A Decision-making Model for Managing Returns in a Circular Economy: A Case of Indian Electronics Industry

Abstract

The notion of a circular economy (CE) has recently gained significant attention, both in research and practice, due to increasing sustainability concerns and legislative requirements. Despite extensive research having been undertaken in this area, there is a paucity of research in developing decision-making models, which may consider life-cycle span of product returns while selecting an appropriate reprocessing option for value reclamation in CE. In this research, we have contributed to the CE literature in three ways. Firstly, we have developed a comprehensive decision-making model that makes a trade-off between different recovery alternatives while considering a wide range of significant criteria to determine the most optimal recovery option. Secondly, we propose a two-phase mathematical model combining the Interval 2-Tuple Linguistic (ITL) model and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to overcome issues related to uncertainty and incomplete information in decision-making. Thirdly, it is one of the first studies to investigate and compare the implementation of product recovery in CE for short life cycle (SLC) vs. long life cycle (LLC) electronic returns. We validate the industrial applicability of the proposed model using real-world data collected from the Indian electronics industry. Our results provide managerial insights, including a focus on repair strategy for SLC returns and on remanufacturing strategy for LLC returns for efficient and effective product recovery in CE.

Keywords: Product recovery, Decision-making, Circular Economy, Electronic Returns, Interval 2-Tuple Linguistic

1. Introduction

The concept of a circular economy (CE) has gained significance both in academia and practice due to its enormous sustainability-related benefits. The growing trend of CE is mainly attributed to an ever-increasing sensitivity towards product recovery due to factors such as extended producer responsibility (EPR), environmental sustainability requirements, brand image, economic benefits, and increasing rate of returns (Savaskan et al., 2004; Jaber and Saadany, 2009; Korhonen et al., 2018; Ullah and Sarkar, 2020). Keong (2008) suggested that returning mobile devices could save about 240,000 tons of virgin resources, which is equivalent to eliminating greenhouse gas emissions from four million road vehicles. Furthermore, the Ellen MacArthur Foundation reported that CE implementation could save net material cost savings of USD 340 to USD 630 billion per year across the European Union (Ellen MacArthur Foundation, 2013). Environmental regulations regarding a CE are also becoming stringent in many countries to protect resources, to save landfill space, to limit the risks triggered by hazardous wastes, and to reduce the amount of incineration and associated airborne contaminants (Bufardi et al., 2004; Cho et al., 2017; Singh and Agrawal, 2018). As shown in Figure 1, the successful implementation of a CE contributes to all three dimensions of sustainable development (Geissdoerfer et al., 2017). Therefore, developing successful recovery operations is of paramount importance and has become an organisational priority due to underlying benefits related to sustainability (economic, environmental, and societal perspectives).

One of the most challenging aspects in the implementation of a CE is managing product returns from customers and recovering residual value by reprocessing (i.e., through resale, repair, refurbish, remanufacture, cannibalisation, recycle, or disposal) of the entire product, or some of its modules, components, and parts (Guide and Van Wassenhove, 2009; De Sousa Jabbour et al., 2019). Several researchers (Rogers and Tibben-Lembke, 1999; Guide et al., 2006; Farhani et al., 2019) have acknowledged that selecting an appropriate product recovery option is one of the most critical issues in CE regarding value reclamation from product returns. The optimal selection of product recovery operation enables the given organisation to maximise their profits (Ferguson et al., 2011). Rogers and Tibben-Lembke (1999) suggested that a CE's efficiency and effectiveness could be enhanced by focusing on selecting suitable recovery options for returns as early as possible. Many studies have attempted to investigate product reprocessing strategies (Yang et al., 2019; Singh and Agarwal, 2018; Cho et al., 2017). However, most recovery decision-making models available in the literature have failed to consider the multiple attributes relevant when evaluating reprocessing options and are mainly based on cost-benefit analysis. Moreover, the existing studies have neglected to investigate the time-sensitivity of products when it comes to recovery strategy. Therefore, there is a need for a comprehensive multi-attribute decision-making (MADM) model to identify the appropriate recovery operation by making a trade-off between multiple attributes and options and with time-sensitivity considerations.

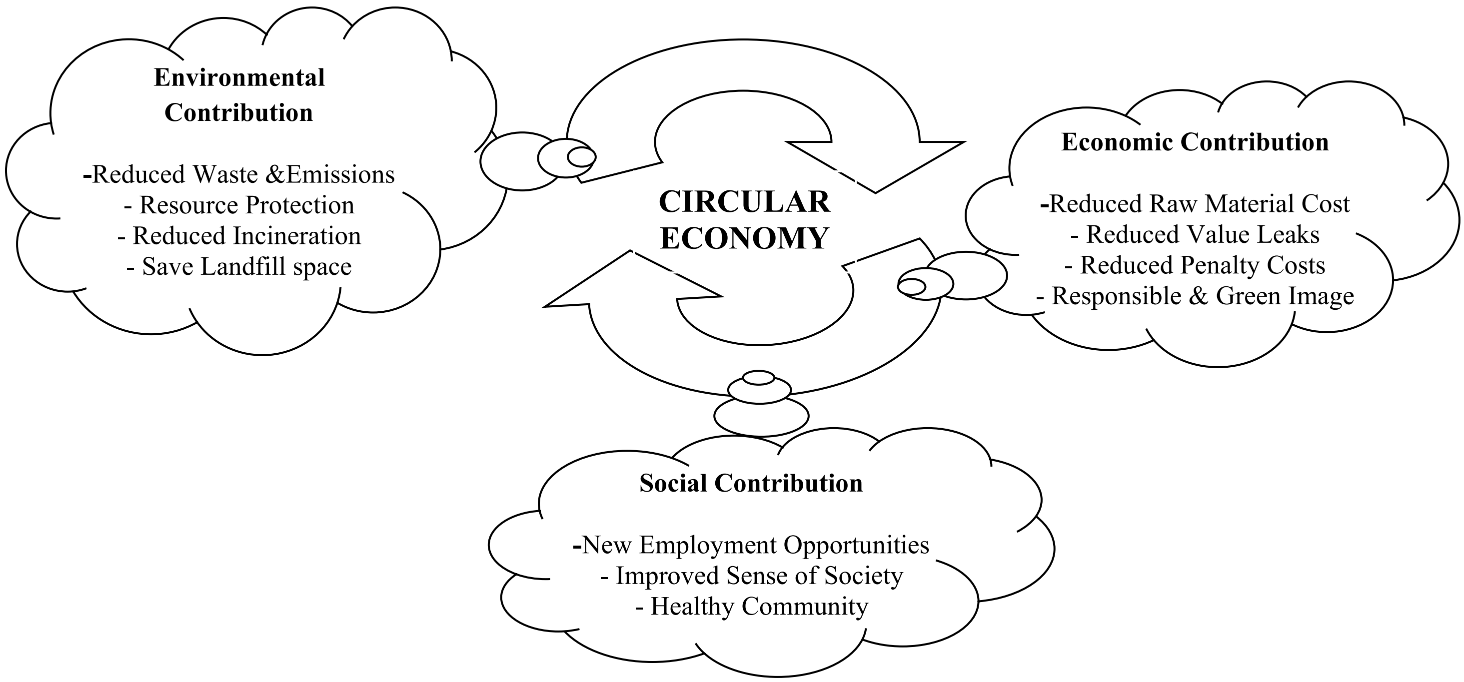

Figure 1: Sustainable Development through Circular Economy (Geissdoerfer et al., 2017).

The development of such an MADM model is of paramount importance to Waste Electrical and Electronic Equipment (WEEE) products due to their potential recovery value and environmental impact. WEEE products have emerged as the fastest-growing waste stream, growing by3–5% per year in the European Union alone (Savage, 2006). The significance and necessity of managing recovery operations for WEEE has been recognised worldwide (Agrawal et al., 2014). Accordingly, we have focused our study on the management of CE for electronic consumer durables such as air-conditioners, washing machines, computers, and mobile phones. The consumer WEEE return items under investigation could be classified into the following two categories: short life-cycle (SLC) goods (i.e. relatively light electronic consumer durables, such as laptops, computers, mobiles, and televisions); and long life-cycle (LLC) goods (i.e. relatively heavy electronic consumer durables, such as air-conditioners, vacuum cleaners, washing machines, and refrigerators). Returned SLC items have a high value erosion rate of about 1% per week, whereas returned LLC items have relatively low depreciation rates (Guide et al., 2006; Guide and Van Wassenhove, 2009; Hui and Gongqian, 2011).

The development of such a recovery strategy decision-making model faces four key challenges. Firstly, the current research related to the time-sensitivity of returns while determining the suitable recovery solution is still in its infancy. The life-cycle of returned products plays a vital role in deciding the order of preference for reprocessing options. Hence, it would be unrealistic to ignore the effect of the life-cycle of returned products during recovery decision-making in a CE. Secondly, a practical product recovery decision-making model should consider a comprehensive set of criteria, including recovery value, quality, environmental impact, and product life-cycle span comprising both qualitative and quantitative aspects. Thirdly, the assessment of reprocessing options in a CE is a challenging task due to the high unpredictability and ambiguity of such an environment (Ma and Kremer, 2015). In many cases, experts provide vague and incomplete assessments that need linguistic terms with different granularities to express their judgments. In such assessments it is challenging to incorporate the use of certain techniques, including fuzzy logic which suffers from information loss while processing linguistic information and thus results in erroneous decisions being made (Liu et al., 2014). Fourthly, multiple criteria trigger trade-off complexity during recovery decision-making since certain recovery options might better serve economic objectives at the expense of environmental goals. To synchronise the economic and ecological benefits simultaneously, there is a need to perform a comprehensive analysis by utilising an effective MADM method involving various recovery strategies and decision-making attributes for product returns. This study attempts to explore these challenges by addressing the following two research questions:

a) What impact does the life-cycle of product returns have on recovery decision-making in a CE?
b) How to manage the trade-off between economic and environmental benefits of product recovery in a CE?

We address these research questions as follows. First, we address the life-cycle issue in product returns by investigating recovery decision-making practices for both SLC and LLC returns followed by a comparative study of their resulting recovery strategies. The study involves two separate cases within the Indian electronics sector. Specifically, the first case study covers SLC mobile phones, while the other case study pertains to LLC air-conditioners. Second, we consider a set of socio-economic and environmental criteria regarding both qualitative and quantitative characteristics to enable a comprehensive evaluation of product recovery strategies against them.

Finally, to address the challenge of an uncertain information environment and multi-attribute problem, we propose an integrated methodology by combining an Interval 2-Tuple Linguistic (ITL) model with Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The ITL model could represent the results in the initial expression domain without any information loss. It would also allow experts to express their judgments using multi-granularity linguistic scales and interval-valued 2-tuples (Zhang, 2012; Liu et al., 2014; Wu et al., 2017). TOPSIS is a well-known conventional technique that assists in decision-making by comparing different options based on the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution concurrently (Hwang and Yoon, 1981). It has been extensively used to solve decision-making problems in various fields (Wu et al., 2010; Behzadian et al., 2010), but not in the context of a CE. The proposed approach is thus an extended TOPSIS for group decision-making with ITL variables.

Our research adds to the existing body of knowledge as well as to the innovation of tools applied in the CE context. While addressing the postulated research questions, this study makes a threefold contribution to the literature. First, we have developed a comprehensive decision-making framework for selecting a suitable reprocessing strategy for product returns based on a set of socio-economic and environmental criteria possessing both quantitative and qualitative aspects. Second, to the best of authors' knowledge, our study is the first to address the conflicting paradigm of managing SLC and LLC returns, and to investigate the impact of product life-cycles on recovery decision-making in a CE. Finally, we have proposed a mathematical model by combining ITL and TOPSIS for decision-making to tackle the challenges associated with uncertainty and incomplete information encountered in the CE literature. Furthermore, the model facilitates the synchronisation of a CE's economic and environmental benefits for organisations.

The rest of the paper is organised as follows: Section 2 provides the theoretical background and literature review; Section 3 describes the ITL-TOPSIS methodology applied in this study; Section 4 illustrates the application of the proposed approach in recovery decision-making; Section 5 presents the results; and, finally, Section 6 includes the conclusion and discussion.

2. Literature Review and Theoretical Background

In the last decade, the notion of a CE has obtained recognition both in research and practice (Ullah and Sarkar, 2020). Growing concerns about the adverse impacts of the increasing rate of returns on the ecosystem have amplified calls to implement a CE (Choudhary et al., 2014). Furthermore, organisations have realised that the scope of a CE is far greater than just addressing regulatory responsibilities. Product recovery eliminates waste and makes companies more resource-efficient while establishing an environmentally responsible brand image (Guide and Van Wassenhove, 2009; Joshi and Gupta, 2019). In a survey, more than 90 percent of purchasers said they would prefer to purchase again from a company if it has convenient product return policies in place (Skinner et al., 2008). Accordingly, the managerial focus has been shifting towards the strategic management of product returns to ensure sustainability in a highly dynamic business environment (Savaskan et al., 2004; Madaan and Choudhary, 2015).

Studies have considered different reprocessing options in the literature so far. One of the earliest research by Thierry et al. (1995) recommended three recovery operations, namely re-use, product recovery management (repair, refurbish, remanufacture, recycle, and cannibalisation), and waste management (landfilling and incineration). De Brito and Dekker (2003) classified the recovery process into two types: direct recovery and process recovery. Subsequently, the recovery options have been stratified by various researchers. Hazen et al. (2012) stated that it is necessary to analyse and recognise the opportunities associated with all recovery options during the decision-making process. A comprehensive list of reprocessing options considered to cover different scenarios in this study is explained in Table 1.

Table 1: Definitions of Reprocessing Options

S. No.	**Reprocessing Options**	**Definition**
1.	Repair	Reprocessing is done with limited product disassembly to bring the returned goods to working order, but quality standards of repaired goods can be lower as compared to new products.
2.	Refurbish	Reprocessing (including replacement of broken and obsolete parts) is done with disassembly up to module level to upgrade the returned goods up to a specified quality level, usually less rigorous as compared to new products.
3.	Remanufacture	Reprocessing is done to bring the quality standards of the returned goods to the level of new products by disassembling the product to the part level and involves greater effort than refurbishing.
4.	Cannibalization	Efforts are made to recover a number of reusable parts by selective disassembly of returned goods, and the quality levels vary depending upon the application.

5.	Recycle	Reprocessing is done to re-use material from the returned goods through various separation processes during which the original identity and functionality of the returned products is lost.
6.	Disposal	Returned products are discarded when all the other recovery options are either extremely expensive or technically unfeasible or when no end market exists.

Figure 2 presents a schematic representation of the CE, considering all the reprocessing options. Raw materials provided by suppliers are used to manufacture products, which then reach customers through distribution and retail channels. In the CE, the used products inclusive of end-of-life, end-of-use and commercial returns are received at various collection centres directly by the manufacturers, or through the retailers or by third parties (Savaskan et al., 2004). After gatekeeping (monitoring the condition of product returns), returns are transported to corresponding recovery centres where the optimal reprocessing options are selected. Accordingly, the residual value is reclaimed from the returns through a suitable recovery option. The products that are repaired or refurbished are sent to secondary markets. Meanwhile, the material recovered by recycling is re-used as raw material by the manufacturers. Elsewhere, the products reclaimed through remanufacturing go to the retailer to be sold as new products, and the manufacturers re-use the parts retrieved through what is known as cannibalisation.

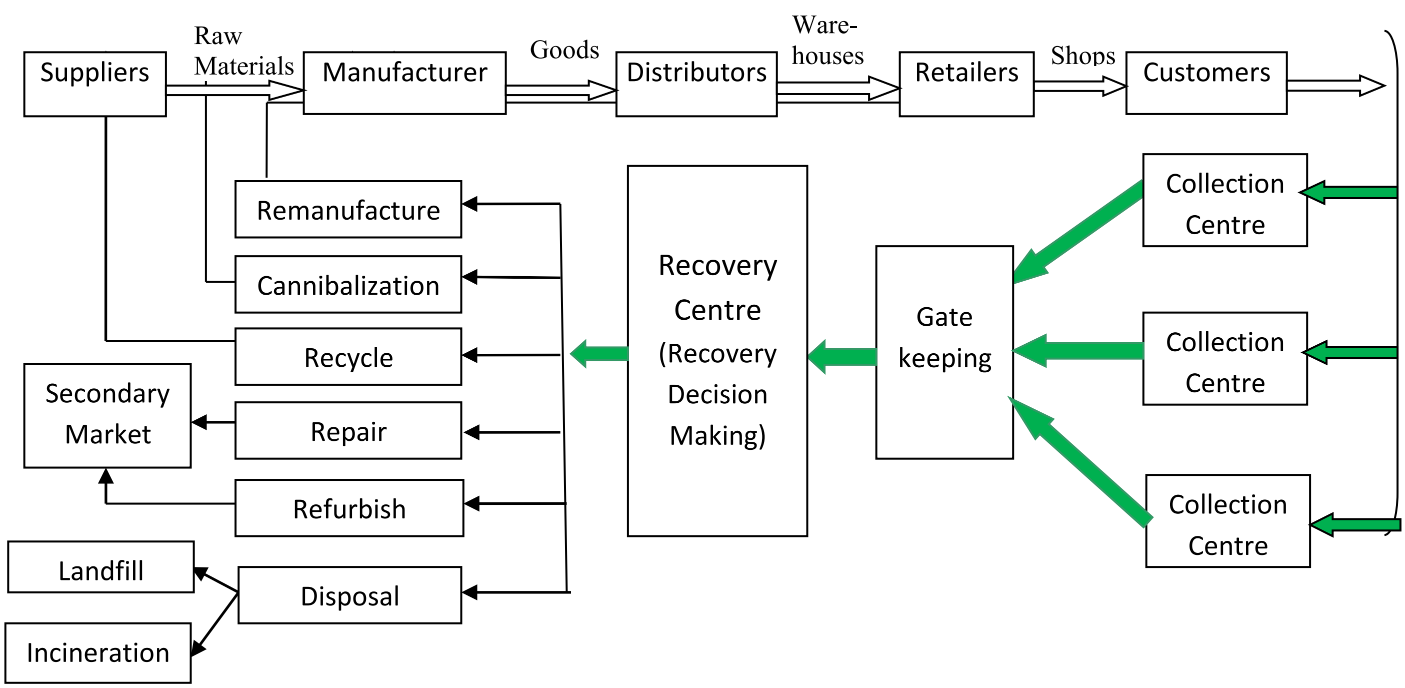

Figure 2: Product Recovery Operations in a CE

A CE offers the opportunity to combine monetary benefits arising from cost reduction, revenue generation, customer retention, and value addition while at the same time practicing environmental stewardship and bringing about societal improvements (Shankar et al., 2018; Joshi and Gupta, 2019). Previous research in the CE domain has focused on various aspects, including: the implications of adopting CE business models (De Sousa Jabbour et al., 2019); third-party remanufacturing (Farhani et al., 2019); lot-sizing (Marshall and Archibald, 2018); network design (Srivastava, 2008); reverse logistics providers (Choudhary et al., 2014); inventory management (García-Alvarado); dismantling sequence (Cong et al., 2017); information management (Toyasaki et al., 2013); and the relationship between a CE and sustainability (Geissdoerfer et al., 2017; Millar et al., 2019). Despite the substantial amount of literature on the concept of a CE, studies focusing on recovery decision-making are still in their infancy. In this regard, a literature review has been carried out to evaluate the available literature in the CE context related to recovery decision-making and its applications. The databases of Google Scholar, Scopus, Science Direct, and ISI Web of Science were used to gather and access relevant articles. The terms "end-of-life," "recovery strategy," "decision-making," "circular economy," "sustainability," and "product recovery" were used in the title, abstract, and keywords sections of the search databases. A total of 93 articles were found initially based on the search string from 2011 to 2020. After considering only peer-reviewed journal articles in English language, the number of papers was reduced to 65. These articles were further reviewed by authors for the final selection of papers. It was found that only 15 papers have investigated product recovery strategies while utilising multi-criteria decision-making (MCDM) methods and are presented in Table 2.

Table 2: Related Studies with focus on reprocessing strategies selection

Previous Studies	Recovery Options Considered	Decision Variables	Product Considered	Solution Approach
Bufardi et al., (2004)	Remanufacturing, Reclamation, Recycling, Incineration, Disposal	Human Health, Quality, Resources, Cost	Vacuum Cleaner	ELECTRE
Gonzalez and Adenso-Diaz (2005)	Disposal, Re-use, Recycling, Disassembly	Profit	Mobile phone	Metaheuristics
Chan and Tong (2007)	Remanufacture/ Reuse, Recycle, Incineration, Landfill	Human Health, Quality, Resource	Vacuum Cleaner	Grey- Relational

				Analysis
Wadhwa et al. (2009)	Remanufacturing, recycling, repair, cannibalization, refurbishing	Cost, Environmental impact, market, quality, legislative factors	Brown goods	Fuzzy TOPSIS
Ziout et al., (2014)	Resale/Re-use, Recycle, Incineration, Fixing, Remanufacture, Refurbishing	Engineering, Business, Environmental, Societal	Fuel Cell	AHP with Cost/Benefit analysis
Ma and Kremer (2015)	Re-use, Remanufacture, Primary & Secondary Recycling, Incineration, Landfill, Special Handling	Economic, Environmental, Social	Gasoline Engine	Fuzzy MCDM
Subulan et al., (2015)	Re-use, Retreading, Recycling, Energy Recovery, Disposal	Profit, Environmental Impact	Tire	Optimization Model
Agrawal et al., (2016)	Re-use, Repair, Remanufacture, Recycle, Disposal	Customer Behavior, Market Condition, Regulations, Environmental Impact, Supply Chain Capability, Product Value, Processing Cost, Number of Returned Product, Quality, Recapturing value	Mobile Phones	Graph Theory Based Approach
Meng et al., (2016)	Recycle, Remanufacture, Re-use	Profit Maximization	Liquid Crystal Display	Co-Evolutionary Algorithm
Cho et al., (2017)	Re-use, Repair, Conditional Repair, Disposal	Total Profit	Computer	Optimization Model
Singh and Agrawal (2018)	Repair, Reconditioning, Remanufacture, Recycle, Disposal	Financial & Non-Financial Implications	Cellular phone	Fuzzy TOPSIS
Farhani et al., (2019)	Re-use, Upgrade, Material Recycling, Waste Management	Profit	Computer	Optimization Model
Jiang et al., (2019)	Replace Defective Component, Reuse, Remanufacturing	Life Span Equilibrium, Value Efficiency, Cost	Lathe	Multi-Obj Optimization
Yang et al., (2019)	-	Social, Economic, Environmental, Technical	Vehicle Management	Picture Fuzzy Theory
Alamerew and Brissaud (2019)	Remanufacturing, re-use, recycling	Business, legal, economic, environment, social	Automotive engine	Multi Criteria Decision Tool

The literature review revealed that the selection of a suitable product recovery strategy has conventionally been seen as a multi-criteria decision-making problem. Many researchers have addressed this problem through optimisation and metaheuristics approaches at the operational level (Jiang et al., 2019; Cho et al., 2017; Meng et al., 2016; Subulan et al., 2015; Gonzalez and Adenso-Diaz, 2005). The optimisation-based problems are quantitative, while a product recovery strategy decision naturally involves quantitative and qualitative (subjective judgment) aspects due to the nature of certain criteria and the confidentiality of the data. When addressing this issue, very few pieces of research have applied multi-attribute decision-making approaches such as TOPSIS and AHP with Fuzzy sets (Alamerew 2019; Singh and Agarwal, 2018; Ziout et al., 2014; Wadhwa et al., 2009). Alamerew (2019) proposed a general multi-criteria decision-making (MCDM) based product recovery selection tool for selecting an end-of-life strategy and applied this in the auto mobile engine case. The study considered a variety of criteria, however it focused on only three end-of-life recovery strategies. Singh and Agarwal (2018) developed a decision-making framework based on fuzzy TOPSIS to prioritise disposition strategies (recovery strategies). They applied the proposed framework in a single cell phone manufacturing company. However, the financial and non-financial criteria considered in the analysis of recovery strategies were not defined. Similarly, Wadhwa (2009) proposed a decision-making framework based on fuzzy TOPSIS and applied this in terms of brown goods in general. Ziout et al. (2014) developed a decision-making framework based on the conventional Analytical Hierarchy Process(AHP) method for selecting a recovery strategy for fuel cells.

The authors noted that these decision-making frameworks have only referred to the fuzziness of data, however, the use of multi-granular linguistic scales were not considered. The latter could enable experts to use linguistic term sets of varying cardinalities according to the uncertainties in their assessments (due to the subjectiveness of their judgment).This concept is discussed in detail in Section 3.1. Moreover, it can also be observed from Table 2 that available studies have not yet considered product usage duration, marginal value of time, resource consumption, and market scenario compatibility, together with other economic, environmental, and social criteria, all of which would allow for comprehensive product recovery decision-making. It is apparent that some previous studies have considered the case of electronic and electrical items, however the impact of the life-cycle of returns (i.e. LLC and SLC electronic/electrical returns) on the order of preference for reprocessing options has scarcely been covered.

Recent review papers have also identified the need for multi-attribute decision-making models in the CE literature (Geissdoerfer et al., 2017; Korhonen et al., 2018).To address these research gaps, this paper contributes to the literature by proposing a decision-making framework that takes into consideration a comprehensive set of qualitative and quantitative criteria, some of which have never previously been considered, as discussed above. Furthermore, the framework considers a broad set of possible recovery strategies, unlike many of the previous studies. The framework can be used to select the optimal recovery strategy for electronic/electrical products given their life-cycle. The framework has employed ITL-TOPSIS as a solution methodology, which was proposed by Liu et al. (2014) for robot selection and evaluation. To the best of the authors' knowledge, this is a novel approach being applied for the first time in the selection of a product recovery strategy problem.

Accordingly, we have developed a two-phase decision model, which can guide organisations in the selection of optimal recovery alternatives for SLC and LLC electronic product returns, taking into consideration a wide range of dimensions. One of the model's fundamental elements is the consideration of various attributes in the analysis process for decision-making. Therefore, the different attributes considered in the decision-making model are discussed in the following sub-section.

2.1 Decision Criteria for the Recovery Decision-making Model

Organisations can improve by identifying the most advantageous recovery option for purposes of value reclamation (Bufardi et al., 2004). Accurate examination of each product return with regard to different aspects is essential in the selection of a suitable reprocessing option (Ziout et al., 2014). Accordingly, for a successful CE, decision-makers need to consider all the relevant attributes during the recovery decision-making process. Specifically, Hazen et al. (2012) identified the following seven factors to be considered in recovery decision-making: supply chain capabilities; costs of reverse logistics; profit; environmental impact; regulations; market considerations; and customer behaviour. Furthermore, a multi-criteria decision-making approach was proposed by Wadhwa et al. (2009) for end-of-life decision-making, considering the cost, quality, environmental, and market factors. Most studies in the literature so far have performed decision-making in the CE context based on individual aspects, such as either profit or cost-benefit analysis (Ferguson et al., 2011; Cho et al., 2017; Farhani et al., 2019) or through recovery value of product returns (Kumar et al., 2007; Gobbi, 2011).

Some studies have explained the time value of returned products, however research considering time value as a decision-making criterion during the selection of reprocessing options remains scarce. Furthermore, most of the papers written have not considered the residual value of product returns during recovery operations. Accordingly, based on the literature review, the current study identified the following criteria to be considered in the development of a recovery decision-making model: product recovery value (PRV); marginal value of time (MVT); reprocessed quality; novel resources requisite; environmental impact; market scenario; and profit (P).

PRV can be defined as the residual value retained by the product when it enters the recovery system. Residual value is the value present in the product when its usage phase ends, where the usage phase is the "time the product stays with the user before it is returned" (Guide et al., 2006). Returned goods with low residual value are assigned to second-class reprocessing options (e.g., recycle, disposal, cannibalisation), and goods with high residual value are assigned to first-class recovery options (e.g., repair, refurbish, and remanufacture) (Gobbi, 2011). A product having a low residual value recovered using a first-class recovery option will involve a very high recovery cost, perhaps even exceeding the profit. Therefore, it is necessary to assign recovery options to the returned products according to their PRV. It is also important to consider, the condition of the used product being returned to CE for recovery.

MVT is the rate of loss in the value of product returns from the instant they are returned until the recovery process is completed. It essentially refers to "the loss in value per unit of time spent awaiting completion of the recovery process" (Hui and Gongqian, 2011). Where the product is nearing the end-of-life, there is a chance that the product may become completely obsolete by the time it is reprocessed, resulting in substantial monetary loss. Accordingly, time-sensitive returns with a high MVT, such as for laptops and cell phones, should be reprocessed quickly via the least time-consuming recovery option.

Reprocessed quality refers to the quality of the reprocessed returns after their value has been recovered through various recovery options. The highest quality products are those reclaimed using the remanufacturing process as their quality is as good as that of new products, followed by refurbished and repaired products (Farhani et al., 2019). The novel resource requisite represents the amount of virgin resources expected to be consumed during the reprocessing of returned products. It is preferable to use options that require the least possible novel resources for value reclamation (Chan and Tong, 2007). Meanwhile, environmental impact here entails measuring the consequences of the recovery options in terms of their ecological effect, and market scenario represents the demand for the secondary products reprocessed through different recovery options. This criterion considers customer's willingness to purchase the secondary product. Profit (P) is the financial benefit associated with each recovery option. It is one of the most influential driving factors that encourage organisations to incorporate the CE into their existing systems. The process for profit calculation in the case of each recovery option is discussed in the following sub-section.

2.2 Profit Calculations

To decide the most appropriate recovery option, it is necessary to calculate the profit inherent in each reprocessing strategy. We use the profit calculation methods developed by Ziout et al. (2014) and González and Adenso-Díaz (2005) as follows:

$$\text{Profit (P)} = \text{Revenue (R)} - \text{Cost (C)} \qquad (1)$$

Here, Revenue = Sales price of the reprocessed product/material – Buy back price of the product return from customers. The reprocessing cost incurred in different reprocessing alternatives and the formula for revenue calculation in the case of recycling and incineration (disposal) is explained in Table 3.

Table 3: Reprocessing Cost associated with Recovery Options

Recovery Options	Cost of Reprocessing
Repair	Cost (repair) = C(disassembly) + C(fixing) + C(reassembly) + C(testing) Where, C(disassembly) = Labor cost x time (disassembly) C(reassembly) = Labor cost x time (reassembly) C(testing) = Cost of testing the repaired product to check its working C(fixing) = Cost spent in repairing
Refurbish	Cost (refurbish) = C(disassembly) + C(refurbishing) + C(reassembly) + C(testing) Where, C(refurbishing) = C(cleaning) + C(replacing obsolete parts) + C(fixing & maintenance)
Remanufacturing	Cost (remanufacture) = C(disassembly) + C(remanufacturing) + C(reassembly) + C(testing) + C(warranty) + C(packing) Where, C(remanufacturing) = C(cleaning) + C(replacing obsolete and damaged parts) + C(upgrading)

Cannibalization	Cost (cannibalization) = C(disassembly) + C(recovering parts & cleaning)
Recycle	Cost (recycle) = C(disassembly) + C(sorting) + C(recycling) Revenue (recycle) = (Material weight reclaimed x value/kg) x % purity
Disposal	In case of land filling; Cost = Mass of material x cost of dumping/ kg In case of incineration; Revenue = Energy produced x selling price of energy Cost = C(product separation) + C(incineration)

2.3 A Conceptual Product Recovery Decision-making Framework

The existing research lacks a comprehensive framework that considers various aspects of product recovery decision-making in a CE. We thus propose a holistic recovery decision-making framework that assimilates all the recovery options and includes significant criteria to determine the most optimal recovery option, as presented in Figure 3.

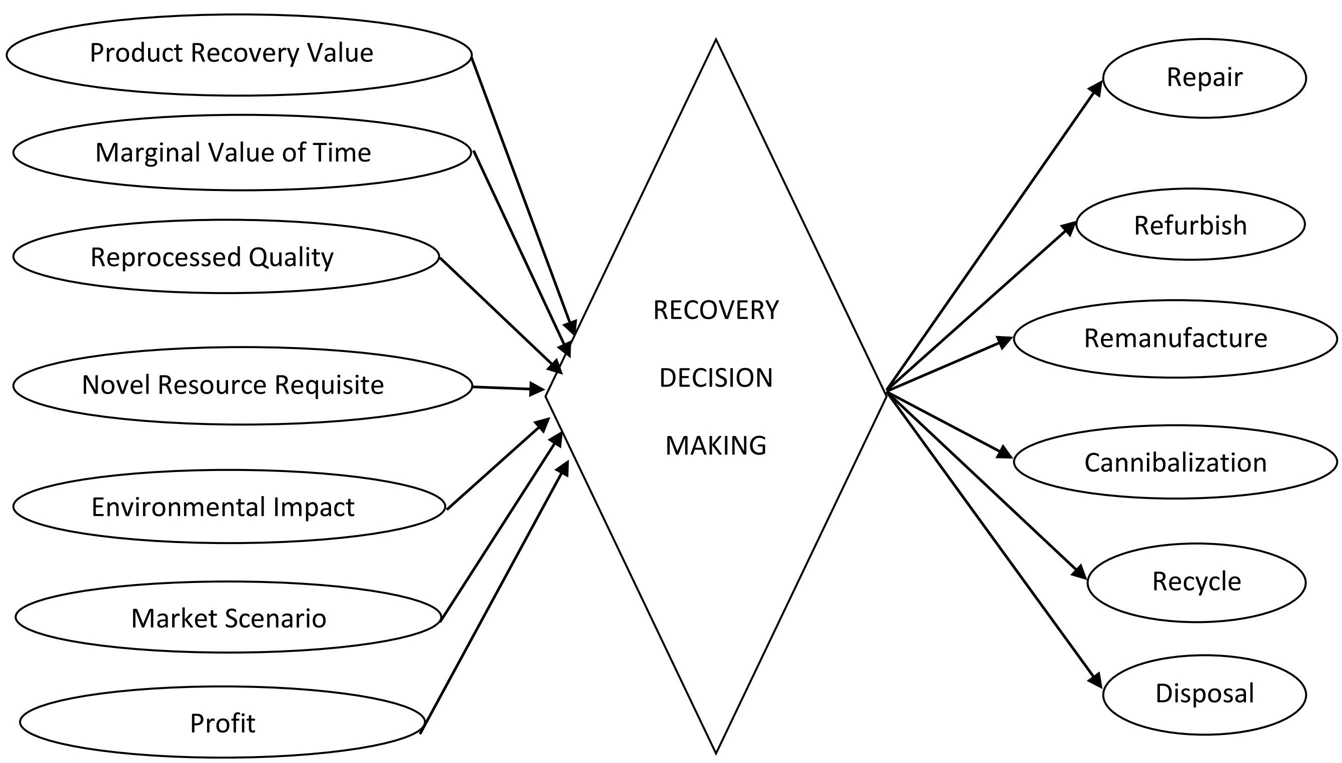

Figure 3: Recovery Decision Making Framework

The criteria for recovery decision-making are often conflicting, and decision-makers need to make trade-offs by identifying the reprocessing option that allows for the best compromise between said criteria. Furthermore, based on the nature and type of data involved in recovery decision-making, optimisation models are not suitable for use as they are efficient in solving a specific aspect of the problem, but not the problem in its entirety (Ziout et al., 2014). Similarly, clustering and classification methods require large sets of training data and are more appropriate for sorting but not prioritising and ranking (Ziout et al., 2014). For a complicated and extensive problem, such as recovery decision-making with various involved aspects, a decision-making method is required that can decode the problem and model it efficiently. Therefore, an integrated multi-attribute decision-making approach combining ITL and TOPSIS is proposed to determine the most suitable recovery option while considering the uncertainty inherent in subjective decision-making. The suggested approach aggregates different decision-makers' inputs on various criteria for reprocessing option selection. It presents results in the initial expression domain to allow for better interpretation without any information loss. The following section explains the proposed methodology.

3. A Two-Phase Decision Model Combining Interval 2-tuple (ITL) and TOPSIS Approach

3.1 Interval 2-Tuple Linguistic Representation Model

Linguistic variables are used in complex and vague situations, where traditional quantitative expressions cannot provide clear explanations (Liu et al., 2015). They describe the ill-defined states with words and sentences in natural language rather than numbers (Liu et al., 2014). The 2-tuple linguistic representation model for handling such situations was first proposed by Herrera and Martinez (2000). It is based on the concept of symbolic translation in which the linguistic assessment information is represented by a 2-tuple that consists of a linguistic term and a numerical value. It can be denoted as (s_i, α), where s_i is a linguistic label of the predefined linguistic term set S, and α is a numerical value representing symbolic translation. Let $S = \{s_i | i = 0,1,\ldots, g\}$ represents a linguistic term set, which is required to have following properties (Herrera and Martinez, 2000, 2001):

- The set is ordered: $s_i > s_j$, if $i>j$;
- Negation operator: $\text{Neg}(s_i) = s_j$ such that $j = g - i$;
- Maximization operator: $\max(s_i, s_j) = s_i$, if $s_i \geq s_j$;

- Minimization operator: min $(s_i, s_j) = s_i$, if $s_i \leq s_j$.

Later, Chen and Tai (2005) proposed a generalized 2-tuple linguistic model and translation function to handle the multi-granular linguistic scales, which cannot be done with the classical 2-tuple model. Multi-granular linguistic scales enable experts to use linguistic term sets with different cardinality according to the number of uncertainties in their assessments (Wu et al 2017).Therefore, experts can have more or fewer terms in the linguistic term set according to their requirements. Zhang (2012) proposed an ITL model that provides a more flexible framework to deal with decision problems using qualitative information and aggregate information coming from different multi-granularity linguistic sets. The rest of the section provides highlights on ITL-TOPSIS methodology. Interested readers are suggested to refer to Liu et al. (2014) for detailed steps of application. Also, the readers are advised to refer to Chen and Tai (2005), Herrera and Martínez (2001), Zhang (2012), and Liu et al. (2014) for 2-Tuple linguistic variables and interval 2-Tuple linguistic variables definitions and operators used in this methodology.

3.2 An Interval 2-Tuple Linguistic TOPSIS Model

The product recovery decision-making is a challenging task, which is characterized by its dependency on many ambiguities and incomplete information. Furthermore, due to the involved qualitative criteria, it is required to initially get the expert inputs in linguistic terms. Most of the literature approaches undergo information loss during linguistic information processing, which leads to imprecise results (Liu et al., 2014). The proposed two-phase approach, extended TOPSIS with the ITL model, overcomes this limitation and can efficiently process the linguistic information (Liu et al., 2015; Wu et al., 2017). It uses the modified TOPSIS method to address linguistic MADM problems in which weights of the attributes are in the form of 2-tuple linguistic variables and values of the attributes are in the form of ITL variables. It has the capability to provide accurate results with incomplete information in ambiguous environments and allows decision-makers to use diverse linguistic terms to express their judgments with a different granularity of uncertainty (Zhang et al., 2012). Accordingly, the proposed methodology is better suited and accurate for handling decision-making problems. The steps of the methodology, ITL-TOPSIS, are illustrated in Figure 4.

Consider a multi-attribute decision-making problem that has l decision-makers DM_k (k = 1, 2,…,l), m alternatives/options A_i (i = 1, 2,…, m), and n decision criteria C_j (j = 1, 2,…, n). A weight, $\lambda_k > 0$ (k = 1, 2, . . ., l) satisfying $\Sigma_{k=1}^{l}\lambda_k = 1$, is assigned to each decision-maker to show their significance in the decision-making process. Let (d_{ij}^{k}) be the linguistic information provided by the k^th^ decision-maker, DM_k on the assessment of A_i with respect to C_j, which is represented in the form of linguistic decision matrix $D_k = (d_{ij}^{k})_{m\,x\,n}$. Let w_j^k be the linguistic weight given to C_j by DM_k so $w_k = (w_1^k, w_2^k, ..., w_n^k)^T$ is the linguistic weight vector given by the k^th^ decision-maker to all the criteria. Moreover, different linguistic term sets can be used by the decision-makers to state their opinions. The procedure of ITL-TOPSIS can be described as follows:

Determine the linguistic decision matrix, $D_k = (d_{ij}^{k})_{m\,x\,n}$.

↓

Translate the linguistic decision matrixinto interval 2-tuple linguistic decision matrix $\widetilde{R_k} = (\tilde{r}_{ij}^{k})_{m\,x\,n}$

↓

Aggregate the decision-makers' opinions to get the comprehensive interval 2-tuple linguistic decision matrix $\widetilde{R} = (\tilde{r}_{ij})_{m\,x\,n}$

↓

Construct weighted interval 2-tuple linguistic decision matrix, $\widetilde{R}' = (\tilde{r}_{ij}')_{m\,x\,n}$

↓

Determine 2-tuple linguistic positive-ideal solution A^+ and negative-ideal solution A^-

↓

Compute separation measures, D^+ & D^-, of each alternative

↓

Calculate the relative closeness coefficient of each alternative RC_i^+

↓

Obtain the final ranking of alternatives.

Figure 4: Steps of proposed methodology

Step 1: Record the assessment of various alternatives on all the attributes provided by the decision-makers in linguistic scales of their preference and represent in the form of a linguistic decision matrix $D_k = (d_{ij}^{k})_{m\,x\,n}$.

Step 2: Translate the linguistic decision matrix into the ITL decision matrix $\widetilde{R_k} = (\tilde{r}_{ij}^{\,k})_{m\,x\,n} = \left[\left((s_{ij}^{k},0),(t_{ij}^{k},0)\right)\right]_{m\,x\,n}$, where $s_{ij}^{k}, t_{ij}^{k} \in S$, $S = \{s_i | \, i = 1,2,...,g\}$ and $s_{ij}^{k} < t_{ij}^{k}$.

Assume that the decision-maker gives his opinion in a set of 3 linguistic terms, which are denoted as

$$S = [(a_0 = \text{Poor (P)}, a_1 = \text{Medium (M)}, a_2 = \text{Good(G)}]$$

Then, it can be translated to a corresponding ITL evaluation through the following ways:

- An assessment such as *poor* is translated as $[(a_0,0),(a_0,0)]$.
- An interval assessment such as *poor-medium*, which implies that the alternative for a certain criterion is evaluated between poor and medium, is translated as $[(a_0,0),(a_1,0)]$.
- *No opinion*, which implies that the decision-maker is not ready to evaluate an alternative for a certain decision criterion. So, the evaluation can lie anywhere between *poor* and *good* and is translated as $[(a_0,0),(a_2,0)]$.

Step 3: This step is to aggregate the decision-makers' opinions to get the comprehensive ITL decision matrix, $\tilde{R} = (\tilde{r}_{ij})_{m\,x\,n}$ and the cumulative 2-tuple linguistic weight of each criterion (w_j, α_{wj}) as shown in Equations 1 and 2.

$$\begin{aligned}\tilde{\boldsymbol{r}} &= [(s_{ij},\alpha_{ij}), (t_{ij}, \varepsilon_{ij})] \\ &= \text{ITWA}\left([(s_{ij}^{1},0),(t_{ij}^{1},0)], [(s_{ij}^{2},0),(t_{ij}^{2},0)], ...,[(s_{ij}^{l},0),(t_{ij}^{l},0)]\right) \\ &= \Delta\left[\tfrac{1}{l}\textstyle\sum_{k=1}^{l}\lambda_k \Delta^{-1}(s_{ij}^{k},0), \tfrac{1}{l}\sum_{k=1}^{l}\lambda_k \Delta^{-1}(t_{ij}^{k},0)\right], \; i = 1,2,...,m;\; j = 1,2,\ldots,n \quad (2)\end{aligned}$$

$$\begin{aligned}(w_j,\alpha_{wj}) &= \text{TWA}\left[(w_j^{1},0),(w_j^{2},0),\ldots,(w_j^{l},0)\right] \\ &= \Delta\left[\tfrac{1}{l}\textstyle\sum_{k=1}^{l}\lambda_k \Delta^{-1}(w_j^{k},0)\right], \; j = 1,2,...,n. \quad (3)\end{aligned}$$

Step 4: This step involves the construction of a weighted ITL decision matrix, $\widetilde{R} = (\tilde{r}_{ij}')_{m\,x\,n}$, as given in Equation 3.

$$\tilde{r}_{ij}' = \left[(s_{ij}', \alpha_{ij}'), (t_{ij}', \varepsilon_{ij}')\right] = (w_j, \alpha_{wj}) \times \left[(s_{ij}, \alpha_{ij}), (t_{ij}, \varepsilon_{ij})\right]$$

$$= \Delta \left[\Delta^{-1}(w_j, \alpha_{wj}) \bullet \Delta^{-1}(s_{ij}, \alpha_{ij}), \Delta^{-1}(w_j, \alpha_{wj}) \bullet \Delta^{-1}(t_{ij}, \varepsilon_{ij})\right], \ i = 1, 2, \ldots, m\ ;\ j = 1, 2, \ldots, n. \quad (4)$$

Step 5: Determine the 2-tuple linguistic positive-ideal solution, A^+ and 2-tuple linguistic negative-ideal solution, A^-as is given below in Equations 4-6.

$$A^+ = [\ (r_1^+, \alpha_1^+), (r_2^+, \alpha_2^+), \ldots\ldots, (r_n^+, \alpha_n^+)], \quad (5a)$$

$$A^- = [\ (r_1^-, \alpha_1^-), (r_2^-, \alpha_2^-), \ldots\ldots, (r_n^-, \alpha_n^-)], \quad (5b)$$

where,

$$(r_j^+, \alpha_j^+) = \begin{cases} \max\{(t_{ij}, \varepsilon_{ij})\}, & \text{for benefit criteria} \\ \min\{(s_{ij}, \alpha_{ij})\}, & \text{for cost criteria} \end{cases} \quad j = 1,2, \ldots n, \quad (6)$$

$$(r_j^-, \alpha_j^-) = \begin{cases} \min\{(s_{ij}, \alpha_{ij})\}, & \text{for benefit criteria} \\ \max\{(t_{ij}, \varepsilon_{ij})\}, & \text{for cost criteria} \end{cases} \quad j = 1,2, \ldots n, \quad (7)$$

Step 6: Determine the separation measures, D^+& D^-, for each alternative based on the n-dimensional Euclidean distance of interval 2-tuples, as shown in Equations 7 and 8.

$$D_i^+ = \Delta\sqrt{\sum_{j=1}^{n}\left[\left(\Delta^{-1}(s_{ij}', \alpha_{ij}') - \Delta^{-1}(r_j^+, \alpha_j^+)\right)^2 + \left(\Delta^{-1}(t_{ij}', \varepsilon_{ij}') - \Delta^{-1}(r_j^+, \alpha_j^+)\right)^2\right]} \ i = 1,2,\ldots,m, \quad (8)$$

$$D_i^+ = \Delta\sqrt{\sum_{j=1}^{n}\left[\left(\Delta^{-1}(s_{ij}', \alpha_{ij}') - \Delta^{-1}(r_j^-, \alpha_j^-)\right)^2 + \left(\Delta^{-1}(t_{ij}', \varepsilon_{ij}') - \Delta^{-1}(r_j^-, \alpha_j^-)\right)^2\right]} \ i = 1,2,\ldots,m, \quad (9)$$

Step 7: Calculate the relative closeness coefficient of each alternative A_i with respect to the 2-tuple linguistic positive-ideal solution A^+, which is computed as presented in Equation 9.

$$RC_i^+ = \Delta\left(\frac{\Delta^{-1}(D_i^-)}{\Delta^{-1}(D_i^+) + \Delta^{-1}(D_i^-))}\right), \text{ where} 0 \leq \Delta^{-1}(RC_i^+) \leq 1. \quad (10)$$

Step 8: Obtain the final ranking of alternatives based on the descending order of their relative closeness coefficients. This implies that the alternative with a higher value of RC_i^+ appears first in the ranking position and is the most optimal alternative better than the others.

4. Application of the Proposed Model in Recovery Decision-making

One of the most popularly used and most appropriate ways of depicting a model's pragmatic significance is illustrating its application in real-world scenarios. In this regard, a quantitative modelling technique based on empirical data has been employed. This paper uses real-world data from the Indian electrical and electronic industry sectors to validate the application of the developed model in recovery decision-making using real-life scenarios. The choice of this method for this research was inspired by existing publications investigating recovery strategies for different products through the application of multi-attribute decision-making methods (Alamerew and Brissaud, 2019; Singh and Agarwal, 2018; Wadhwa et al., 2009).The data collection method began with a literature review identifying criteria and product recovery strategy as explained in Section 2.The data were then validated through focus group sessions with experts and their subsequent input using the MADM method to decide on optimal recovery strategies. The details regarding data collection from experts are explained in subsequent sub-sections.

4.1 Problem Background

The application of the proposed ITL-TOPSIS-based decision-making model in determining the most suitable recovery options for electronic returns in a CE has been illustrated in this section using linguistic data collected from Indian organisations. The Indian electronics industry is worth approximately USD 65 billion and has been predicted to soon increase to USD 400 billion (Agrawal et al., 2014). Meanwhile, the e-waste generated in India amounts to approximately 146,000 tons per year and is growing at a rate of 10 percent per year (CII, 2006). Furthermore, most Indian organisations do not have a formal structure in place to manage the CE channel of electronic returns, and there is a need for an efficient system to handle e-waste (Agrawal et al., 2014). Hence, this research has aimed to facilitate an efficient recovery decision-making system to properly manage electronic returns in the Indian scenario. Product returns vary based on their life-cycles; SLC products have high value erosion rates compared to their LLC counterparts. Life-cycle is a significant factor that influences recovery decision-making. Therefore, the present study determines and compares recovery decision-making for SLC and LLC electronic returns individually with the help of the ITL-TOPSIS-based approach using data from the Indian context. Accordingly, the application of the model is illustrated using two cases (Case I: SLC returns & Case II: LLC returns), and results are obtained and compared for different scenarios.

4.2 Case I: Application of the Model in Recovery Decision-making for SLC Returns

The recovery decision-making problem for light electronic devices such as mobiles, laptops, and computers is considered to be determining the ranking of optimal reprocessing options for SLC products. Commonly, light consumer electronic durables are believed to have a short lifespan of about five years. In this case, we investigate the recovery options for a time-sensitive electronic product (mobile phone), which was returned after a span of two years of usage.

4.2.1 Data Collection

To evaluate recovery options in the case of SLC returns, focus group sessions were conducted with three expert committees, bearing in mind the qualitative nature of the considered criteria and the lack of statistical data. The expert committees were selected from three established multinational organisations in the Indian electronics sector. Organisations in this sector deal in numerous electronic products, including mobile phones and the management of associated returns. Two particular organisations in this sector have a turnover in the range of USD 50-80 billion and have approximately 100,000 employees working across the globe. Another organisation has a turnover of US 870 million and more than 10,000 employees. Experts were selected according to two major principles: first, they had to have professional experience in the electronics industry, especially in dealing with time-sensitive products. Second, the experts had to have sound knowledge and experience in CE, including the various recovery options and the handling of time-sensitive returns. Appropriate experts within each organisation were identified based on their professional responsibilities and appropriate recommendations.

Each expert committee consisted of three to four experts with professional experience ranging from 5-15 years and considered organisational specialists in the relevant domain. Selected experts included managers, area managers, heads, senior consultants, and analysts working in various domains including supply chain management, sustainability, corporate social responsibility, operations, and research and development. In each focus group session, first a basic explanation was provided about the research objectives, with expected outcomes and possible implications for practitioners, followed by a description of each considered criteria to inform the experts. Next, the experts were individually asked to linguistically evaluate all recovery options with respect to each of the considered criteria (for the return of the given mobile phone) in the provided questionnaire using a scale of their choice (five-point, sevenpoint, or nine-point scale). In the last step, each committee was requested to discuss their thoughts, and a single input linguistic assessment was obtained with the consent of all members to avoid individual bias. The importance of all decision-makers was considered equal in this case. Due to their privacy policies, experts refused to disclose the exact figures required for profit calculation and, hence, we had to consider profit as a qualitative attribute in this case. Accordingly, the inputs for the assessment concerning profit were obtained in linguistic terms only for each recovery strategy in this case (mobile phones). The inputs of expert committees are depicted as EC1, EC2, and EC3, respectively. Based on their judgments, the most suitable recovery option for time-sensitive returns was determined through the ITL-TOPSIS approach (described in the previous section) as follows:

Step1: The assessments of reprocessing alternatives on each decision criteria provided by the expert committees are presented in Table 3 in the form of a decision table. The linguistic term sets A, B, and C employed by the expert committees EC_1, EC_2 and EC_3 respectively for the analysis are as follows:

A (EC_1) $\longrightarrow$ [a_0=Very Poor (VP),a_1= Poor (P), a_2=Fair (F), a_3=Good (G), a_4=Very Good (VG)]

B (EC_2) $\longrightarrow$ [b_0=Very Poor (VP),b_1= Poor (P), b_2= Moderately Poor (MP),b_3=Fair (F),b_4= Moderately Good (MG), b_5= Good (G), b_6=Very Good (VG)]

C (EC_3) $\longrightarrow$ [c_0=Extremely Poor (EP),c_1= Very Poor (VP),c_2= Poor (P),c_3= Moderately Poor (MP), c_4=Fair (F), c_5= Moderately Good (MG), c_6= Good (G), c_7= Very Good (VG), c_8= ExtremelyGood (EG)]

The expert committees evaluate the relative importance of criteria by a set of 7 linguistic terms, D, which are denoted as follows, and the assessments are shown in Table 4.

D (Weights) $\longrightarrow$[d_0=Very Low (VL),d_1= Low(L), d_2= Medium Low(ML),d_3=Medium(M),d_4= Medium High (MH), d_5= High (H), d_6=Very High (VH)]

Step 2: The linguistic assessments presented in Table 4 and Table 5 are translated into ITL variables, and 2-tuple linguistic variables, respectively (Step 2 explained in the previous section) and are shown in Table 6 and Table 7.

Table 4: Linguistic Decision Table for SLC Return

Expert Committees	End of Life Options	Product Recovery Value	Marginal Value of Time	Processed Quality	Novel Resources Requisite	Environmental Aspect	Market Scenario	Profit
EC1	Repair	VG	VG	G	G	VG	VG	VG
	Refurbish	G	G	G	F	F-VG	G-VG	G-VG
	Remanufacture	P-F	P	VG	VP-P	P-G	P	P
	Cannibalization	P	P	P	P	P-G	P	P
	Recycle	F	F	G	F	P	F	F
	Disposal	VP	VP	P	G	VP	VP	VP
EC2	Repair	VG	G	G-VG	G	G-VG	G-VG	G
	Refurbish	G	MG-VG	G	MG	MG	G	G
	Remanufacture	MP	P	G	MP	F	MP	P-MP
	Cannibalization	P	MP	MP	P	MP	P-MP	P
	Recycle	F	F	F-G	MP-F	P	F	F-MG
	Disposal	VP	P	VP	G	VP	P	VP
EC3	Repair	VG-EG	VG	G-VG	VG	VG	EG	VG
	Refurbish	VG	G-VG	G	G	VG	VG	G
	Remanufacture	MP-F	MP	VG	P	MG	F	P
	Cannibalization	MP	P	MP	MP	F	MP	MP
	Recycle	MG	F	F	F	MP	MG	MG
	Disposal	VP	VP	P	F	EP	VP	VP

Table 5: Linguistic Weights of Criteria for SLC Return

Expert Committees		Product Recovery Value	Marginal Value of Time	Processed Quality	Novel Resources Requisite	Environmental Aspect	Market Scenario	Profit
EC1		H	H	MH	ML	MH	VH	VH
EC2		VH	MH	M	M	M	VH	H
EC3		MH	M	MH	M	ML	H	VH

Table 6: ITL Decision Table for SLC Return

Expert Committees	End of Life Options	Product Recovery Value	Marginal Value of Time	Processed Quality	Novel Resources Requisite	Environmental Aspect	Market Scenario	Profit
EC1	Repair	$[(a_4,0)(a_4,0)]$	$[(a_4,0)(a_4,0)]$	$[(a_3,0)(a_3,0)]$	$[(a_3,0)(a_3,0)]$	$[(a_4,0)(a_4,0)]$	$[(a_4,0)(a_4,0)]$	$[(a_4,0)(a_4,0)]$
	Refurbish	$[(a_3,0)(a_3,0)]$	$[(a_3,0)(a_3,0)]$	$[(a_3,0)(a_3,0)]$	$[(a_2,0)(a_2,0)]$	$[(a_2,0)(a_4,0)]$	$[(a_3,0)(a_4,0)]$	$[(a_3,0)(a_4,0)]$
	Remanufacture	$[(a_1,0)(a_2,0)]$	$[(a_1,0)(a_1,0)]$	$[(a_4,0)(a_4,0)]$	$[(a_0,0)(a_1,0)]$	$[(a_1,0)(a_3,0)]$	$[(a_1,0)(a_1,0)]$	$[(a_1,0)(a_1,0)]$
	Cannibalization	$[(a_1,0)(a_1,0)]$	$[(a_1,0)(a_1,0)]$	$[(a_1,0)(a_1,0)]$	$[(a_1,0)(a_1,0)]$	$[(a_1,0)(a_3,0)]$	$[(a_1,0)(a_1,0)]$	$[(a_1,0)(a_1,0)]$
	Recycle	$[(a_2,0)(a_2,0)]$	$[(a_2,0)(a_2,0)]$	$[(a_3,0)(a_3,0)]$	$[(a_2,0)(a_2,0)]$	$[(a_1,0)(a_1,0)]$	$[(a_2,0)(a_2,0)]$	$[(a_2,0)(a_2,0)]$
	Disposal	$[(a_0,0)(a_0,0)]$	$[(a_0,0)(a_0,0)]$	$[(a_1,0)(a_1,0)]$	$[(a_3,0)(a_3,0)]$	$[(a_0,0)(a_0,0)]$	$[(a_0,0)(a_0,0)]$	$[(a_0,0)(a_0,0)]$

EC 2	Repair	$[(b_6,0)(b_6,0)]$	$[(b_5,0)(b_5,0)]$	$[(b_5,0)(b_6,0)]$	$[(b_5,0)(b_5,0)]$	$[(b_5,0)(b_6,0)]$	$[(b_5,0)(b_6,0)]$	$[(b_5,0)(b_5,0)]$
	Refurbish	$[(b_5,0)(b_5,0)]$	$[(b_4,0)(b_6,0)]$	$[(b_5,0)(b_5,0)]$	$[(b_4,0)(b_4,0)]$	$[(b_4,0)(b_4,0)]$	$[(b_5,0)(b_5,0)]$	$[(b_5,0)(b_5,0)]$
	Remanufacture	$[(b_2,0)(b_2,0)]$	$[(b_1,0)(b_1,0)]$	$[(b_5,0)(b_5,0)]$	$[(b_2,0)(b_2,0)]$	$[(b_3,0)(b_3,0)]$	$[(b_2,0)(b_2,0)]$	$[(b_1,0)(b_2,0)]$
	Cannibalization	$[(b_1,0)(b_1,0)]$	$[(b_2,0)(b_2,0)]$	$[(b_2,0)(b_2,0)]$	$[(b_1,0)(b_1,0)]$	$[(b_2,0)(b_2,0)]$	$[(b_1,0)(b_2,0)]$	$[(b_1,0)(b_1,0)]$
	Recycle	$[(b_3,0)(b_3,0)]$	$[(b_3,0)(b_3,0)]$	$[(b_3,0)(b_5,0)]$	$[(b_2,0)(b_3,0)]$	$[(b_1,0)(b_1,0)]$	$[(b_3,0)(b_3,0)]$	$[(b_3,0)(b_4,0)]$
	Disposal	$[(b_0,0)(b_0,0)]$	$[(b_1,0)(b_1,0)]$	$[(b_0,0)(b_0,0)]$	$[(b_5,0)(b_5,0)]$	$[(b_0,0)(b_0,0)]$	$[(b_1,0)(b_1,0)]$	$[(b_0,0)(b_0,0)]$
EC3	Repair	$[(c_7,0)(c_8,0)]$	$[(c_7,0)(c_7,0)]$	$[(c_6,0)(c_7,0)]$	$[(c_7,0)(c_7,0)]$	$[(c_7,0)(c_7,0)]$	$[(c_8,0)(c_8,0)]$	$[(c_7,0)(c_7,0)]$
	Refurbish	$[(c_7,0)(c_7,0)]$	$[(c_6,0)(c_7,0)]$	$[(c_6,0)(c_6,0)]$	$[(c_6,0)(c_6,0)]$	$[(c_7,0)(c_7,0)]$	$[(c_7,0)(c_7,0)]$	$[(c_6,0)(c_6,0)]$
	Remanufacture	$[(c_3,0)(c_4,0)]$	$[(c_3,0)(c_3,0)]$	$[(c_7,0)(c_7,0)]$	$[(c_2,0)(c_2,0)]$	$[(c_5,0)(c_5,0)]$	$[(c_4,0)(c_4,0)]$	$[(c_2,0)(c_2,0)]$
	Cannibalization	$[(c_3,0)(c_3,0)]$	$[(c_2,0)(c_2,0)]$	$[(c_3,0)(c_3,0)]$	$[(c_3,0)(c_3,0)]$	$[(c_4,0)(c_4,0)]$	$[(c_3,0)(c_3,0)]$	$[(c_3,0)(c_3,0)]$
	Recycle	$[(c_5,0)(c_5,0)]$	$[(c_4,0)(c_4,0)]$	$[(c_4,0)(c_4,0)]$	$[(c_4,0)(c_4,0)]$	$[(c_3,0)(c_3,0)]$	$[(c_5,0)(c_5,0)]$	$[(c_5,0)(c_5,0)]$
	Disposal	$[(c_1,0)(c_1,0)]$	$[(c_1,0)(c_1,0)]$	$[(c_2,0)(c_2,0)]$	$[(c_4,0)(c_4,0)]$	$[(c_0,0)(c_0,0)]$	$[(c_1,0)(c_1,0)]$	$[(c_1,0)(c_1,0)]$

Table 7: 2-Tuple Criteria Weights and Aggregated Weights for SLC Return

Expert Committees	**Product Recovery Value**	**Marginal Value of Time**	**Processed Quality**	**Novel Resources Requisite**	**Environmental Aspect**	**Market Scenario**	**Profit**
EC1	$(e_5,0)$	$(e_5,0)$	$(e_4,0)$	$(e_2,0)$	$(e_4,0)$	$(e_6,0)$	$(e_6,0)$
EC2	$(e_6,0)$	$(e_4,0)$	$(e_3,0)$	$(e_3,0)$	$(e_3,0)$	$(e_6,0)$	$(e_5,0)$
EC3	$(e_4,0)$	$(e_3,0)$	$(e_4,0)$	$(e_3,0)$	$(e_2,0)$	$(e_5,0)$	$(e_6,0)$
Aggregated Weights	0.833	0.667	0.611	0.444	0.5	0.944	0.944

Step 3: The aggregated ITL assessment of recovery options and aggregated weights of the criteria are computed using Equations 2 and 3 and are given in Table 8 and Table 7, respectively.

Step 4: The comprehensive weighted ITL decision matrix is determined using Equation 4 and is shown in Table 9.

Table 8: Aggregated ITL Decision Table for SLC Return

End of Life Options	**Product Recovery Value**	**Marginal Value of Time**	**Processed Quality**	**Novel Resources Requisite**	**Environmental Aspect**	**Market Scenario**	**Profit**
Repair	Δ[0.958, 1]	Δ[0.903,0.903]	Δ[0.778,0.875]	Δ[0.819,0.819]	Δ[0.903, 0.958]	Δ[0.944, 1]	Δ[0.903,0.903]
Refurbish	Δ[0.819, 0.819]	Δ[0.722,0.875]	Δ[0.778,0.778]	Δ[0.639,0.639]	Δ[0.0.681,0.847]	Δ[0.819,0.903]	Δ[0.778,0.861]
Remanufacture	Δ[0.319, 0.444]	Δ[0.264,0.264]	Δ[0.903,0.903]	Δ[0.194,0.278]	Δ[0.458, 0.625]	Δ[0.361,0.361]	Δ[0.222,0.278]
Cannibalization	Δ[0.264, 0.264]	Δ[0.278,0.278]	Δ[0.319,0.319]	Δ[0.264,0.264]	Δ[0.361, 0.528]	Δ[0.264,0.319]	Δ[0.264,0.264]
Recycle	Δ[0.542, 0.542]	Δ[0.500,0.500]	Δ[0.583,0.694]	Δ[0.444,0.500]	Δ[0.264, 0.264]	Δ[0.542,0.542]	Δ[0.542,0.597]
Disposal	Δ[0.042, 0.042]	Δ[0.097,0.097]	Δ[0.167,0.167]	Δ[0.694,0.694]	Δ[0, 0]	Δ[0.097,0.097]	Δ[0.042,0.042]

Table 9: Weighted ITL Decision Table for SLC Return

End of Life Options	Product Recovery Value	Marginal Value of Time	Processed Quality	Novel Resources Requisite	Environmental Aspect	Market Scenario	Profit
Repair	Δ[0.798, 0.833]	Δ[0.602,0.602]	Δ[0.476,0.535]	Δ[0.364,0.364]	Δ[0.452,0.479]	Δ[0.891,0.944]	Δ[0.852,0.852]
Refurbish	Δ[0.682, 0.682]	Δ[0.482,0.584]	Δ[0.475,0.475]	Δ[0.284,0.284]	Δ[0.340,0.424]	Δ[0.773,0.852]	Δ[0.734,0.813]
Remanufacture	Δ[0.266, 0.370]	Δ[0.176,0.176]	Δ[0.552,0.552]	Δ[0.086,0.123]	Δ[0.229,0.313]	Δ[0.341,0.341]	Δ[0.210,0.262]
Cannibalization	Δ[0.220, 0.220]	Δ[0.185,0.185]	Δ[0.195,0.195]	Δ[0.117,0.117]	Δ[0.181,0.264]	Δ[0.249,0.301]	Δ[0.249,0.249]
Recycle	Δ[0.451, 0.451]	Δ[0.334,0.334]	Δ[0.356,0.424]	Δ[0.197,0.222]	Δ[0.132,0.132]	Δ[0.512,0.512]	Δ[0.512,0.564]
Disposal	Δ[0.042, 0.035]	Δ[0.065,0.065]	Δ[0.102,0.102]	Δ[0.308,0.308]	Δ[0, 0]	Δ[0.092,0.092]	Δ[0.040,0.040]

Step 5: The 2-tuple linguistic positive-ideal solution A^+ and 2-tuple linguistic negative-ideal solution $A^-$are determined with the help of Equations 5 – 7 and are given below:

$$A^+ = [\Delta(0.833), \Delta(0.602), \Delta(0.552), \Delta(0.364), \Delta(0.479), \Delta(0.944), \Delta(0.852)] \quad (11)$$

$$A^- = [\Delta(0.042), \Delta(0.065), \Delta(0.102), \Delta(0.086), \Delta(0), \Delta(0.092), \Delta(0.040)] \quad (12)$$

Step 6: The separation measures, D^+ and D^-, for each alternative with respect to the positive-ideal and negative-ideal solutions (Equation 11-12) are computed using Equations 8-9 and are shown in Table 10.

Step 7: The closeness coefficients for each alternative are calculated with Equation 10 and are shown in Table 10.

Table 10: Separation Measures and Closeness Coefficients for SLC Return

End of Life Options	D_i^+	D_i^-	RC_i^+	Rank
Repair	0.135	2.318	0.945	1
Refurbish	0.401	2.009	0.834	2
Remanufacture	1.616	0.970	0.375	4
Cannibalization	1.799	0.608	0.253	5
Recycle	1.1623	1.25	0.518	3
Disposal	2.341	0.314	0.118	6

Step 8: The ranking of recovery options for a two-year-old mobile phone (considered as SLC product) is determined based on the relative closeness coefficient, and the results obtained are as follows:

Repair >Refurbish>Recycle>Remanufacture>Cannibalization>Disposal (13)

It can be deduced from the results that repair is the most feasible recovery option followed by refurbish, resale and so on.

4.3 Case II: Real-World Application of the Model in Recovery Decision-making for LLC Returns

This section illustrates the recovery decision-making process for heavy LLC electronic consumer durables such as air-conditioners, refrigerators, and washing machines. Commonly, heavy consumer electronic durables are believed to have a lifespan of about 15-20 years. For the sake of comparison, in this case, we investigate the recovery options for an LLC electronic product (air-conditioner), which has been returned after two years' usage. We therefore consider the same usage span of two years for both LLC and SLC returns so that after the analysis, the priority order within the portfolio of recovery strategies can be compared for returned products of different life-cycles. Doing so will help us to understand whether the recovery strategy for SLC and LLC returns used for the same period would be similar or different. Had we covered different usage spans, such a comparison would not be feasible as the condition of returned product is likely to vary according to the duration of usage. In the second case, similar to the previous case, focus group sessions were conducted with three expert committees comprising three to four experts to obtain data to enable the assessment of reprocessing options. In this case, expert committees are made up of representative from three multinational organisations in the Indian electronics sector. Two of the organisations are similar to the one considered in the case of SLC returns, while the other is a multinational electronics company with a turnover of about USD 1 billion and about 10,000working employees. The data were collected in a similar manner as explained in the previous section for SLC returns. The inputs of expert committees are represented asEC_1', EC_2' andEC_3' respectively. The importance of all decision-makers is considered to be equal in this case too. Furthermore, based on the experts' inputs, the most suitable recovery option is determined for the LLC electronic returns through the ITL-TOPSIS methodology using data from the Indian context likewise in the previous section.

The assessment of recovery options with respect to each of the criteria and the significance of each of the criteria as outlined by the expert committees for the LLC returns are given in Table 11 and Table 12, respectively. In terms of profit criteria, calculations are performed for each recovery option with the help of data provided by a vendor dealing in the reprocessing of the considered product return. The expert committees EC_1', EC_2' and EC_3'have used the linguistic term sets $A', B' and\ C'$ respectively to analyse reprocessing options and linguistic term set $D'$when deciding the weights of each criterion as follows:

A' (EC_1') → [a_0=Very Poor (VP), a_1= Poor (P), a_2=Fair (F), a_3=Good (G), a_4=Very Good (VG)]

B'(EC_2') → [b_0=Very Poor (VP), b_1= Poor (P), b_2= Moderately Poor (MP),b_3=Fair (F),b_4= Moderately Good (MG), b_5= Good (G), b_6=Very Good (VG)]

C' (EC_3')→[c_0=Extremely Poor (EP),c_1= Very Poor (VP),c_2= Poor (P),c_3= Moderately Poor (MP), c_4=Fair (F), c_5= Moderately Good (MG), c_6= Good (G), c_7= Very Good (VG), c_8= Extremely Good (EG)]

D' (Weights) → [d_0=Very Low(VL),d_1= Low(L), d_2= Medium Low(ML), d_3=Medium(M), d_4= Medium High(MH), d_5= High(H), d_6=Very High(VH)]

Table 11: Linguistic Decision Table for LLC Return

Expert Committees	**End of Life Options**	**Product Recovery Value**	**Marginal Value of Time**	**Processed Quality**	**Novel Resources Requisite**	**Environmental Aspect**	**Market Scenario**
EC_1'	Repair	G	G-VG	VP-P	F-G	F-VG	F
	Refurbish	F-G	G-VG	P-F	F	F-VG	P-F
	Remanufacture	F	P	VG	VP-P	P-G	G-VG
	Cannibalization	P	F	F	P	P-G	P-G
	Recycle	P-VP	-	G	VP	P-VP	P
	Disposal	VP	-	-	VG	VP	VP
EC_2'	Repair	MG	F-G	VP	G	G	MG
	Refurbish	F-G	MP-MG	MP	MG	MG	MP
	Remanufacture	F	P-MP	G-VG	VP-MP	F	G
	Cannibalization	P-MP	P-MP	P-F	P	F-MG	F
	Recycle	P	P-F	MG-VG	VP	P	F
	Disposal	VP	-	-	G	VP	P
EC_3'	Repair	VG	G-VG	P	G	VG	F
	Refurbish	G	MG	F	F	G	MG
	Remanufacture	MG	MP	VG-EG	P	MP	VG
	Cannibalization	MP	F	F-MG	MP	F	G
	Recycle	VP	MP-VP	F-VG	VP	P	MP
	Disposal	EP	VP	-	VG	EP	VP

Table 12: Assigned and Aggregated Criteria Weights for LLC Return

Expert Committees	Product Recovery Value	Marginal Value of Time	Processed Quality	Novel Resources Requisite	Environmental Aspect	Market Scenario	Profit
EC_1'	MH	M	ML	L	L	H	VH
EC_2'	VH	ML	MH	M	M	H	VH
EC_3'	H	M	M	ML	ML	VH	H
Aggregated Weights	0.833	0.444	0.5	0.333	0.333	0.888	0.944

The information regarding the eight main components of the product return (air conditioner) and their assembly and disassembly costs (calculated with the help of equations presented in Table 1) are shown in Table 13. The reprocessing cost associated with each recovery option for the considered LLC return calculated with the help of Table 1 and the associated profit (calculated with the help of Equation 1) is presented in Table 14. The detailed calculations for the same are shown in APPENDIX I. Furthermore, the calculated profit is normalized as per the traditional TOPSIS method (Hwang and Yoon, 1981) and is shown in Table 14.

Table 13: Information about the Eight Main Components of the LLC Product Return

Components	Price for New part (Rs)	Price for Second Hand Part (Rs)	Disassembly Cost (Rs)	Assembly Cost (Rs)
A	6500	1500	16.66	20.00
B	1200	250	8.33	8.33
C	1500	100	5.00	8.33
D	6500	2500	9.96	6.64
E	6500	2500	9.96	6.64
F	250	-	1.66	4.98
G	5000	1000	20.00	20.00
H	1500	-	6.66	10.00

Table 14: Profit Computation for Recovery Options for LLC Return

Recovery Options	Reprocessing Cost	Selling Price	Profit	Normalized Profit
Repair	363.10	7500	3086.90	0.432
Refurbish	1113.10	8000	2886.90	0.404
Remanufacture	4313.10	11000	2686.90	0.376
Cannibalization	578.21	7850	3271.79	0.458
Recycle	1578.21	6500	2271.79	0.318
Disposal	-	5000 (Scrap dealer)	1000	0.140

The linguistic assessment of the LLC product return and the decision criteria are converted into ITL variables and 2-tuple linguistic variables, respectively. The weighted ITL decision matrix computed for the LLC return is shown in Table 15.

Table 15: Weighted ITL Decision Table for LLC Return

End of Life Options	Product Recovery Value	Marginal Value of Time	Processed Quality	Novel Resources Requisite	Environmental Aspect	Market Scenario	Profit
Repair	Δ[0.728, 0.728]	Δ[0.295,0.400]	Δ[0.041,0.083]	Δ[0.231,0.258]	Δ[0.245,0.300]	Δ[0.492,0.492]	Δ[0.407]
Refurbish	Δ[0.485, 0.647]	Δ[0.252,0.338]	Δ[0.180,0.222]	Δ[0.184,0.184]	Δ[0.212,0.268]	Δ[0.356,0.431]	Δ[0.381]
Remanufacture	Δ[0.450, 0.450]	Δ[0.116,0.141]	Δ[0.451,0.500]	Δ[0.027,0.092]	Δ[0.124,0.180]	Δ[0.727,0.800]	Δ[0.354]
Cannibalization	Δ[0.219, 0.265]	Δ[0.172,0.197]	Δ[0.194,0.270]	Δ[0.087,0.087]	Δ[0.138,0.212]	Δ[0.444,0.591]	Δ[0.432]
Recycle	Δ[0.080, 0.149]	Δ[0.043,0.277]	Δ[0.319,0.437]	Δ[0.013,0.013]	Δ[0.045,0.074]	Δ[0.333,0.333]	Δ[0.300]
Disposal	Δ[0, 0]	Δ[0.018,0.314]	Δ[0,0.5]	Δ[0.300,0.300]	Δ[0, 0]	Δ[0.086,0.086]	Δ[0.132]

Furthermore, the 2-tuple linguistic positive-ideal solution $A^{+'}$ and 2-tuple linguistic negative-ideal solution $A^{-'}$ obtained for the LLC return with the help of Equations 5 – 7 are as follows:

$$A^{+'} = [\Delta(0.728),\Delta(0.400),\Delta(0.500),\Delta(0.258),\Delta(0.300),\Delta(0.800),\Delta(0.432)]$$

$$A^{-'} = [\Delta(0), \Delta(0.018), \Delta(0),\Delta(0.013), \Delta(0), \Delta(0.086), \Delta(0.132)]$$

The separation measures, D^+ and D^-, and the closeness coefficients of each alternative are calculated with Equations 8-9 and are given in Table 16.

Table 16: Separation Measure and Closeness Coefficient for LLC Return

End of Life Options	$\boldsymbol{D_i^+}$	$\boldsymbol{D_i^-}$	$\boldsymbol{RC_i^+}$	**Rank**
Repair	0.768	1.390	0.644	2
Refurbish	0.792	1.148	0.592	3
Remanufacture	0.665	1.380	0.674	1
Cannibalization	0.988	0.911	0.480	4
Recycle	1.274	0.738	0.367	5
Disposal	1.660	0.708	0.299	6

The obtained priority order of reprocessing options for an air-conditioner returned after a usage span of two years based on the descending order of closeness coefficients is as follows:

Remanufacture >Repair >Refurbish >Cannibalization>Recycle> Disposal (14)

It can be inferred from the results that for a returned LLC product with two years' usage, remanufacturing is the most feasible recovery option, followed by repair, refurbishment, and so on. Detailed discussions about the results and associated managerial implications are presented in the following sections.

To illustrate the effectiveness of the proposed ITL-TOPSIS approach, a solution for the problems defined in the above two cases is determined using fuzzy TOPSIS. For this purpose, first, the expert inputs, which are in different scales, are converted to a single five-point scale as the fuzzy approach does not support multi-granular scales. Based on the fuzzy-TOPSIS approach, the order of preference with regard to suitable recovery strategies is determined for returned SLC and LLC products, as presented in Table 17.

Table 17: Priority order of Recovery Strategies based on Fuzzy TOPSIS

End of Life Options	**SLC Returns**		**LLC Returns**	
	$\boldsymbol{RC_i^+}$	**Rank**	$\boldsymbol{RC_i^+}$	**Rank**
Repair	0.994	1	0.649	1
Refurbish	0.885	2	0.569	2
Remanufacture	0.370	4	0.548	3
Cannibalization	0.208	5	0.387	4
Recycle	0.540	3	0.249	5
Disposal	0.059	6	0.223	6

It can be observed from the results shown in Table 17 that, for SLC returns, the order of preference for recovery strategies obtained through fuzzy TOPSIS is similar to the one obtained using ITL-TOPSIS. However, the order of preference for strategies obtained for returned LLC products using fuzzy TOPSIS is different. This may be due to the fact that in the analysis of LLC returns, there is missing information with regard to a number of inputs. Also, the attribute profit is considered quantitatively and not as a qualitative criterion. The findings show that the fuzzy approach is insufficient to handle the missing information and multi-granular scales. Furthermore, the fuzzy approach works on the extension principle that results in a loss of information and inaccurate outcomes. Moreover, unlike ITL- TOPSIS, in fuzzy TOPSIS the final scores cannot be converted to the initial linguistic term set, which renders the understanding of results more complicated. Accordingly, it can be inferred that the ITL-TOPSIS-based approach can serve as a better model in situations where information is uncertain and/or incomplete.

5. Results

Exponential growth in technology and improved standards of living have led to a significant increase in the use of electronic products. As a result, the number of electronic returns is escalating at an alarming rate, and the lack of efficient recovery channels is resulting in wastage of resources and environmental degradation (Ullah & Sarkar, 2020), which impedes the main objectives of the CE. Furthermore, products have different life-cycles, and thus the returns do not have identical qualities and conditions. Hence, for returns with varying life-cycles, unique recovery plans are required. Accordingly, in this study, a decision-making model has been developed for the selection of an appropriate recovery strategy that can facilitate efficient value reclamation from electronic returns with different life-cycles (i.e. LLC and SLC electronic returns).

There are always uncertainties associated with the condition, quality, type, and remaining life of returned products, which makes product recovery a challenging task in the context of a CE. Furthermore, many quantitative and qualitative approaches suffer from vagueness in recovery decision-making due to incomplete data sets or the unavailability of data articulated as exact numbers (Yang and Li, 2002; Ma 2015). Therefore, instead of methodologies requiring accurate data, linguistic assessment is preferred (Ma, 2015). Accordingly, we propose an integrated approach based on ITL and TOPSIS to solve the product recovery decision-making problem. The suggested methodology uses multi-granular linguistic scales for the analysis and allows experts to provide fragmentary inputs and to express their assessments in range form to overcome the uncertainty issues.

The comparison of the order of preference for recovery options as presented in Equations 13&14 shows that repair is the most feasible recovery option for SLC returns with high value erosion rates. Similarly, remanufacture is the most appropriate recovery strategy for LLC returns. Commonly, light electronic consumer durables such as mobile phones, laptops, and computers have a short lifespan and become obsolete frequently. Accordingly, it is necessary to reprocess these time-sensitive returns as a priority so that they can be put up on the secondary market as soon as possible for maximum value reclamation. Therefore, repairing SLC returns to bring them into working condition is the most suitable strategy, as this requires less time and reduces the environmental impact. The outcome here is consistent with earlier research suggesting that a slow recovery of SLC returns in a CE can result in a loss of 10% of total product value (Guide et al., 2006).

On the other hand, heavy electronic consumer durables such as vacuum cleaners, air-conditioners, and washing machines have a comparatively long lifespan. Hence, remanufacturing the returned LLC products to bring them to a similar level of new products (in terms of working efficiency, appearance, warranty, packaging, etc.) is the best recovery option to profitably compete on the market. This finding is in line with previous studies, which suggested that remanufacturing has environmental and economic benefits for industries as well as customers, especially in the case of electronic products with a long life-cycle (Cho, 2016; Ma et al., 2015; Fahrani, 2019). Remanufacturing is the most sustainable recovery approach as it extends the product life-cycle and retains the highest residual value with minimum toxic potential while maintaining the geometrical form of the returned product (Lee, 2010; Ma et al., 2015).

Upon further analysis of the results, it can be inferred that in terms of profit and market scenario, repair is the better approach for SLC returns in comparison with the other options. This may be due to the fact that for SLC returns time is of the essence from both a market and profit perspective, and repair strategy is the most efficient in that aspect. Meanwhile, cannibalisation and recycling are among the least preferred recovery strategies for SLC returns due to their time-sensitivity. In the case of LLC returns, cannibalisation derives the maximum profit as most parts of a two-year-old LLC product would still be in good working condition and could be effectively used in other products as required. However, when it comes to the market scenario criterion, remanufacturing is the best recovery option for LLC returns. It can thus be observed that for both SLC and LLC returns, disposal is found to be the least preferred strategy due to the associated adverse environmental, social, and economic impacts. The findings here are based on the inputs of six expert committees from the Indian electronics industry and can be adapted for other electronic returns with similar life-cycles and characteristics. Furthermore, one of the aspects affecting recovery decision-making is the condition of the returned product, which has been captured by the PRV attribute in the analysis. Hence, the developed model can be adapted to determine the recovery strategy for any kind of returns.

6. Conclusion & Discussions

As an initial study to investigate the impact of product life-cycle on recovery decision-making, this study is highly timely and significant given the growing recognition of a CE, especially in the electronics industry. To address the postulated research questions, this study has dealt with the conflicting paradigm of managing recovery operations for SLC and LLC returns while considering the contradictory objective of synchronising economic and environmental benefits simultaneously in a CE.

A two-phase decision-making model to facilitate recovery decision-making in a CE has been developed using the ITL representation model and TOPSIS. The proposed model incorporates the uncertainty and diversity of decision-makers' assessments and is thus more pragmatic than previous efforts in the existing literature. The ITL-TOPSIS-based approach is more precise in linguistic information processing and could present the results in the initial expression domain without any information loss, unlike other conventional techniques. The results have indicated that repair is the optimal recovery strategy for SLC returns with fast value erosion rates, while for LLC returns with slow value erosion rates, remanufacturing is the best-suited option. Our results have significant managerial and theoretical implications.

6.1 Theoretical Implications

This study addresses two imperative research questions related to the life cycle of returns and economic-environmental trade-off in recovery decision making and thereby makes the following theoretical contributions to the existing CE literature. Firstly, this study proposes a comprehensive recovery decision-making model that takes into consideration a wide range of dimensions, synchronising economic and environmental aspects. Most of the existing research until now has been based on cost-benefit analysis only and has not focused on product life-cycle, usage duration, and other aspects of product returns during recovery strategy selection. This study therefore contributes by incorporating the suggestions of some recent studies to include environmental aspects during recovery decision-making (Jiang et al., 2019). Secondly, our research overcomes many of the limitations of the existing literature. Indeed, it is one of the first studies to conceptualise and differentiate recovery decision-making for SLC and LLC returns in a CE. It determines the most optimal recovery strategy for SLC and LLC returns independently, and compares the order of preference for both. Thirdly, the applicability and convenience of the developed ITL-TOPSIS-based model has been demonstrated for recovery decision-making in a CE. The model is generic and can be adapted to determine the recovery strategy for any kind of returns, unlike most of the available models in the literature, which have been developed for particular products (Jiang et al., 2019; Ziout et al., 2014). The proposed model considers the uncertainty and lack of information associated with returns in a CE.

6.2 Managerial Implications

This research offers numerous useful insights related to a CE for managers, policymakers, and investors. Firstly, one of the key implications for managers is that they need to develop different recovery strategies to manage SLC and LLC returns in a CE to attain more sustainable performance. It is evident from the results that the most suitable recovery strategy for SLC returns could be different from that for LLC returns. Secondly, the proposed model will help managers to strike a balance between economic and environmental trade-offs by considering a wide range of contradictory criteria, facilitating the development of sustainability capabilities in a CE. This outcome is aligned with the CE literature to have suggested that applying only the economic perspective is not a suitable way of managing returns (Guide et al., 2009). Thirdly, as suggested by Guide et al. (2009), instead of being complicated, models need to provide practical solutions. Pertinently, the proposed decision-making model can be adapted according to organisational requirements and developed into a platform with a simple user interface. This would facilitate timely decision-making for different life-cycle returns, taking into account various perspectives, which is necessary as delays often lead to maximum value being lost on returns. Finally, the findings present an order of preference in the portfolio of strategies for SLC and LLC electronics returns, synchronising both economic and environmental benefits. It serves as a call to action for managers to better manage returns and to avoid the possibly harmful consequences of neglecting environmental aspects such as customer backlash, product boycott, decreased share value, and government-imposed penalties.

Furthermore, the research provides encouragement for policymakers to indirectly influence the sustainability benefits of a CE by differentiating policies for SLC and LLC returns. Policies should ensure that organisations consider environmental aspects in CE operations rather than just focusing on profit. Such an approach could be promoted by offering benefits in the form of subsidies, public recognition, and technical support to the organisations that do take into consideration sustainability aspects in line with the proposed recovery decision-making framework. Policymakers need to ensure seamless integration between policy formulation and implementation, especially in the CE domain, by putting relevant checkpoints in place. Finally, the findings could be insightful for investors who are advised to screen organisations with regard to their sustainability focus in a CE and their compliance with environmental regulations.

6.3 Limitations of Current Research and Suggestions for Future Research

The research adds value to the CE knowledge pool and provides a foundational framework upon which to extend work in a very promising area of recovery decision-making. However, the study has a few limitations, which ought to be considered and overcome in any future research. First, our study is based on the Indian electronics sector as most returned products are from this sector. The life-cycle of products and other aspects would of course be different for returns in other sectors. Future research could determine suitable recovery strategies for returns in other sectors using the proposed comprehensive framework. Second, we have extensively covered economic and environmental aspects only for recovery decision-making. Although the considered attributes cover social aspects as well implicitly, future research could more explicitly include the societal impact of recovery strategies during decision-making in a CE. Third, this study has been conducted exclusively in the context of India, a developing economy. A similar study could be conducted for developed economies and the findings therefrom could be compared to glean better insights that could help the developing economies in their CE implementation. Finally, we have not considered risk aspects during recovery decision-making, which could be explored in future research.

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APPENDIX I

The information regarding the disassembly and assembly timings of various parts of the white product as provided by the vendor and the calculated costs for the same are given below in Table 17. The Labor charge is Rs 100/hr. As from Table 1:

C(disassembly) = Labor cost x time (disassembly)
C(reassembly) = Labor cost x time (reassembly)

Table 18: Information for parts of returned white product

Parts	Disassembly time (Min)	Assembly time(Min)	Disassembly cost (Rs)	Assembly cost (Rs)

A	10	12	16.66	19.99
B	5	5	8.33	8.33
C	3	5	4.99	8.33
D	6	4	9.96	6.64
E	6	4	9.96	6.64
F	1	3	1.66	4.98
G	12	12	19.99	19.99
H	4	6	6.66	10.00
			78.21	84.89

The reprocessing cost for all the considered EOL options is calculated with the help of Table 1 as shown below in Table 18.

Table 19: Reprocessing Cost of EOL Options

Recovery Options	**Cost of Reprocessing**
Resale	No reprocessing is required therefore, Cost (resale) = Zero.
Repair	Cost (repair) = C(disassembly) + C(fixing) + C(reassembly) + C(testing) = 78.31 + 200 + 84.89 + 50 = 363.10
Refurbish	Cost (refurbish) = C(disassembly) + C(refurbishing) + C(reassembly) + C(testing) = 78.31 + 900 + 84.89 + 50 = 1113.10
Remanufacturing	Cost (remanufacture) = C(disassembly) + C(remanufacturing) + C(reassembly) + C(testing) + C(warranty) + C(packing) = 78.21 + 2300 + 84.89 + 100 + 1500 + 250 = 4313.10
Cannibalization	Cost (cannibalization) = C(disassembly) + C(recovering parts & cleaning) = 78.21 + 500 = 578.21
Recycle	Cost (recycle) = C(disassembly) + C(sorting) + C(recycling) = 78.21 + 1500 = 1578.21
Disposal	Sold to scrap dealer in Rs 5000 without any work so Cost = 0

The profit is calculated according to Equation 1 as:

Profit (P) = Revenue (R) – Cost (C)

Where, Revenue = Sales price of the reprocessed product/material – Buy back price of product from customers.

Table 20: Profit computation for EOL options

EOL options	Reprocessing Cost	Buy Back Price	Selling Price	profit
Resale	Zero	4000	7000	3000
Repair	363.10	4000	7500	3086.90
Refurbish	1113.10	4000	8000	2886.90

Remanufacture	4313.10	4000	11000	2686.90
Cannibalization	578.21	4000	7850	3271.79
Recycle	1578.21	4000	6500	2271.79
Disposal	Zero	4000	5000 (Scrap dealer)	1000