of the consumption behavior	Willingness to pay and purchase decision	Multivariate Statistics
Boyer *et al*. [38]	2021	Theoretical multilevel circular economy score	Low WTP	Willingness to pay and purchase decision	Inferential Statistics and Multivariate Statistics
Chen *et al*. [34]	2020	Choice behavior theory	Low customer acceptance and awareness; lack of a study of stated preferences	Willingness to pay and purchase decision	Regression and Econometrics: Inferential Statistics
This Study	2026	Random utility theory and choice behavior theory	Complexity of consumption behavior; lack of a study on stated preference; lack of study in emerging countries	Willingness to pay and purchase decision	Multivariate statistics; regression and econometrics; latent variables and classification modeling

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[22], [29], and the theory of planned behavior [23], [25], [26], [28], [33], to interpret consumer adoption, purchasing intentions, and behavioral attitudes. Your theories outline that consumer decisions are influenced by attitudes, subjective norms, and perceived behavioral control, as well as individual decision-making. Later research broadened the theoretical scope by including, e.g., SOR theory [24], [32], signaling theory [30], and sharing economy theory [27], and identified theories tied to sustainability, such as TBL theory [35] and circular economy-related frameworks [38], [39]. These methods mirror the emerging focus on sustainability orientation, environmental value, product knowledge, and circular consumption behaviors to understand consumers' intentions toward remanufactured products. Recent research has also incurporated predictive and business-driven approaches, such as Big Data Analytic Frameworks [40], CRISP-DM [36], Online Review Characteristics [37], and Choice Behavior Theory [34]. It reflects a transition from relatively simplistic behavioral intention models to more elaborate approaches that incorporate consumer preference structures, digital information, and more sophisticated decision-making mechanisms.

As a theoretical development in this realm, this study utilizes the random utility theory [31] and choice behavior theory [34] as the foundation of this research. Random utility theory well supports the analysis of consumer trade-offs and preference structures in purchasing decisions, but CBT better serves to help develop an understanding of the ways consumers evaluate the attributes available in remanufactured products within a decision environment. The integration of these theories is appropriate to fill the research gaps highlighted with reference to consumer behavior complexity, lack of stated preference modeling approach, and absence of empirical evidence from future emerging countries.

The dependent variables in RP studies have evolved from rather vague behavioral intention constructs to more decision-oriented and economic-related outcomes. The majority of early studies leveraged purchase and behavioral intentions [16], [22], [23], [24], [25], [26], [27], [28], [29], [32], [33], [37], while more recent studies began examining WTP and purchase decision variables [21], [30], [34], [38]. Such a transition indicates the growing demand to explore whether consumers will accept remanufactured products and whether they will act upon such acceptance when making real-world product value-based choices.

Based on this development, the current research considers purchase decision as the dependent variable because purchasing behavior is a more valid reflection of consumers' actual buying choices than general measures based on purchase intention. In the context of remanufactured products, after considering perceived quality, functionality, environmental value, and economic benefits, purchase decisions are closely associated with consumers' willingness to pay. Although the questionnaire did not explicitly include price variables in each choice task, the respondents were provided with preliminary information before completing the survey, including a presentation explaining the differences between remanufactured (certified refurbished) and new laptops, particularly regarding product characteristics and relative price differences (Fig. 1). Therefore, the evaluations and choices of the respondents were formed under an informed decision-making context, where willingness to pay implicitly reflected their purchase decision preferences toward remanufactured laptops. This approach is consistent with previous studies that position WTP as a representative of consumer valuation and decision-making behavior toward sustainable products [21], [30], [34], [38].

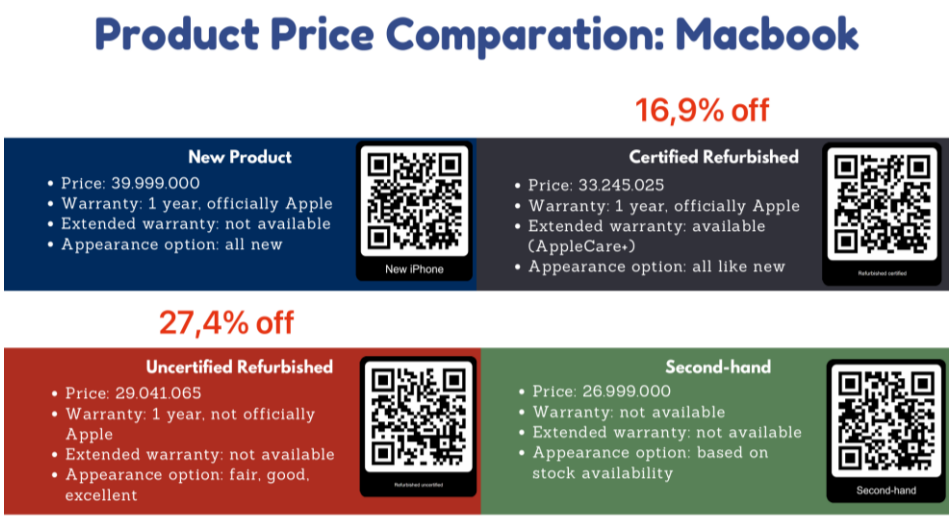


Fig. 1. Price comparison between remanufactured and new laptops

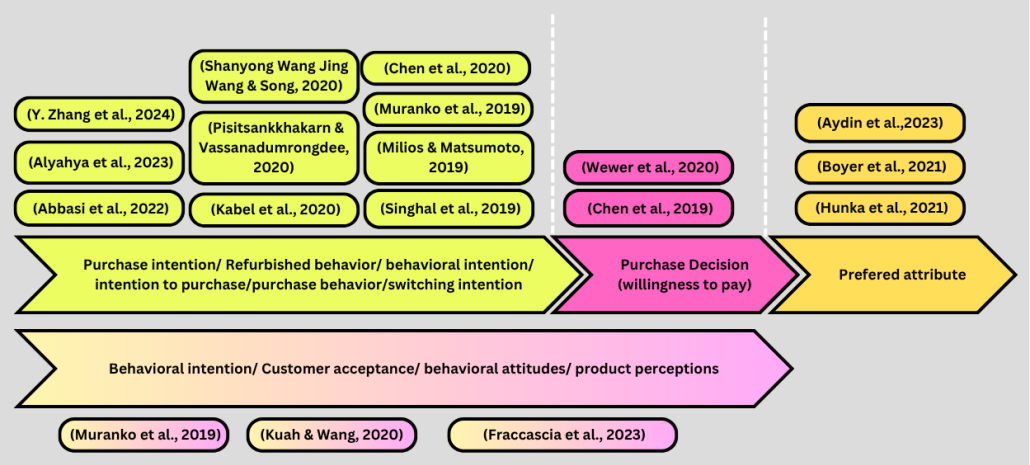


Fig. 2. Classification and evolution of dependent variables in remanufactured product research

Fig. 2 shows the classification and evolution of dependent variables in the research on remanufactured products. Earlier studies predominantly focused on behavioral-oriented variables, such as purchase intention, behavioral intention, purchase behavior, and switching intention [16], [22], [23], [24], [25], [26], [27], [28], [29], [32], [33], [37], to explain consumer acceptance and attitudes toward remanufactured products. Several studies have also emphasized customer acceptance, behavioral attitudes, and product perceptions [16], [22], [23], [27]. More recent studies have shifted toward decision-oriented variables, particularly purchase decisions represented by WTP [21], [29], [34], [38], as well as preferred attributes and premium feature preferences [31], [35], [38]. This evolution signals a shift from an understanding of willingness to behave to an understanding of actual consumer value and trading behavior. The study uses purchase decision/WTP as the dependent variable in the current research, largely because this step gives a better reflection of actual consumer choices for remanufactured products based on this line of research development. Moreover, studies that investigated WTP in emerging country contexts are less compared to behavioral intention-based studies.

2.2. Mathematical evolution of analytical paradigms

Across remanufacturing research, methods of measuring consumer acceptance have shown a clear evolution where analytical sophistication has increased to address the unique challenges of this sector (Fig. 3). Compared with conventional products, remanufactured goods are subject to a greater degree of quality uncertainty, (perceived) functional and performance risk, environmental concerns, and price–value trade-offs. These multiple characteristics require more sophisticated and better-founded modeling approaches [21], [27], [37]. Consequently, along with the evolution of research on remanufacturing, the predominant analytical abstractions at play in current remanufacturing studies have gradually evolved from representing a simplified structure to probabilistic models that directly model preference heterogeneity and decision uncertainty.

In the early days of remanufacturing research, consumer acceptance was primarily investigated using statistical comparison approaches (e.g., mean difference tests and association analyses) [16], [24], [38]. The remaining 6 studies either compared buyer perceptions between new and remanufactured products or measured the effects of information disclosure. While this approach was valuable for identifying resistance or skepticism, it did not model the causal mechanisms underlying acceptance. Many regression-based predictive models have been proposed with the association of purchase intention with measurable predictors such as perceived quality, risk perception, environmental concern, and price sensitivity [21], [26], [27], [29], [33], [34]. This phase facilitated directional effect estimation but presupposed linear, additive relationships and homogeneous consumer responses. With the evolution of the field, researchers turned to latent construct of net-effect logic across consumers. Configurational modeling (most notably structural equation modeling (SEM)) in definition acceptance as latent variable formed by constructs such as trust, perceived value, and sustainability orientation [16], [25], [28], [30], [32], [37], [41]. This not only provided stronger theoretical integration by combining measurement and structural models but also operated with a symmetric, consistent application approaches were later used to deal with the complex decision-making process, capturing causal asymmetry, or how combinations of conditions jointly bring about high acceptance [22], [32]. Although this perspective

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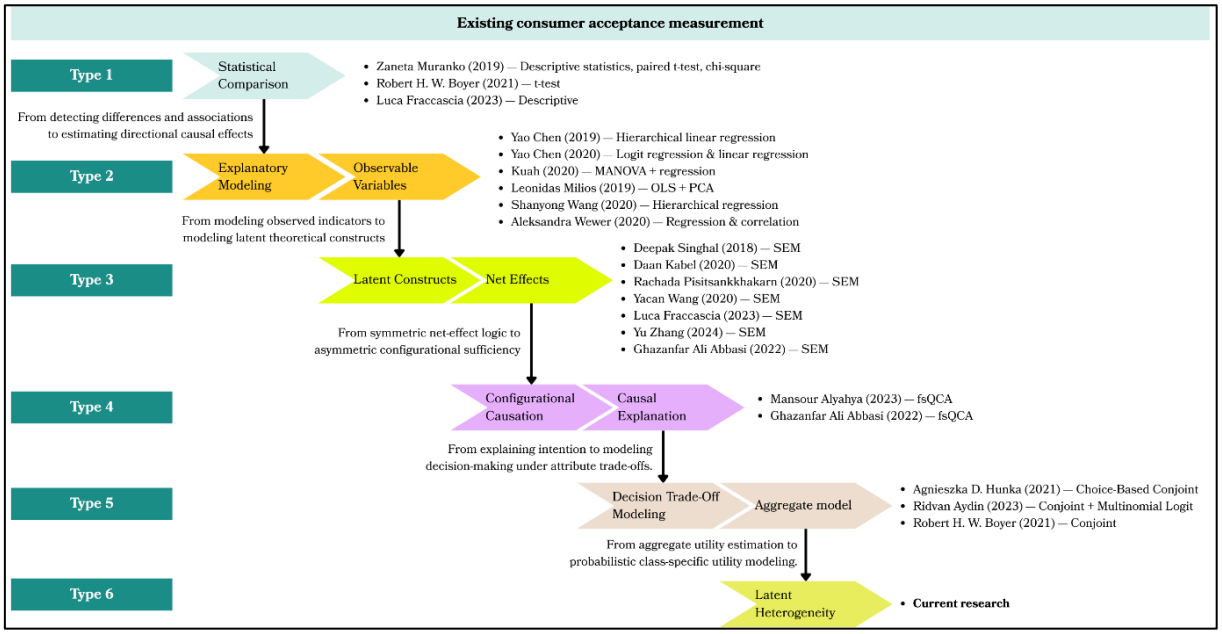


Fig. 3. Classification of analytical frameworks in consumer acceptance studies in the remanufacturing context

allowed for numerous variations in corresponding attributes that could proceed toward similar evaluations, it was a view that predominantly focused on the interpretation of intention rather than making explicit trade-offs among desirable features.

Utility-based decision modeling via Cardiff and discrete choice experiments was the first real shift in substantial [31], [35], [38]. At this point, acceptance was instrumentalized as a probabilistic option derived from the systematic preference sorting of competing attributes, including price, warranty, device condition, and environmental certification, indicating a shift from attitudinal explanation to behavioral decision modeling. Latent class–based models, which account for preference heterogeneity, have recently been used to estimate utilities. This approach avoids homogeneous assumptions and facilitates acceptance analysis about segments characterized by different structures of utility for consumers, thus providing greater relevance for the strategies or policies proposed.

2.3. Theoretical background

It is important to distinguish between CBT and RUT, as they serve different but complementary roles in this study. Choice behavior theory provides a conceptual explanation of how consumers evaluate alternatives and make purchase decisions by considering psychological, social, and contextual factors. Theories such as the Theory of Planned Behavior (TPB) [16], [23], [25], [26], [28], [33], Stimulus–Organism–Response (SOR) [24], [32], [37], and Signaling Theory [42] contribute to understanding the mechanisms that influence consumer perceptions, attitudes, intentions, and behaviors. In contrast, RUT serves as the mathematical and choice-modeling foundation for analyzing observed choices and estimating underlying preferences. Under RUT, consumers are assumed to select the alternative that provides the greatest utility, allowing the inference of latent preference structures from observed choice behavior through distinct choice models. Therefore, CBT explains the determinants of consumer decision-making, whereas RUT provides the analytical framework for quantifying the relative influence of those determinants through utility estimation.

The consumer's purchase decision is not simply a function of intention or perception; rather, it is a multi-criteria decision-making process in which consumers assess multiple product attributes simultaneously and weigh them against each other. In some cases, such as a remanufactured laptop, a consumer may want to swoop out new for less expensive esthetics, which are not 100% requirement, but functionality and warranty during purchase is typically something that they will not budge on. However, this instantiation does not account for the complex nature of consumer behavior as modeled by TPB, SOR, or signaling theory [43], [44].

As an illustrative example, the TPB is widely used to elucidate intention-based consumer behavior through attitudes, subjective norms, and perceived behavioral control. However, in the case of remanufactured products, TPB may be too parsimonious due to considerable differences in consumer perceptions and knowledge [45], [46], [47], as it does not account for the heterogeneity of preference structures or situational and contextual factors shaping purchasing decisions.

Similarly, the SOR framework and signaling theory highlight the importance of both external environmental stimuli or informational cues and perceived product signals as determinants of consumer behavior. Such concepts are especially valuable in explaining the mechanisms of consumers' perceived functional and emotional responses. However, they are not specifically designed to measure the relative importance of competing product attributes or to assess the trade-offs consumers make between multiple decision criteria [43], [44]. Thus, despite their usefulness in explaining rational choice behavior at the aggregate level, they are not intended for attribute-based utility estimation, necessitating preference-based analytical methods in case the goal is to pick and rank the most important attributes of consumer purchase decisions.

This study builds on a factor-based model derived from systematic literature review (SLR) and aligned with random utility theory logic (RUT), which is commonly applied to choices modeling, to fill these gaps in the literature. The model enables an attribute-level analysis of WTP determinants, allowing the researcher to measure not only if but how strongly each factor such as functionality expectation, perceived safety, or informational influence impacts the consumer's decision to pay for a remanufactured product [48], [49]. This approach is particularly suitable for contexts such as Indonesia's remanufacturing market marked by consumer uncertainty, preference volatility, and low category familiarity.

The MaxDiff analysis is a technique based on the RUM principles. Most studies using MaxDiff in the healthcare area have had patients with concerns regarding response reliability and validity [50], [51]. To counteract this, we designed the MaxDiff questionnaire by asking the participant only about the best and worst (Case 1 / Object Case). Conventional ranking techniques are also based on Likert scales and are subjective and qualitative due to ambiguous interpretation among respondents [26], [52], [53]. Using MaxDiff, the respondents' perceptions are further apart, and the findings are stronger and sounder [54], [55], [56]. Given that the remanufactured market is embryonic and the extent to which consumers are prepared to accept remanufactured products varies, a more structured perspective on consumer types is necessary. Latent class analysis (LCA), a popular method of consumer segmentation, classifies consumers based on latent variables representing non-observable consumer preferences or behavior that can be derived and estimated from data [57], [58], [59]. These latent variables reveal the hidden values of specific attributes such as preferences for remanufactured products demand it to different degrees within the target group, with specific customer value categories, and remain indifferent at a certain level. LCA outcomes allow the identification of the most receptive customer segments, and marketing efforts can then focus on educating and influencing less receptive segments [60], [61], [62].

2.4. Design of the research stimulus

Six adoption-relevant factors were identified as salient evaluative cues shaping consumer responses to remanufactured laptops in the stimulus design phase of the Cardiff experiment. These factors grounded in theoretical foundations and prior empirical evidence were systematically translated into experimentally manipulable attributes and corresponding levels for inclusion in the choice tasks.

2.4.1. *Informational social influence*

Informational social influence refers to an individual's tendency to conform to others' opinions based on information obtained as evidence in judgment. According to Wang *et al*. [26], informational social influence has an influence, although it is not significant and has a positive correlation. The higher the informational social influence received by consumers, the higher their likelihood of purchasing the product [16].

2.4.2. *Green knowledge*

Compared with new products, remanufactured products can save energy and materials, thus significantly reducing the negative impact on the environment, according to Alyahya *et al.* [22], who described green knowledge. The higher the green knowledge of consumers, the higher their likelihood of purchasing the product.

2.4.3. *Perceived consumer effectiveness*

Perceived consumer effectiveness is a domain-specific belief that individual consumers find it worthwhile to try to preserve and improve the environment. According to Fraccasia *et al*. [16], perceived consumer effectiveness has a significant influence and is positively correlated. The higher the perceived consumer effectiveness, the higher their likelihood of purchasing the product.

2.4.4. *Functionality expectation*

Functionality expectation refers to the consumer's hope that the remanufactured product will work as it should. The higher the product functionality expectations, the lower the perceived functionality risk for the product; therefore, a higher chance exists that the consumer will purchase the remanufactured product [16].

2.4.5. *Perceived safety*

Perceived safety plays a key role during the purchasing phase; in particular, the more the product is perceived as safe by a consumer, the higher their likelihood of purchasing the product [16].

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2.4.6. *Environmental consciousness*

Environmental consciousness refers to an individual's awareness and concern about environmental issues, which influences their purchasing behavior toward more sustainable choices. According to Abbasi *et al*. [32], environmental consciousness has a significant effect and is positively correlated with consumers' likelihood of purchasing the product.

3. RESEARCH METHODS

3.1. The methodological framework

The methodology employed in this study consists of three phases (Fig. 4a): (1) attribute development, (2) utility estimation, and (3) market segmentation. In the first phase, a systematic literature review (SLR) was conducted following the PRISMA approach to identify the key determinants influencing consumer acceptance of remanufactured products. Studies were coded from a supply-side and a (or the) demand-side perspective. Next, as this study focuses on purchase decisions regarding remanufactured laptops in particular, we only conducted a literature search for consumer acceptance-based investigations on the demand side. The identified constructs, indicators, and measurement items were then screened and consolidated to remove redundancy and achieve conceptual relevance. This resulted in the extraction of six factors representing considerations toward consumer purchase decision regarding remanufactured laptops, which include function, expectation, perceived safety, perceived consumer effectiveness, environmental consciousness (referred to as green knowledge), and informational social influence. Based on these factors, a MaxDiff questionnaire was designed using BIBD.

The second phase, Utility Estimation, focuses on deriving individual-level preference structures using the MaxDiff approach. This questionnaire included an introduction section that first provided some basic knowledge regarding the definition of remanufactured products and supported additional examples of Indonesian cases to make respondents have the same perception. Respondents were then instructed on the MaxDiff response mechanism, where they repeatedly selected the most important (best) and least important (worst) attribute from a subset of attributes presented in each choice task (Fig. 4b). Before large-scale deployment, the questionnaire was pilot tested with 20 respondents and three experts to evaluate clarity, usability, and content validity. Feedback from the pilot study was incorporated into the final questionnaire design. Data collection was conducted in September 2024 across four universities located in Surabaya, Indonesia, yielding 434 valid responses (4 responses were removed due to expired response time) from undergraduate students. Respondents were recruited using a convenience sampling approach. Although all participating universities were located in the same city, the respondents originated from diverse regions of Indonesia. Therefore, the sample captures variation in geographic backgrounds at the individual level rather than through institutional location.

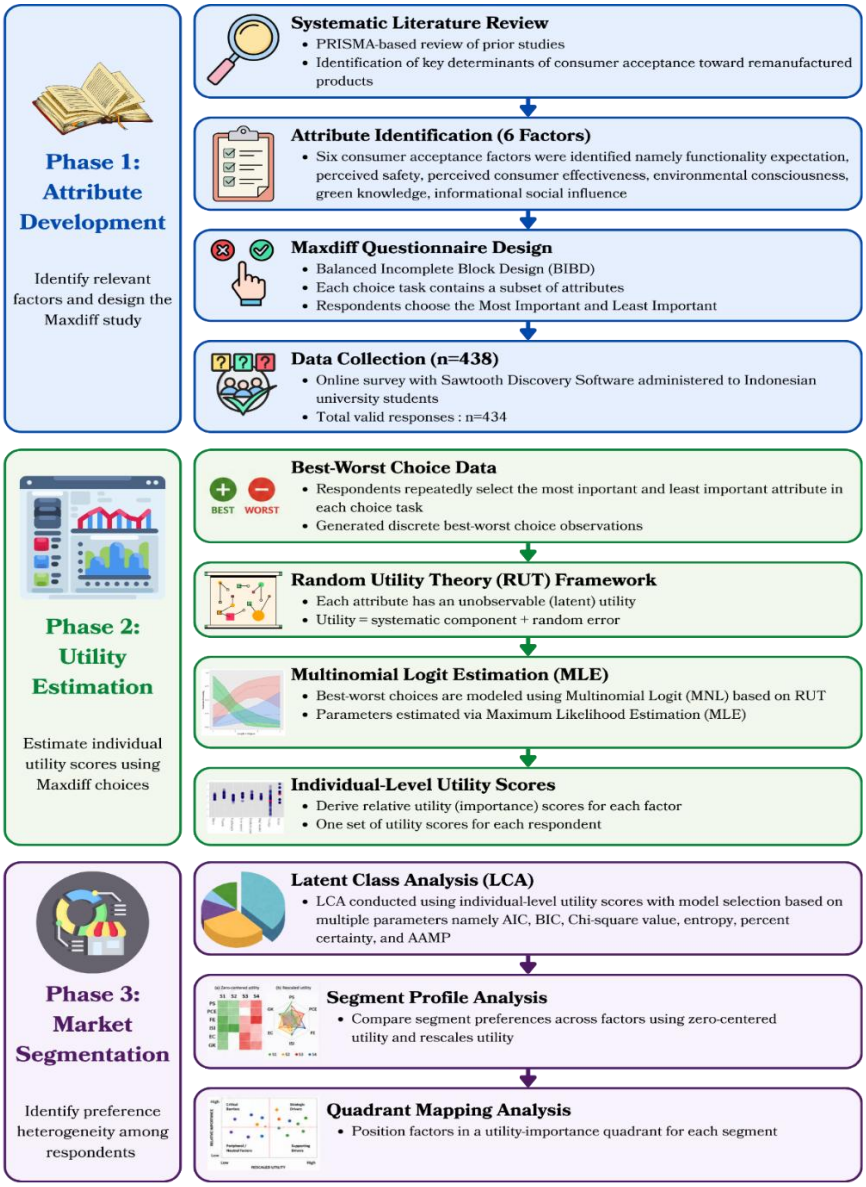
The resulting best–worst choice data were analyzed within the RUT framework. RUT assumes that every alternative attribute's utility consists of a systematic part and an unobservable error term. MLE was subsequently used to estimate the best–worst choices observed by the MNL model. This produced individual-level estimates, resulting in utility scores per respondent. Importantly, the MaxDiff method generates estimates of relative utility and preference importance as opposed to simulated choice market probabilities, market shares, or direct WTP measures. The utility scores obtained here should be viewed as indicators of how important each factor is relative to other factors affecting consumers' purchase decisions for remanufactured laptops.

In the next phase, MSA used LCA with the individual-level utility scores from MaxDiff estimation. The best fitting number of latent classes was identified using a multi-criteria joint examination of AIC, BIC, chi-square statistics, entropy, percent certainty, and AMP. Two supplementary analyses were conducted after assessing the best latent class solution. We first performed Segment Profile Analysis (as zero-centered utility and rescaled utility values) to identify segments using their preferences. Second, a Quadrant Mapping Analysis was performed to assign the six factors in order of relative usefulness and significance into strategic drivers, critical barriers, supporting drivers, and peripheral/neutral factors.

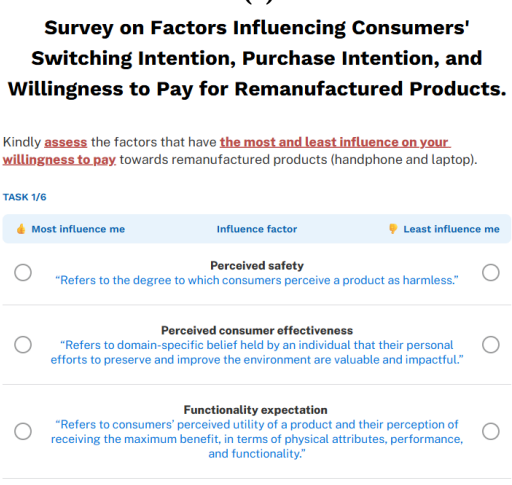
3.2. Statistical estimation procedure

In the MaxDiff experiment, the respondents were repeatedly presented with subsets of product attributes and asked to identify the most and least important attribute in each choice set. These best–worst selections constitute discrete choice observations rather than direct ratings. The MaxDiff experiment defines the data collection procedure, whereas the MNL model constitutes the estimation procedure used to recover latent utility parameters from the observed best–worst choices. Accordingly, the observed choices were analyzed within the RUT framework, in which the probability of selecting a best–worst pair is determined by differences in the attributes' latent utilities. Consequently, the MNL model serves as the estimation framework for recovering latent utility parameters from the observed MaxDiff choices. Although the estimation process relies on multinomial choice probabilities, the resulting outputs are relative utility scores and attribute rankings rather than simulated market choice probabilities or WTP estimates.

The utility parameters were estimated using the



(a)



(b)

Fig. 4. (a) Methodological framework and (b) online questionnaire interface

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random utility theory framework. The utility that respondent *i* derives from alternative *j* in choice task *t* is decomposed into a systematic and a stochastic component.

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} \quad (1)$$

where V_{ijt}denotes the deterministic component of utility and $\varepsilon_{ijt}$is an independently and identically distributed (iid) error term.

Under the RUT framework, respondents are assumed to select the attribute with the highest utility as the "best" and the attribute with the lowest utility as the "worst" within each choice set. Following the sequential exploded logit formulation commonly adopted in MaxDiff analysis, the MNL model was used to estimate the observed best–worst choices as a sequence of multinomial choices.

The systematic utility was specified as a linear additive function of the observed attributes as follows:

$$V_{ijt} = \boldsymbol{\beta}' \boldsymbol{X}_{ijt} \quad (2)$$

where $\mathbf{X}_{ijt}$represents the vector of observed attribute levels and $\boldsymbol{\beta}$denotes the vector of utility coefficients to be estimated. Each coefficient reflects a given factor's relative contribution to overall choice utility.

Following the sequential exploded logit formulation commonly adopted in MaxDiff analysis, the best–worst selections of the respondents were represented as a sequence of multinomial choices. Accordingly, the probability of each observed choice was estimated using the MNL model. Assuming that the error terms follow an Extreme Value Type I distribution, the probability that respondent $i$selects alternative $j$in task $t$is given by the MNL model:

$$P_{ijt} = \frac{\exp(V_{ijt})}{\sum_{m=1}^{J} \exp(V_{imt})} \quad (3)$$

where Jdenotes the number of alternatives within each set of choices.

Thus, the MNL model provides the statistical mechanism through which latent utility parameters are estimated from the observed MaxDiff choices of respondents. Although the estimation procedure relies on choice probabilities, this study's primary outputs are relative utility scores and attribute preference rankings. These estimates represent each attribute's comparative importance and are not intended to predict market shares or estimate consumers' willingness to pay.

The model parameters were estimated via MLE by maximizing the log-likelihood function:

$$\ln \mathcal{L}(\boldsymbol{\beta}) = \sum_{i=1}^{N} \sum_{t=1}^{T} \ln P_{i,y_{it},t} \quad (4)$$

where y_{it}represents the alternative chosen by respondent $i$in task t.

Note that the choice probabilities defined by Equation (6) are used solely as the statistical mechanism for estimating latent utility parameters from the observed MaxDiff choices. In this study, these probabilities are not interpreted as simulated market choice probabilities, market shares, or direct WTP measures. Instead, the estimated utility coefficients are transformed into relative utility scores that reflect each attribute's comparative importance. Consequently, the primary outputs of the MaxDiff analysis are relative importance scores and preference rankings rather than consumer purchase behavior or monetary valuation predictions.

4. RESULTS AND DISCUSSION

4.1. Data quality and quantity assessment results

The sample size was determined using the three methods outlined in Slovins' formula (Equation 5) and Cochran's formula (Equation 6), as well as a software-based recommendation based on the data obtained by Conjointly. The output of Slovin's technique was 400 respondents, whereas the Cochran formula described it as 385 respondents. The Conjointly platform at least 300 respondents for stable estimation in DS experiments. Given the relative results, we applied the most conservative threshold of 400 respondents to guarantee model robustness/statistical power/fit design for this analysis.

$$n = \frac{N}{1+N\,(e)^2} \quad (5)$$

where n= sample size; N= population size; and e= margin of error

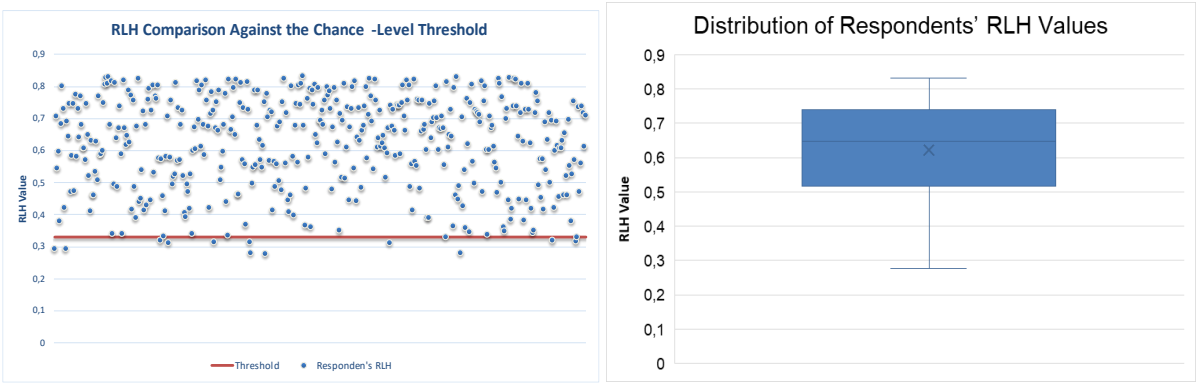
$$n = \frac{N\frac{z^2 p(1-p)}{e^2}}{\frac{z^2 p(1-p)}{e^2} + N - 1} \quad (6)$$

where n = sample size; N = population size; e = margin of error; z = z-score (confidence level); and p = sample proportion

The number of data collected and the goodness-of-fit was assessed. In terms of quantity, the final dataset surpassed the basic sample size of 400 respondents. Respondents were recruited from several cities in Indonesia to ensure that they are geographically dispersed to improve representativeness.

In terms of overall model fit and response quality, the RLH was used for an individual-level goodness-of-fit statistic. RLH, as defined in Equation (7), is the geometric mean of the predicted probabilities of the chosen alternatives across all choice tasks.

$$RLH_i = \left(\prod_{t=1}^{T} P_{i,t}\right)^{\frac{1}{T}} \quad (7)$$



(a) **(b)**

Fig. 5. (a) Distribution of the RLH values of the respondents compared with the chance RLH benchmark, (b) Boxplot distribution of the RLH values of the respondents

This statistic quantifies the extent to which the respondents' choices are predicted by those from the estimated model. This is a good indication of a systematic preference pattern and an acceptable fit for the model, as high RLH values indicate more consistent preferences at that level, whereas low RLH values indicate random or inconsistent answers.

Under the null model assumption (pure random choice), the expected RLH equals $1/J$, where J is the number of alternatives per choice task. Since each task contained 3 alternatives, the null RLH benchmark was therefore $1/3 = 0.333$. Any RLH value above this benchmark indicates that the predictive performance is superior to random response. Fig. 5a shows that the majority of respondents achieved RLH values substantially above the chance benchmark of 0.333, with most values concentrated between approximately 0.5 and 0.7 (Fig. 5b). Only a very small number of respondents were located near or below the threshold line, indicating minimal random or inconsistent response behavior within the dataset.

The distribution pattern also demonstrates that the respondents tended to provide stable and structured preference judgments throughout the MaxDiff tasks. The concentration of RLH values in the upper range that the estimated model effectively captured respondents' underlying preference structures. Therefore, the overall RLH distribution supports the reliability of the collected responses and indicates satisfactory predictive performance of the estimated MaxDiff model.

4.2. Utility-based examination of purchasing decision factors

Model fit and response consistency were evaluated using the RLH, defined as the geometric mean of the predicted probabilities of the chosen alternatives across tasks:

$$RLH_i = \left(\prod_{t=1}^{T} P_{i,t}\right)^{1/T} \quad (8)$$

An RLH value exceeding the null benchmark $1/J$indicates predictive performance superior to random responding. The utility values represent the degree of importance assigned by respondents to each factor influencing their likelihood of purchasing remanufactured laptops (Fig. 4). A higher utility score indicates a stronger influence or greater perceived importance of that factor in consumer decision-making.

The reported utility values represent relative preference importance derived from the MaxDiff evaluation rather than monetary valuation or simulated market demand estimation. Table 2 presents the aggregate utility estimation results obtained from the individual-level MaxDiff preference scores. Functionality expectation emerged as the dominant utility factor with the highest mean utility value (mean = 28.41, standard error (SE) = 0.58, 95% confidence interval [CI] = 27.26–29.53), followed by perceived consumer effectiveness (mean = 24.32, SE = 0.49, 95% CI = 23.33–25.26) and perceived safety (mean = 17.98, SE = 0.58, 95% CI = 16.85–19.14).

Taken together, the findings that consumers evaluate remanufactured laptops mainly based on performance assurance with respect to perceived effectiveness and reliability concerns as opposed to purely environmental or social motivations. Conversely, informational social influence exhibited the lowest utility value (mean = 7.13, standard error (SE) = 0.46, 95% confidence interval [CI] = 6.24–8.03), followed by green knowledge (mean = 10.17, SE = 0.45, 95% CI = 9.30–11.06) and environmental consciousness (mean = 11.99, SE = 0.47, 95% CI = 11.07–12.93), suggesting that environmental awareness and social influence play comparatively weaker roles in shaping consumer purchase decisions toward remanufactured laptops. The high standard deviation values indicate considerable variation in consumer choice at the respondent level, which is not unexpected given that this study sample was composed of individuals whose selections should reflect some heterogeneity among their consumer preferences.

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Table 2. Summary of individual-level utility estimation derived from the maxdiff model

Independent Variable	Mean	Standard Deviation	Standard Error	Lower Confidence Level	The upper Confidence Level
Functionality expectation	28.41	12.09	0.58	27.25	29.54
Perceived consumer effectiveness	24.32	10.27	0.49	23.33	25.26
Perceived safety	17.98	12.18	0.59	16.86	19.13
Environmental consciousness	11.99	9.88	0.47	11.12	12.89
Green knowledge	10.17	9.40	0.45	9.28	11.08
Informational social influence	7.125	9.53	0.46	6.21	8.07

The standard errors are still small (because of the large data sample size), suggesting a stable aggregate utility estimation. This finding adds more evidence to the relevance of LCA for capturing heterogeneous consumer preference patterns across market segments. Additionally, all lower confidence interval values for each factor examined were greater than zero, highlighting positive utility contributions across these explored factors. The relatively large standard deviation values, particularly for perceived safety (SD = 12.18) and functionality expectation (SD = 12.09), also substantial heterogeneity in the respondents' utility structures. This finding supports the relevance of LCA in capturing heterogeneous consumer preference patterns across market segments.

4.3. Latent class-based examination for preference heterogeneity and maturity

The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), percent certainty, chi-square values, entropy, and average maximum membership probability (AMMP) were jointly considered to determine the optimal number of latent classes in the Latent Class Analysis (LCA) [63]. Rather than selecting the model solely based on statistical fit, the final decision also considered model parsimony, interpretability, and managerial usefulness. Although models with five and six classes produced slightly lower AIC and BIC values, the incremental improvement in model fit became progressively smaller as model complexity increased. Therefore, the four-class solution represented the best balance among statistical fit, classification quality, model parsimony, and the practical interpretability of the resulting market segments. Moreover, the four segments remained relatively balanced in size, consisting of Segment 1 (23.5%), Segment 2 (26.2%), Segment 3 (23.2%), and Segment 4 (27.1%), thereby providing meaningful and managerially useful customer groups for subsequent analysis.

For the four-class model with 434 respondents, entropy was calculated using all respondents' posterior membership probabilities. The entropy formula is expressed as follows:

$$Entropy = 1 - \frac{-\sum_{i=1}^{N}\sum_{k=1}^{K} p_{i,k} ln\,(p_{i,k})}{N ln\,(K)} \quad (9)$$

where N= total number of respondents ($N = 434$); K= number of latent classes ($K = 4$); and $p_{i,k}$= posterior probability that respondent $i$belongs to class k

For example, respondent ID 66ac54557a5b6c9c4e8bf2c9, who became the 1st respondent ($i = 1$) in the four-class solution, had the following posterior membership probabilities.

$$p_{1,1} = 0.9818, p_{1,2} = 0.0164, \underset{p_{1,3} = 0.0018, p_{1,4} = 0.0001}{}$$

The entropy contribution for respondent $i = 1$ was calculated as follows:

$$\sum_{k=1}^{4} p_{ik}\, ln\,(p_{ik}) \quad (10)$$

Thus:

$$\begin{aligned}&(0.9818 \times \ln(0.9818)) + (0.0164 \times \ln(0.0164)) \\ &\quad + (0.0018 \times \ln(0.0018)) \\ &\quad + (0.0001 \times \ln(0.0001)) \\ &= -0.0180 - 0.0673 - 0.0114 - 0.0009 \\ &= -0.0974\end{aligned}$$

This value represents the entropy contribution of a single respondent. Subsequently, the same calculation was repeated for all $N = 434$ respondents.

$$\sum_{i=1}^{434}\sum_{k=1}^{4} p_{ik} \ln\,(p_{ik}) \quad (11)$$

Then, the overall entropy for the four-class model was computed using the following:

$$Entropy = 1 - \frac{-\sum_{i=1}^{434}\sum_{k=1}^{4} p_{ik} \ln\,(p_{ik})}{434 \times \ln\,(4)} \quad (12)$$

Fig. 6 shows a summary of fit statistics, classification quality, and model complexity across competing latent class solutions. The four-class model marks the level of a statistical fit that will provide diminishing improvement and sustain high

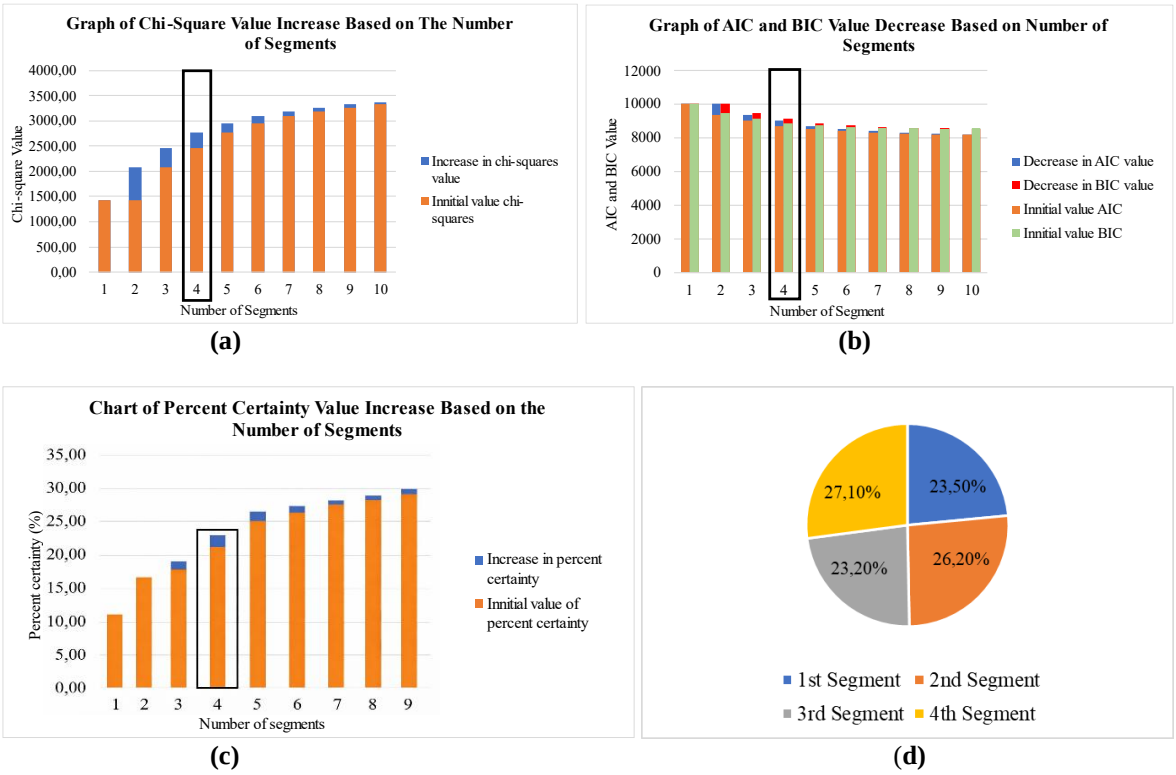


Fig. 6. Comparison of (a) chi-square test, (b) AIC and BIC, (c) percent certainty values in each class, and (d) segment size

classification accuracy along with manageable interpretability for managerial purposes. The results indicate that increasing the number of classes continuously improved the model fit, as reflected by decreasing the AIC and BIC values. The AIC value decreased from 9011.44 in the three-class model to 8710.47 in the four-class model, 8541.80 in the five-class model, and 8418.96 in the six-class model. Similarly, the BIC value declined from 9122.92 to 8861.30, 8731.98, and 8648.49. These results indicate that additional classes improved the model's statistical fit.

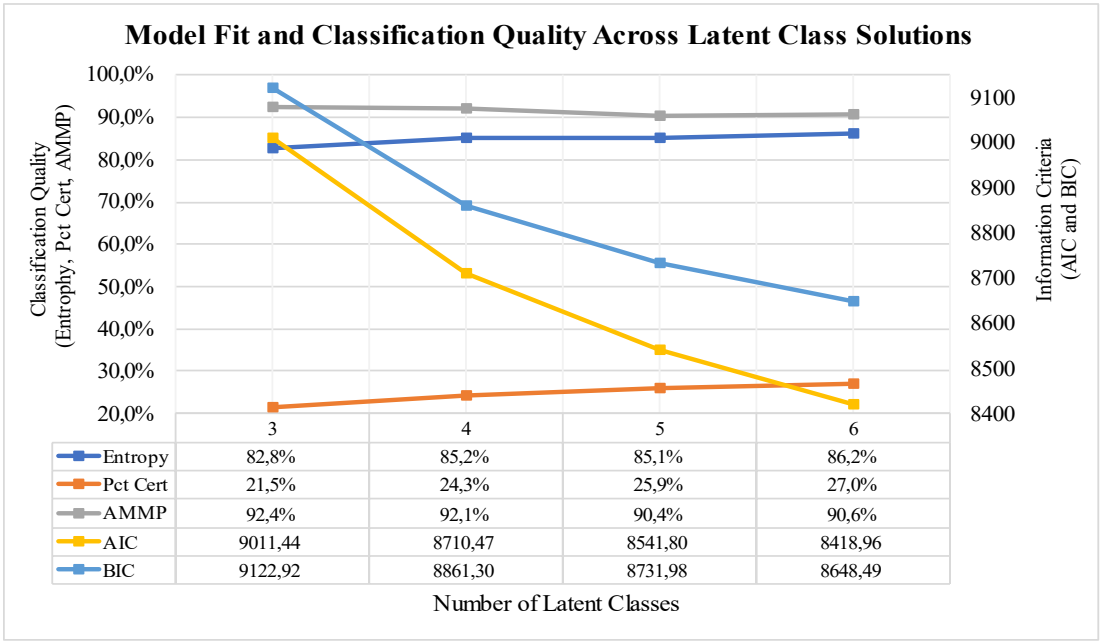


Fig. 7. Trade-off analysis for optimal latent class solution selection

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In parallel, the classification quality also improved as the number of classes increased (Fig. 7). The entropy value increased from 82.8% in the three-class model to 85.2% in the four-class model. The four-class model achieved an entropy value of 0.852, indicating good classification quality. In LCA, entropy values above 0.80 are generally considered to reflect high classification accuracy and clear separation among latent classes, whereas values closer to 1 indicate greater certainty in class assignment [64], [65]. Therefore, the obtained entropy value that the respondents were assigned to the four latent classes with a high degree of certainty. Likewise, the percentage certainty increased progressively from 21.5% to 24.3%, 25.9%, and 27.0%, respectively. These findings indicate stronger segment differentiation and robust classification with additional classes.

However, the magnitude of improvement became progressively smaller beyond the four-class solution. Although the five- and six-class models generated slightly lower AIC and BIC values and marginally higher entropy values, the additional gains were relatively limited compared with the increase in segmentation complexity. Furthermore, the average maximum membership probability (AMMP) slightly decreased after the four-class model, declining from 92.4% in the three-class model to 92.1% in the four-class model, 90.4% in the five-class model, and 90.6% in the six-class model. Although the AMMP slightly decreased from 92.4% in the three-class solution to 92.1% in the four-class solution, the reduction was minimal (0.3 percentage points) and remained well above the commonly recommended threshold of 0.70–0.80 for acceptable classification quality [66]. This slight decrease reflects the expected trade-off between improving model fit and maintaining classification certainty when an additional latent class is introduced. Considering the simultaneous improvement in entropy, AIC, BIC, chi-square statistics, and percent certainty, the minor reduction in AMMP does not undermine the four-class solution's robustness.

Therefore, the four-class model was selected as the most appropriate latent class solution because it provided the best balance between model fit, classification quality, segment interpretability, and model parsimony. Additionally, the four-class solution produced meaningful and clearly differentiated behavioral profiles while maintaining relatively balanced segment sizes.

LCA generated four segments and different utility values for each consumer category. Table 3 presents the total zero averages derived from the LCA for different market segments. All these utility values can be interpreted as the average preference structure of respondents in each segment and present a first descriptive analysis about the characteristics of consumers' evaluation of the attributes examined above. Nevertheless, the utilities are summary measures computed at the individual segment level and thus cannot indicate whether the observed differences between segments differ significantly at the respondent level. Accordingly, a subset of the analysis was completed to characterize and visualize differences in utilities across latent classes reflected in the segmentation model.

To statistically verify these differences, one-way ANOVA was conducted using individual-level raw utility scores rather than aggregated segment utilities. The preliminary assessment indicated that the assumption of homogeneity of variances was violated. Therefore, Welch's ANOVA was employed as a more robust alternative to conventional ANOVA. Welch's analysis of variance (ANOVA) is particularly appropriate for latent class segmentation studies because it remains reliable under unequal variances and unequal sample sizes across groups [67], [68]. Welch ANOVA was performed as a descriptive follow-up analysis to characterize differences in utility scores among the latent classes identified by the LCA model. Because the latent classes and utility scores originate from the same analytical framework, the ANOVA results are intended to illustrate and summarize segment differences rather than serve as an independent inferential validation of the segmentation solution.

The Welch ANOVA results in Table 4 demonstrated statistically significant differences across the four segments for all examined variables ($p < 0.001$). Specifically, perceived safety produced an F-value of 2766.38 ($df = 3, 226.545$; $p < 0.001$) with an adjusted R^2 of 95.76%. Perceived consumer effectiveness yielded an F-value of 3310.79 ($df = 3, 220.176$; $p < 0.001$) and an adjusted R^2 of 95.90%. Functionality expectation showed an F-value of 2225.51 ($df = 3, 227.564$; $p < 0.001$) with an adjusted R^2 of 95.19%. Informational social influence generated

Table 3. The aggregate utility value for every segment

Independent Variable	1st Segment	2nd Segment	3rd Segment	4th Segment
Perceived safety	10.57	17.02	-47.42	26.34
Perceived consumer effectiveness	16.51	32.94	16.98	18.50
Functionality expectation	-32.01	40.73	52.58	43.58
Informational social influence	-55.33	9.12	-31.65	-56.42
Environmental consciousness	44.67	-40.54	2.24	-13.43
Green knowledge	15.6	-59.27	7.26	-18.56

Table 4. Summary of the welch ANOVA results across consumer segments

Independent Variable	Welch's F	Df (Between and Within)	p-value	Adjusted R^2	The Highest Mean Segment
Perceived safety	2766.38	(3, 226.545)	< 0.001	95.76%	Segment 4 (1.3846)
Perceived consumer effectiveness	3310.79	(3, 220.176)	< 0.001	95.90%	Segment 2 (1.0834)
Functionality expectation	2225.51	(3, 227.564)	< 0.001	95.19%	Segment 4 (2.3620)
Informational social influence	1740.46	(3, 231.060)	< 0.001	95.08%	Segment 2 (0.1447)
Environmental consciousness	2486.54	(3, 219.597)	< 0.001	95.32%	Segment 1 (0.7154)
Green knowledge	2612.33	(3, 223.258)	< 0.001	95.26%	Segment 1 (0.2141)

an F-value of 1740.46 (df = 3, 231.060; $p < 0.001$) and an adjusted R^2 of 95.08%. Environmental consciousness produced an F-value of 2486.54 (df = 3, 219.597; $p < 0.001$) with an adjusted R^2 of 95.32%, whereas green knowledge yielded an F-value of 2612.33 (df = 3, 223.258; $p < 0.001$) and an adjusted R^2 of 95.26%.

After detecting significant Welch ANOVA results, Games–Howell post hoc comparisons were used to determine which segments differed. This procedure was chosen because it does not assume equal variances and is therefore compatible with the Welch ANOVA methodology. While the post hoc test confirmed that all pairwise segment comparisons were significantly different, it also demonstrated that these segments represent fundamentally different preference structures.

These utility score differences are statistically significant ($p < 0.01$) and provide further descriptive support of the preference divergence illustrated by the derived latent classes while also enabling the interpretation of the resulting segment profiles (Fig. 8). Segment 4 exhibited the highest mean utility values for perceived safety (mean = 1.3846) and functionality expectation (mean = 2.3620), suggesting that product reliability, safety assurance, and functional performance are prioritized by consumers in this segment. Segment 1 showed the highest mean values for environmental consciousness (mean = 0.7154) and green knowledge (mean = 0.2141), indicating a more environmentally oriented and sustainability-aware consumer profile. Segment 2 demonstrated the strongest PCE (mean = 1.0834), reflecting a stronger belief that individual purchasing decisions can positively contribute to environmental outcomes. In contrast, Segment 3 displayed relatively high functionality expectation (mean = 1.7441) while simultaneously exhibiting negative utility toward informational social influence (mean = -1.1152), suggesting that external social information more independently drives and less influences purchasing decisions in this segment.

The zero-centered utility values (Fig. 8a) extracted from the latent class estimate were used for the profile analysis. For example, zero-centered utility scaling normalizes the estimated utilities to a mean of zero, resulting in positive and negative utility scores. Positive utility values indicate a relatively split preference direction toward the relevant attribute (i.e., toward self-oriented), and negative values indicate a relative negative preference orientation within the overall preference structure. This form of visualization helps to capture the directional nature of consumer preference increases and identify preference drivers vs. relative barriers.

Nevertheless, notwithstanding their theoretical soundness, zero-centered utility scaling encounters several challenges as a tool for visual profiling and inter-segment comparison. Since the utility values are centered at zero, meaning that they neither add nor subtract from their components when using this scale for analysis, comparing preference intensity across segments may be more challenging. Negative values may visually inflate the difference between attributes, even though utility estimates are absolute (not relative) measures of preference strength. As a result, this can make the interpretation of segment profiles using raw zero-centered utilities less intuitive particularly for managerial and strategic conversations.

To overcome this issue, the utility values were later converted into rescaled utility scores using min–max normalization. We scale the original utility estimates from each segmentation part into a standardized 0–100 scale, preserving their relative preference structure across attributes and segments. The equation used for the transformation was as follows:

$$U_i' = \frac{U_i - U_{\min}}{U_{\max} - U_{\min}} \times 100 \quad (13)$$

where U_i' represents the rescaled utility score; U_i denotes the original zero-centered utility value; $U_{\min}$ refers to the minimum utility value observed across all attributes and segments; and $U_{\max}$ indicates the maximum utility value observed across all attributes and segments.

Preference patterns across latent segments were visualized using the rescaled utility scores. A min–max normalization procedure was used to transform the

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modeled utility values on to a common 0–100 scale without loss of their relative ordering. The radar chart shown in Fig. 8b represents one example of the application of this approach. The rescaled values cannot be interpreted to represent differences in utility estimates exactly as they are from the original estimates. The distance between attributes may be exaggerated by extreme utility values because the transformation is based on the global minimum and maximum of all utility values across all attributes and segments. Consequently, the radar chart is a descriptive visual representation of relative preferences and segment profiles, but it is not intended as a defense for interpreting specific differences in baseline preference intensities.

All utility values were converted into positive preference intensity scores ranging from 0 to 100 through this transformation. Rescaled scores closer to one indicate more intense preference orientations toward a given attribute, whereas those closer to zero indicate comparatively lower levels of preferences toward that same attribute. Most importantly, the rescaling procedure preserves the ordering of preferences and improves interpretability and inter-segment comparability.

The corresponding rescaled utility values were visualized with a radar chart (Fig. 8b) showing the consumer segment preferences structures. The radar visualization allows us to see clearly which motivate-onal patterns are moving each segment. More pronoun-ced outward expansions signify greater identity-based preference intensity for particular attributes, whereas inward contractions signify a lesser identity-based preference orientation. In comparison to the zero-centered chart, the radar chart provides a clearer visualization of segment heterogeneity and helps inter-pret the behavioral logic that governs each consumer group.

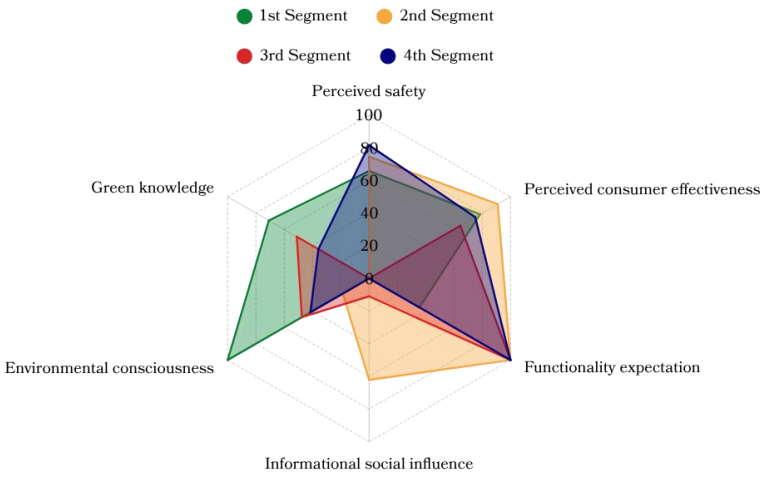
4.4. Utility intensity and relative importance

Two complementary measures were employed for the quadrant mapping analysis (Figure 9): utility intensity and relative importance. The utility intensity is defined as the value of the estimated utility score for each attribute in terms of its min–max rescaled value within a common 0–100 scale. It indicates consumer preference strength for an attribute within a segment.

Meanwhile, relative importance indicates how much each attribute contributes to the whole preference landscape by segment. This was computed by taking

Independent Variable	1st Segment	2nd Segment	3rd Segment	4th Segment
Perceived safety	0,13	0,55	-1,47	1,38
Perceived consumer effectiveness	0,35	1,08	0,61	1,03
Functionality expectation	-0,39	1,38	1,74	2,36
Informational social influence	-1,01	0,14	-1,12	-2,97
Environmental consciousness	0,72	-1,27	0,06	-0,75
Green knowledge	0,21	-1,88	0,17	-1,06

(a)



(b)

Fig. 8. Consumer segment profile based on (a) zero-centered utility and (b) rescaled utility

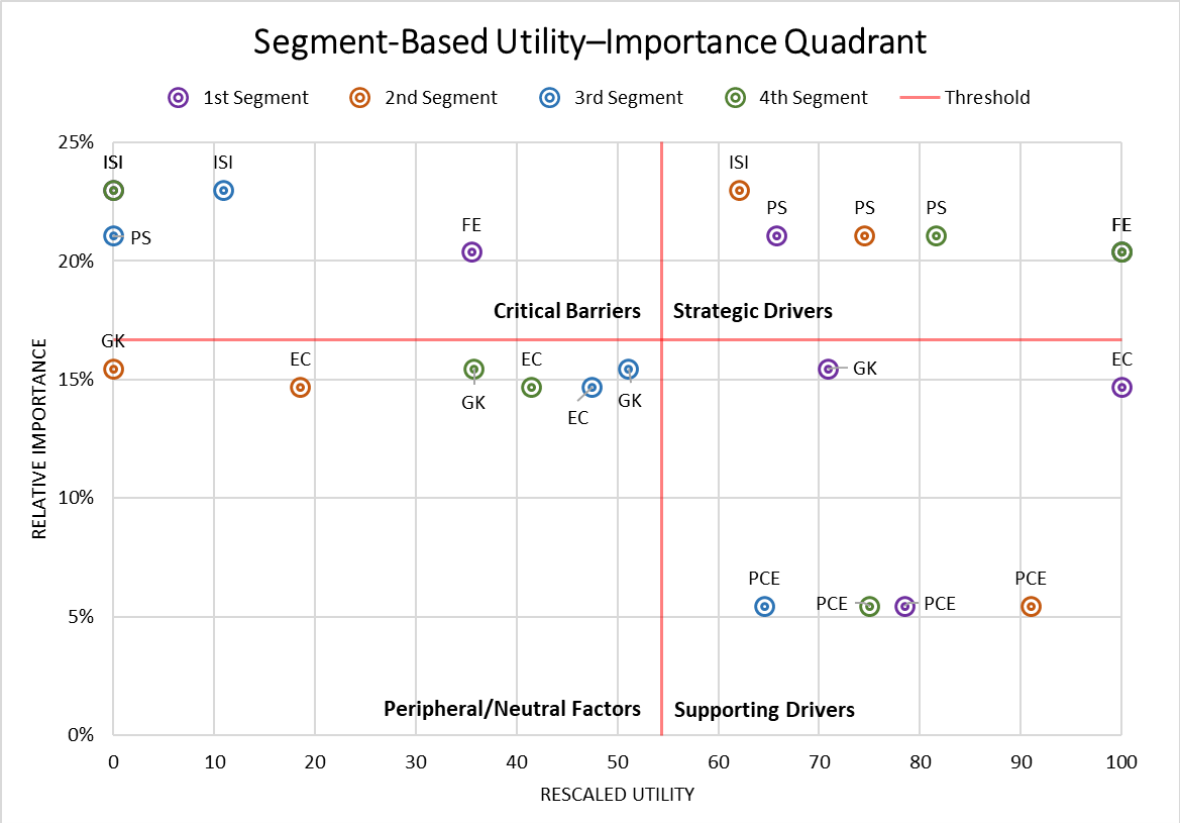


Fig. 9. Quadrant mapping of rescaled utility (utility intensity, x-axis) and relative importance (percentage contribution to the overall preference structure, y-axis) by consumer segment

the utility value of each attribute, dividing it by the sum of the utility values for all attributes evaluated in that segment, and expressing that number as a percentage.

$$RI_i = \frac{U_i'}{\sum_{j=1}^{m} U_j'} \times 100 \quad (14)$$

where RI_i= relative importance of attribute i; U_i'= rescaled utility score of attributes i; and m= total number of evaluated attributes.

Thus, utility intensity is the strength of preference, and relative importance represents the contribution of each attribute to explaining the total decision structure. In general, although both dates are based on the estimated utility values, they provide information beyond what the other measure tells us and should not be equated with each other.

4.4.1. *Segment 1: Environmentally committed consumers*

Based on Fig. 9, Segment 1 provides a preference structure oriented toward sustainability with PS lying in the strategic-driver quadrant. The table shows that both utility intensity and relative importance are high for PS, indicating that safety assurance operates as a key important factor in regulating consumer acceptance. Consumers in Segment 1 are highly eco-oriented; nevertheless, they need to be sure of product reliability and risk reduction before any positive purchase intentions concerning remanufactured products.

In the supporting-driver quadrant, we have GK, EC, and PCE. As shown in the quadrant, EC and GK fit this category as they are next to positive anchors (ES) that increase consumer preference but are below the first strategic threshold. Likewise, consumers are convinced that their purchasing decisions can materially impact environmental betterment which serves as a kind of motivational add-on rather than the primary decision driver appears to be what PCE says. In aggregate, these enabling drivers lend evidence that sustainability values are on-brand for this segment's behavioral direction.

Functionality expectation (FE) and informational social influence (ISI) are placed in the critical-barrier quadrant. This implies that while these traits are of relatively high importance, they display comparatively low utility intensity. Notably, ISI shows that external-related behaviors, such as persuasion, peer pressure, and social appraisal, do not work in persuading this group. Similarly, FE indicates that functional performance-related values take second place within their intrinsic value orientation. This indicates that no attributes lie in the peripheral or neutral-factor quadrant, and all evaluated variables are perceived as meaningful influences on consumer decision-making in this segment.

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4.4.2. *Segment 2: Rational and socially reinforced consumers*

Based on Fig. 9, Segment 2 shows a preference structure around the balance of all three categories among all identified segments. The strategic-driver quadrant consists of the 3 factors Perceived Safety (PS), Informational Social Influence (ISI), and Expectation of Functionality (FE). The finding of FE as a key factor positioned in this quadrant aligns with product functionality and technical performance being recorded as major drivers of the intention to purchase. However, PS notes that consumers in this segment require reliability and safety assurance.

Interestingly, ISI is also a strategic driver in Segment 2, indicating that social information, peer recommendations, and external validation play an important role in consumer acceptance of remanufactured products. Unlike other segments, social influence functions as a barrier instead of a driver, which clearly distinguishes segment 2 from the rest.

In the supporting-driver quadrant, PCE is one of the 3 attributes which generate relatively lower utility compared to importance yet high impact on behavior. This implies that shoppers in Segment 2 think morally that their purchases can generate good for the atmosphere, but this belief functions more as an additional motivator than a decision-making factor.

At the same time, EC and GK are located in the neutral-factor quadrant. Their placement that awareness of sustainability and environmental literacy has little to no impact on preference formation in this segment. As such, consumers in Segment 2 are less likely to measure remanufactured products in terms of intrinsic environmental values and more so through pragmatic, socially normative, or functional assessments. The critical-barrier quadrant contains no attributes, indicating low resistance to the evaluated attributes.

4.4.3. *Segment 3: Independent performance-oriented consumers*

Based on Fig. 9, Segment 3 shows an almost exclusively performance-based preference hierarchy. FE is the only attribute in the strategic-driver quadrant, implying that technical performance and functional capability are the main drivers of consumer preference in this segment. Consumers do not trust remanufactured products without an unbiased evaluation of product quality and performance.

In the supporting-driver quadrant, PCE appears as a strong upholder but tends to be less significant; it uses more utility intensity than importance. This indicates that beliefs about improving the environmental contributions of individuals positively influence purchase intention but are always less relevant than functional motivations.

This critical-barrier quadrant contains informational social influence (ISI) and perceived safety (PS). The ISI type indicates that consumers in this segment are moderately impervious to social influence, peer pressure, and external consumption pressures. The placement of PS within the barrier region implies that safety concerns may also prevent more favorable acceptance toward remanufactured products, even with a high importance given to safety evaluations.

Finally, EC and GK exhibit a neutral-factor quadrant position, implying that within this segment, sustainability-related values and environmental literacy have only minor influences on purchasing behavior. Thus, Segment 3 represents autonomous and performance-oriented consumers who would not purchase remanufactured products for environmental or social reasons but rather purely according to functional performance.

4.4.4. *Segment 4: Consumers driven by safety and performance*

Based on Fig. 9, segment 4 has the most utilitarian itch of all four identified segments. The strategic-driver quadrant consists of PS and FE, whereby safety assurance and FE are the devout influencers on purchase intention for this segment. PS and FE being positioned at the same time in the strategic-driver region that consumers (in Segment 4) evaluate remanufactured goods objectified mainly by reliability, durability, and risk reduction.

In the supporting-driver quadrant, PCE has information utility intensity that is moderately high relative to other dimensions notwithstanding being relatively less important. This suggests that although consumers are aware of the environmental repercussions that might arise from their buying habits, such considerations act only as secondary reinforcements to safety and performance assessments.

At the top, right-hand extreme: ISI. If ISI is in this corner quadrant because social influence and peer-driven communications strategies have no impact on this population, consumers in Segment 4 seem to rely mostly on independent, rational product evaluation rather than social approval or others' consumption patterns. EC and GK were located in the neutral-factor group quadrant, indicating that eco-oriented motives and eco-knowledge are not driving factors for forming preferences. Overall, segment 4 represents rational and risk-sensitive consumers whose acceptance of remanufactured products is based mostly on safety assurance and functional reliability rather than environmental or social considerations.

4.5. Scenario-based analysis of preference stability

The stability of the identified preference structure was tested under scenario-based perturbation,

Table 5. Sensitivity analysis for utility value

Independent Variable	Baseline Score	Scenario			
		110%	115%	90%	85%
Functionality expectation	28.41	31.25	32.67	25.57	24.15
Perceived consumer effectiveness	24.32	26.75	27.97	21.89	20.67
Perceived safety	17.98	19.78	20.68	16.18	15.28
Environmental consciousness	11.99	13.19	13.79	10.79	10.19
Green knowledge	10.17	11.19	11.70	9.15	8.64
Informational social influence	7.13	7.84	8.20	6.42	6.06

simulating proportional variations across all utility values (Table 5). This means that the attributes' relative ordering is robust to proportional utility movements (10% and 15%). In all simulated scenarios, the most powerful predictor was expected functionality, followed by perceived consumer effectiveness and perceived safety (Fig. 10). While higher baseline utility values result in larger absolute changes for attributes, the relationship between attribute values is proportional and does not lead to rank reversal. This finding indicates that the global ranking described in this study is maintained across the examined perturbation scenarios.

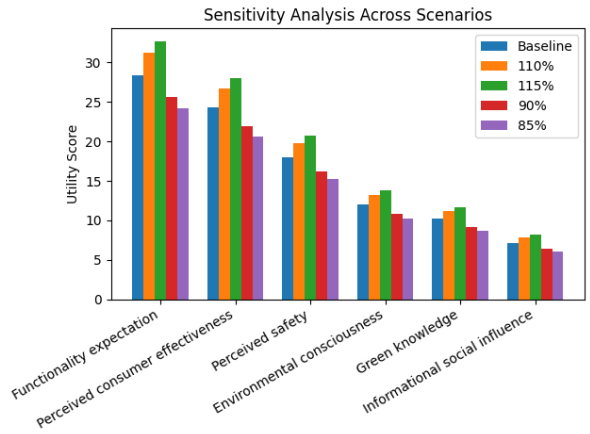


Fig. 10. Sensitivity analysis results

Additionally, the attributes linked to environmental factors environmental consciousness, green knowledge, and informational social influence still exert moderate effects under all relevant simulations. This rank pattern remains persistent because it is not significantly altered by a reasonable proportional change in the utility values of the attribute levels. Consequently, while the results should not be seen as a formal test of parameter robustness, model validity, or external generalizability, they do support the interpretation that ranking is stable across different utility conditions.

4.6. Managerial implications

This study generates several critical managerial implications for firms in the remanufactured electronics information market. Second, functionality expectation dominance shows that consumers mainly assess remanufactured laptops based on performance reliability [43]; therefore, firmsClick or tap here to enter text. should staff sufficient technical quality assurance (e.g., standard refurbishment process, performance benchmark, and long-term warranty) [38], which is most effective in enhancing perceived value. Second, because perceived safety is so important, particularly in terms of reducing the perception of risk, certification schemes, information provisions, and third-party quality verification could play a key role in ensuring product quality. Third, the moderate strength of PCE that sustainability messaging has not yet lost its relevance but needs to be worded in such a way as to relate individual consumption choices with concrete environmental effects. Nonetheless, the consistently low importance scores for environmental consciousness, green knowledge, and informational social influence suggest that strategies based solely on environmental or social appeal are not likely to have a significant impact on consumers purchasing the product. Instead, they should pursue a hybrid positioning solution that combines ranking in functional benefits with robust sustainability advantages.

The results of this study apply only to the undergraduate student group because they may not represent different consumer groups in Indonesia, such as working professionals, households, business users, and older consumers who have different purchasing power product preferences and sustainability perceptions toward remanufactured laptops. Moreover, this study implemented a choice-based Cardiff experiment as its stated preference design. However, while this way of summarizing what consumers would return in trade-offs is constructive for understanding the priorities among the product attributes commonly used to influence purchasing choices, hypothetical choices may not match decisions taken under real purchasing situations. Consequently, the study recorded purchase decision predilections rather than purchase behavior, indicating that the results reflect professed valuations rather than verifiably consummated marketplace purchases. Moreover, the study was conducted within the Indonesian context, where awareness and adoption of remanufactured

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electronic products are still in the introductory phase. As a result, the results could not be fully generalizable to other countries with differing rates of market maturity, environmental awareness, and consumer characteristics. Future research should use a broader consumer population, revealed preference or actual purchasing data, and cross-country comparisons for analysis to make the findings more generalizable and externally valid.

4.7. Theoretical implications

The implications of these findings for consumer behavior and sustainable consumption literature are provided next. The results first provide strong empirical support for the explanatory power of RUT [31] in parsing purchase decisions as trade-off–based in nature, showing preference responses reflect choices between competing alternatives due to relative attribute utility, rather than explanations based on isolated attitudinal constructs. Functional expectation and perceived safety dominance reinstate the importance of classical utility maximization and perceived risk perspectives, where consumers focused on instrumental/required/regressive attributes while evaluating remanufactured products. Second, the generally low impact of environmental attitude and green knowledge raises questions about the predictive validity of attitudinal models documenting intention systems [23], [25], [26], [28], [33], in economic evaluation that seemed to suggest a conclusiveness of intention systems for explaining actual decision behavior. This result agrees with the increasing body of literature on the attitude–behavior gap, showing that pro-environmental attitudes do not necessarily translate into purchasing behavior. Third, the stability of attribute importance across sensitivity scenarios further bolsters the theoretical support for an additive utility structure by demonstrating that consistent and generalizable patterns in consumer preferences are produced by moderate parameter variation within a plausible range. These findings add to the theoretical understanding of consumer decision-making in remanufactured product situations by highlighting the dominance of functional and risk-related attributes over normative and environmental aspects.

In addition, the MaxDiff design used in this study estimates relative preference importance for factors affecting purchase decisions rather than direct economic WTP estimates or market choice probabilities.

5. CONCLUSION

This study adds to the literature on remanufactured product acceptance by investigating consumer purchase decisions regarding remanufactured laptops using a utility-based and trade-off-oriented lens. In contrast to conventional intention-based approaches that build on prediction models, this study conceptualizes consumer decision-making as an evaluation process that simultaneously considers psychological, informational, and evaluative factors for our dependent variable under perceived uncertainty and value trade-offs. The results indicate that when evaluating remanufactured laptops, consumers care more about functional expectation, perceived consumer effectiveness, and perceived safety than environmental or social aspects.

Theoretically, the study contributes to elucidating the extent to which random utility theory and choice-based approaches can be applied to consumer valuation and purchase decisions for remanufactured products in the context of emerging markets, where uncertainty about durability and trust is particularly pronounced. This indicates that consumer acceptance of remanufactured electronics is heterogeneous across market segments, which has also been amplified by integrating both Cardiff and latent class analysis. The practical implication of these findings is that firms and policymakers should prioritize approaches to reinforce consumer trust via performance assurance, transparency in communicating quality, certification mechanisms, and reliable warranty systems rather than focusing predominantly on environmental messaging. Therefore, the results of this research need to be considered within the context of the consumer group: undergraduate students, which illustrates a pertinent yet small market for remanufactured laptops. Hence, the managerial implications do not primarily pertain to the general consumer base but rather to young, secure, and tech-savvy consumers in developing markets. Future studies should recruit consumers from other demographic groups to address the external validity of these conclusions for the overall market.

Nevertheless, several limitations should be highlighted. Most studies targeted only undergraduate student consumers and used a stated preference design, which may not reflect real purchase behavior or other potential Indonesian consumer groups. Furthermore, the specific context of Indonesia may affect the results' validity in countries with different market maturity and consumer profiles. Future studies should consider multiple demographic segments, substantive revealed preference or actual transaction data, and cross-country comparison to enhance external validity and insight into how consumers make choices around purchasing remanufactured goods

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