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Circular Economy Determinants in Electronics Supply Chain: A Pythagorean Fuzzy Clustering Approach

Samiksha Budakoti[1,*], Vishal Gupta[2]

[1]Research Scholar, JIIT, Sector-62, Noida, U.P. 201309, India; Asst. Prof., I.T.S, Ghaziabad, U.P. 201007, India

[2]Asst. Prof., JIIT, Sector-62, Noida, U.P. 201309, India

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Abstract

The realignment from traditional linear models to circular economy has become indispensable in Electronics industry of developing nations such as India. This transition is crucial to combat issues related to resource scarcity and burgeoning e-waste. This research seeks to determine and classify the pivotal determinants impacting circular economy assimilation in India's electronics supply chain. An extensive literature review coupled with feedback from industry and academic experts, identified twenty-three such determinants. These determinants were integrated with six supply chain stages in order to develop a structured questionnaire. A five-point linguistic scale was used in the questionnaire to gather expert responses on each determinant-stage combination. The experts' responses were then converted to Pythagorean fuzzy numbers for quantitative analysis of the information. Using multi-criteria decision-making framework involving aggregation, score function and normalization, a de-fuzzified similarity matrix of determinants was obtained. Ward's method of agglomerative hierarchical clustering in RStudio was applied to the similarity matrix in order to obtain four different clusters of determinants. Strategic and technological determinants formed cluster 1; regulatory and resource-efficiency determinants were highlighted in cluster 2; cluster 3 reflected market and network drivers; macro-institutional and contextual determinants were represented in cluster 4. These clusters together indicate varied yet interconnected determinants affecting implementation of circular economy practices in India's electronics supply chain. The robustness of the study was also validated by performing sensitivity analysis of the results. This analysis resulted in a mean Adjusted Rand Index of 0.862 reflecting a high degree of consistency in the analytical results. By integrating two robust quantitative methodologies, this research introduces a novel empirical framework for classification of circular economy determinants. This study can aid policymakers, industry practitioners and academicians to formulate coordinated measures for circular economy adoption in India's electronics supply chains.

Keywords: Circular Economy, Supply Chain, Clustering, Determinants, Electronics, MCDM

1. Introduction

The electronics sector has observed substantial growth in the recent past. The sector is widely acknowledged for its contribution in supporting economic development, especially in emerging economies like India [1], [2], [3]. The substantial growth in the use of consumer and industrial electronic items can be attributed to growing population & urbanization, rising incomes and technological evolution [4]. Although this advancement has contributed positively to the economic transformation in the form of rising GDP and employment levels, yet the concerns related to resource scarcity and surmounting e-waste are alarming [5]. Electronic items comprise of both valuable and hazardous components. While appropriate extraction of valuable components is important to ensure resource efficiency, inadequate management of hazardous materials after End-of-Life product can pose serious environmental threat in countries where unorganized recycling mechanisms still exist [6], [7]. Traditional "take-make-dispose" models do not account for ecological concerns related to environment & resource degradation and hence these approaches are unsustainable in the long run [8]. Consequently, circular economy (CE) models offer a viable substitute by addressing these issues through the adoption of 10R principles i.e. "Refuse, Rethink, Reduce, Reuse, Repair, Refurbish, Remanufacture, Repurpose, Recycle and Recover" [9], [10]. Using CE approaches in electronics supply chain (ESC) supports material recovery, thus lowering the dependence on virgin materials and significantly mitigating ecological

*Corresponding author: Samiksha Budakoti (bsamiksha003@gmail.com)
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footprint through resource efficiency [11]. A large number of interrelated determinants affect the integration of CE practices in ESC [12]. Studies on drivers and barriers impacting implementation of CE especially in manufacturing sectors have been carried out in the past [13], [14]. However, existing research often look at the factors individually or in isolated segments which limits the understanding of their overall interaction across all stages of a supply chain (SC) [7], [15]. Assessing multiple connected factors across SC stages is a complex phenomenon involving uncertainty and subjectivity. Multi-criteria decision making (MCDM) and clustering approaches can be suitable methods in this contextual setting [16], [17], [18], [19].

This study attempts to ascertain and categorize the principal determinants influencing CE adoption in India's ESC. Twenty-three determinants of CE adoption were identified through a detailed literature review which were then aligned with six stages of ESC. A structured questionnaire was used to collect expert responses in the form of linguistic ratings. These linguistic variables were mapped to Pythagorean fuzzy (PF) numbers to obtain PF decision matrices corresponding to each expert's evaluation. These matrices were combined into an aggregated decision matrix which was then de-fuzzified to obtain a normalized decision matrix. Using Ward's method of Agglomerative Hierarchical Clustering (AHC) on the normalized matrix, four coherent clusters of determinants were attained. The clusters present a clear and organized view of how technological & organizational, regulatory, market, and macro-institutional determinants come together to influence CE outcomes. With the integration of PF MCDM and AHC, this research provides an empirical classification of CE determinants supporting decision makers design unified courses of action for CE adoption in India's ESCs.

2. Literature Review

The literature suggests that CE practices are important for developing countries, where rapid industrial growth has increased waste and environmental problems [20]. Research on CE in the electronics sector, particularly in India, largely emphasizes ranking factors, with limited efforts to organize them into meaningful clusters under uncertainty [21]. The extant literature on CE in the electronics sector provides limited empirical validation and lacks clear frameworks to guide implementation [22]. Previous studies have highlighted the potential of fuzzy clustering, but its use in the Indian electronics supply chain is still limited [23].

The initial set of factors for CE implementation was identified through a review of literature on CE, sustainable SCs, and e-waste/WEEE management. Relevant studies were collected from databases such as Google Scholar, Scopus, Web of Science, and ScienceDirect using keywords including "circular economy," "electronics industry," "electronics supply chain," "critical success factors," "drivers," "enablers," and "determinants". Retrieved articles were evaluated against predefined inclusion criteria, namely relevance to circular economy implementation, identification of adoption factors, and publication in peer-reviewed journals. The screening process excluded duplicate entries, non-English publications, conference abstracts, editorials, and studies lacking direct relevance to the study. The initial review identified a broad set of 39 determinants. To avoid repetition, determinants with comparable meanings or definitions were grouped together. The refined list was validated by domain experts from academia and industry with experience in circular economy and electronics supply chain management. As a result, 23 determinants were selected and mapped to six stages of the ESC. The CE determinants were labelled CE1 to CE23 and six SC stages were labelled S1 to S6 for ease of identification. The 23 determinants are illustrated in table 1 with a brief description of all the determinants.

Table 1. Determinants of CE adoption in India's Electronics supply chains.

Label	Determinant	Description	Reference(s)
CE1	Government policies and regulations	Strong, clear, and enforced policies, including eco-labelling, tax incentives, design standards, and green procurement (e.g. EPR regulations, E-Waste (Management) Rules,2022)	[1], [24], [25], [26]
CE2	Economic Incentives and subsidies	Availability of funding, financial incentives, such as subsidies and tax breaks	[1], [24], [26]
CE3	Extended Producer Responsibility (EPR)	Enforcing producer accountability for end-of-life product management	[27]
CE4	Competitive advantage	Reputation & brand image, open global markets, and cost benefits	[28], [29]
CE5	Consumer demand and awareness	Growing consumer preference for sustainable products and increased awareness	[24]
CE6	Digital technologies/ Technological advancement	Adoption of Industry 4.0 technologies	[30]
CE7	Innovation	Development and adoption of novel ideas, technologies, business models, and processes.	[1]

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CE8	Stakeholder collaboration	Partnerships across supply chains, including with informal sectors, NGOs, and government	[1], [21], [25], [28]
CE9	Knowledge sharing and training	Platforms for sharing best practices and workforce upskilling	[26]
CE10	Management commitment and leadership	Top management support and strategic alignment with CE goals	[26], [31]
CE11	Awareness campaigns	Public education and awareness initiatives that foster behavioral change	[21], [32], [33]
CE12	Environmental management systems	A structured framework helping organizations systematically manage their environmental impacts, reduce waste, improve efficiency, and ensure legal compliance	[1]
CE13	Reverse logistics infrastructure	Efficient systems for collecting, sorting, and processing e-waste	[34]
CE14	Supply chain integration	Both vertical and horizontal integration with partners and customers.	[30], [35]
CE15	Organizational agility and collaboration	Flexible, collaborative approaches among stakeholders	[36]
CE16	Cultural enablers	Motivated leadership and a strong environmental culture within organizations	[29]
CE17	Environmental standards and certification	Confirming compliance with the rules or benchmarks	[16], [28], [32]
CE18	Investment recovery	Ability to recoup value and financial returns from used, obsolete, excess, or discarded assets and materials	[26], [33]
CE19	Information sharing along value network	Systematic, timely, and accurate exchange of relevant data, knowledge, and operational information among all interconnected stakeholders in a value chain or supply network.	[37]
CE20	Population and Urbanization	Influence of increasing population size and density (especially in urban areas) on the demand for resources.	[32], [38], [39]
CE21	Job creation opportunities	Potential to generate new employment positions for individuals.	[40]
CE22	Global sustainability goals and commitment	Extent to which organizations embrace and act upon international sustainability frameworks—such as the United Nations SDGs, ESG standards.	[1], [25]
CE23	Potential to optimize resource usage	Maximizing resource efficiency and minimizing virgin inputs without compromising output.	[15]

The 6 stages of SC adopted in this study are demonstrated in table 2.

Table 2. Stages in a supply chain (Adapted from [41]).

Label	Supply Chain stage
S1	Conceptualization/Planning
S2	Design
S3	Sourcing & Manufacturing
S4	Distribution & Use
S5	Collection & Return
S6	Recovery & Processing

3. Methodology

This study adopts an exploratory quantitative method to determine and group the parameters driving CE practices in India’s ESC. Figure 1 depicts the flowchart of the methodology adopted in this research. The flowchart presents the complete research framework by illustrating the logical sequence of the methodological stages undertaken to achieve the study objectives. The study employed purposive sampling to include five experts—four from industry and one academic having expertise in the relevant domain, to represent both practical and theoretical viewpoints. In PF and linguistic MCDM applications, the use of small expert panels, usually consisting of 3–6 members, is a standard practice [19]. The experts are usually highly experienced professionals who are carefully selected to capture their expert judgements for group decision making [42]. All the experts included in this study possess more than 25 years of experience in the pertinent field. Senior industry professionals were selected because of their direct involvement in key business functions, making them well suited to evaluate the practical importance of the determinants. The academic expert contributed theoretical and research-based insights, helping to complement and balance the industry perspectives. To ensure adequate representation of perspectives across India's electronics supply chain, the industry experts were purposefully selected from diverse functional domains, including engineering, delivery, quality/waste management, program management and possessed complementary expertise in sustainability and circular economy practices. Senior managers/Heads of departments working in organizations that are members of India Cellular & Electronics Association (ICEA) were contacted to identify suitable industry experts. “ICEA is the principal industry body representing the electronics industry in India” [43]. One senior professor working as Area Chair of Operations & Supply Chain Management in a leading University of India was also included as an expert in the study.

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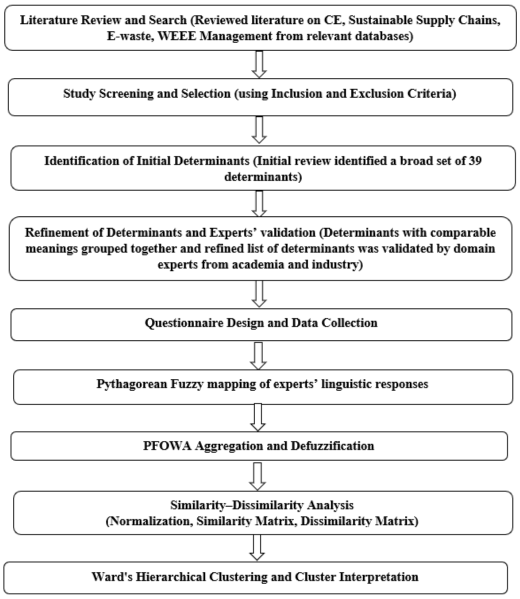

Figure 1. Flowchart of the proposed methodology

A structured questionnaire was then developed to collect expert evaluations of each determinant at different SC stages using a five-point linguistic scale ("Very Low (VL)," "Low (L)," "Medium (M)," "High (H)," and "Very High (VH)"). The questionnaire was administered individually to the experts via e-mail, and each expert independently provided linguistic assessments based on their knowledge and experience. The completed questionnaires were subsequently returned via e-mail for analysis. This approach ensured independent expert evaluations and mitigated potential bias arising from group interactions. In research, linguistic scales are typically used to capture qualitative judgments which are characterized by imprecision and vagueness [44]. These linguistic ratings were then mapped to PF numbers to quantify the expert judgements for further analysis. The PF numbers mapped to the linguistic terms are shown in table 3.

Table 3. Pythagorean fuzzy numbers corresponding to linguistic terms (Adapted from [48]).

Linguistic term	Abbreviation	Pythagorean fuzzy number
Very Low	VL	(0.1, 0.9)
Low	L	(0.3, 0.8)
Medium	M	(0.5, 0.6)
High	H	(0.7, 0.4)
Very High	VH	(0.9, 0.1)

The linguistic-to-PF mapping was adapted from [48] a commonly used framework in the literature. The adopted scale satisfies the mathematical properties of PF sets while ensuring methodological consistency and comparability with previous studies. PF numbers are suitable for dealing with uncertainty and subjectivity in expert opinions. While intuitionistic fuzzy sets become invalid when the combined membership and non-membership degrees exceed one, PF sets address this limitation of intuitionistic fuzzy sets by allowing greater flexibility in membership and non-membership values [45]. PF sets are represented in the (μ, ν) format where each linguistic term is characterized by a membership value (μ) and a non-membership value (ν) satisfying the condition $\mu^2 + \nu^2 \leq 1$ [46]. PF sets are widely preferred over intuitionistic, interval-valued intuitionistic, and standard hesitant fuzzy sets owing to their greater flexibility, broader representational power, and improved capability to model uncertainty in multi-criteria decision-making contexts [47].

Each linguistic label was assigned a PF number resulting in a 23×6 decision matrix corresponding to each expert's evaluation. Thereafter, the five decision matrices were combined to generate an aggregated evaluation matrix. Each expert was given an equal weight of 0.2 in the analysis. All experts received the same weight as they fulfilled the predefined selection criteria, had more than 25 years of experience and possessed comparable levels of experience and expertise. Although the experts represented different functional domains, their expertise was considered complementary, with no objective basis for assigning differential importance. Therefore, equal weights were assigned to ensure balanced representation of expert opinions and to minimize subjectivity.

"The PF ordered weighted averaging operator" developed by Zhang [46] is applied to aggregate the information from the five experts, using (2). Before applying the PFOWA operator, the individual PF evaluations provided by the experts were ordered according to their score values in descending order. For a PFN $\beta_j = P\left(\mu_{\beta_j}, \nu_{\beta_j}\right)$, the score value is given by:

$$s(\beta_j) = \mu_{\beta_j}{}^2 - \nu_{\beta_j}{}^2 \tag{1}$$

The ordered evaluations were then combined using the PFOWA operator and the assigned expert weights. Definition: Let $\beta_j = P\left(\mu_{\beta_j}, \nu_{\beta_j}\right)$, $j = 1,2,\dots,n$, be a set of Pythagorean Fuzzy Numbers (PFNs). A Pythagorean Fuzzy Ordered Weighted Averaging (PFOWA) operator of dimension n is defined as follows:

$$\begin{aligned} PFOWA(\beta_1, \beta_2, \dots, \beta_n) &= w_1\beta_{\sigma(1)} \oplus w_2\beta_{\sigma(2)} \oplus \dots \oplus w_n\beta_{\sigma(n)} \\ &= P\left(\sqrt{1 - \prod_{j=1}^{n}\left(1 - \mu^2_{\beta_{\sigma(j)}}\right)^{(w_j)}}, \prod_{j=1}^{n} \upsilon_{\beta_{\sigma(j)}}{}^{w_j}\right) \end{aligned} \tag{2}$$

w_j represents the degree of importance associated with β_j satisfying $w_j \geq 0$ ($j = 1,2,\dots,n$) and $\sum_{j=1}^{n} w_j = 1$, and $(\sigma(1), \sigma(2), \dots, \sigma(n))$ is a permutation of $(1, 2, \dots, n)$ such that $\beta_{\sigma(j-1)} \geq \beta_{\sigma(j)}$ ($j \in \{2, 3, \dots, n\}$" [46].

A sample calculation of the PFOWA aggregation process is presented below to enhance clarity:

Consider the expert evaluations: [P (0.7,0.4); P (0.5,0.6); P (0.7,0.4); P (0.7,0.4); P (0.7,0.4)]. The score values of each PF numbers computed using (1) are (0.33), (-0.11), (0.33), (0.33), and (0.33), respectively. Thus, the ordered PFNs are: [P (0.7,0.4); P (0.7,0.4); P (0.7,0.4); P (0.7,0.4); P (0.5,0.6)]. Applying the PFOWA operator with equal weights (W=(0.2,0.2,0.2,0.2,0.2)), the aggregated PFN is [P (0.67,0.43)] which is valid since [(0.67)2+(0.43)2=0.63<1].

The aggregated PF numbers were de-fuzzified into crisp values using a scoring mechanism commonly applied in fuzzy MCDM. The PF score function [48] used for analysis is presented below. "The score function matrix $R = (r_{ij})_{m\times n}$, where $i = 1,2,\dots,m$ and $j = 1,2,\dots,n$, is obtained for each PF number $p_{ij} = (\mu_{ij}, \nu_{ij})$ using (3).

$$r_{ij} = \mu_{ij}^2 - \nu_{ij}^2 - \ln(1 + \pi_{ij}^2) \tag{3}$$

$\pi_{ij} = \sqrt{1 - \mu_{ij}^2 - \nu_{ij}^2}$ represents the indeterminacy degree" (Source: [48]).

Using the normalization equation stated in (4), the score matrix R is converted into an orthonormal PF matrix $R' = (r'_{ij})_{m\times n}$

The normalized values for benefit criteria ($j \in B$) and cost criteria ($j \in C$) are calculated as follows.

$$\begin{cases} r'_{ij} = \dfrac{r_{ij} - r_j^-}{r_j^+ - r_j^-}, & j \in B \\ r'_{ij} = \dfrac{r_j^+ - r_{ij}}{r_j^+ - r_j^-}, & j \in C \end{cases} \tag{4}$$

$r_j^- = \min\limits_i r_{ij}$, $r_j^+ = \max\limits_i r_{ij}$ (Source: [48]).

For the purpose of normalization, all 23 determinants are treated as benefit-type criteria because they represent factors that positively contribute to the adoption of CE practices. Consequently, the higher the evaluation score, the more significant the determinant. Thus, only the benefit-type normalization formulation is utilized in the analysis. The cost-type normalization expression is included only to ensure methodological comprehensiveness.

The correlation coefficient for each pair of criteria is determined using (5). (Source: [48]). The correlation coefficient was used to measure the relationship between pairs of determinants based on their normalized evaluation values. It was chosen because the clustering analysis seeks to identify determinants with similar evaluation patterns, making it suitable for developing the similarity matrix used in hierarchical clustering.

$$\rho_{jk} = \frac{\sum_{i=1}^{m} \left(r'_{ij} - \overline{r_j}\right)\left(r'_{ik} - \overline{r_k}\right)}{\sqrt{\sum_{i=1}^{m} \left(r'_{ij} - \overline{r_j}\right)^2}\sqrt{\sum_{i=1}^{m} \left(r'_{ik} - \overline{r_k}\right)^2}} \tag{5}$$

After constructing the correlation-based similarity matrix, the similarity values were converted into dissimilarities using $d_{jk} = 1 - \rho_{jk}$, where ρ_{jk} represents the correlation coefficient between determinants $j$and k. This step was performed because Ward's hierarchical clustering algorithm operates on distance or dissimilarity values. The generated distance matrix served as the basis for grouping similar determinants through hierarchical clustering.

In complex multi-criteria settings, hierarchical fuzzy clustering is often applied to find hidden structures and group similar features [49]. It enables the grouping of factors into clusters that collectively support CE implementation across the SC. This study applies Ward's method of agglomerative hierarchical clustering technique in RStudio to obtain coherent clusters of determinants. Ward's method is a bottom-up approach which starts with an observation merging it into a cluster [50]. This is done by minimizing variation within each cluster [51].

4. Results and Discussion

4.1. Results

This study combines PF-MCDM and Agglomerative Hierarchical Clustering to examine patterns among determinants related to CE adoption in India's ESC. It develops a data-driven classification of CE factors that handles uncertain expert inputs and uses hierarchical relationships to support effective decision-making.

Linguistic responses of each expert were converted into PF numbers using Linguistic-PF mapping. The five PF matrices corresponding to expert evaluation were combined using PF ordered weighted averaging operator from (2) to obtain the aggregated PF decision matrix. Excerpt of the aggregated matrix representing the combined evaluations of all the experts is depicted in table 4. Due to space constraints, table 4 to table 7 present only a representative excerpt of the dataset used in this study. The complete datasets can be accessed through the repository indicated in the Data Availability Statement presented in Section 6.2.

Table 4. Aggregate Pythagorean fuzzy decision matrix

	CE1	CE2	CE3	…	…	CE21	CE22	CE23
S1	(0.67, 0.43)	(0.67,0.41)	(0.53, 0.59)	…	…	(0.60, 0.50)	(0.70, 0.38)	(0.58, 0.54)
S2	(0.67, 0.43)	(0.69, 0.39)	(0.58, 0.54)	…	…	(0.47, 0.66)	(0.69, 0.40)	(0.74, 0.31)
S3	(0.72, 0.36)	(0.64, 0.47)	(0.74, 0.33)	…	…	(0.47, 0.64)	(0.64, 0.44)	(0.75, 0.29)
S4	(0.72, 0.36)	(0.72, 0.36)	(0.47, 0.64)	…	…	(0.47, 0.64)	(0.67, 0.41)	(0.69, 0.39)
S5	(0.81, 0.23)	(0.74, 0.33)	(0.77, 0.27)	…	…	(0.69, 0.39)	(0.76, 0.29)	(0.74, 0.33)
S6	(0.73, 0.35)	(0.72, 0.36)	(0.77, 0.27)	…	…	(0.74, 0.33)	(0.70, 0.38)	(0.85, 0.17)

The de-fuzzified matrix with crisp values obtained using (3) is demonstrated in table 5. The transition from ambiguous assessments to definitive scores is a standard component of fuzzy MCDM processes. This process is applied to convert aggregated PF numbers into distinct values.

Table 5. Defuzzied decision matrix

	CE1	CE2	CE3	…	…	CE21	CE22	CE23
S1	-0.0480	-0.0435	-0.3827	…	…	-0.2193	0.0340	-0.2715
S2	-0.0480	0.0079	-0.2715	…	…	-0.5100	0.0058	0.1467
S3	0.0872	-0.1257	0.1434	…	…	-0.5031	-0.1182	0.1758
S4	0.0872	0.0872	-0.5031	…	…	-0.5031	-0.0435	0.0079
S5	0.3478	0.1434	0.2317	…	…	0.0079	0.2021	0.1434
S6	0.1143	0.0872	0.2317	…	…	0.1434	0.0340	0.4716

Applying (4) to the de-fuzzified matrix resulted in the normalized score matrix as indicated in table 6. The process normalizes all criterion values to a common scale, typically ranging from 0 to 1, to ensure comparability and eliminate differences in measurement scales.

Table 6. Normalized score decision matrix.

	CE1	CE2	CE3	…	…	CE21	CE22	CE23
S1	0.0000	0.3057	0.1639	…	…	0.4449	0.4752	0.0000
S2	0.0000	0.4964	0.3153	…	…	0.0000	0.3870	0.5628
S3	0.3417	0.0000	0.8799	…	…	0.0105	0.0000	0.6019
S4	0.3417	0.7912	0.0000	…	…	0.0105	0.2333	0.3759
S5	1.0000	1.0000	1.0000	…	…	0.7926	1.0000	0.5584
S6	0.4101	0.7912	1.0000	…	…	1.0000	0.4752	1.0000

Equation (5) was applied on the normalized score matrix to attain the similarity matrix as presented in table 7. The similarity matrix demonstrates the correlation coefficient between each pair of determinants. It should be noted that the correlation matrix was primarily used to evaluate associations among determinants and aid clustering. Therefore, the negative correlations should be viewed as indicative of differing evaluation patterns rather than causal or mutually exclusive links. Such relationships show that the perceived influence of determinants can differ across contexts, demonstrating the diverse nature of CE adoption. The results show that the determinant groups reflect distinct viewpoints and priorities, justifying their categorization into separate clusters.

Table 7. Similarity/Correlation matrix.

	CE1	CE2	CE3	…	…	CE21	CE22	CE23
CE1	1.00	0.61	0.65	…	…	0.52	0.62	0.37
CE2	0.61	1.00	0.12	…	…	0.56	0.73	0.30
CE3	0.65	0.12	1.00	…	…	0.61	0.31	0.72
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
CE21	0.52	0.56	0.61	…	…	1.00	0.70	0.40
CE22	0.62	0.73	0.31	…	…	0.70	1.00	0.02
CE23	0.37	0.30	0.72	…	…	0.40	0.02	1.00

The distance matrix derived from the correlation matrix, as previously stated was used as an input for performing agglomerative hierarchical clustering. Ward's method was used in RStudio to obtain four clusters of determinants. To find the optimal number of clusters, Silhouette index for different cluster solutions was computed. Although the maximum Silhouette Index was observed for the two-cluster solution, the resulting partition was considered overly broad that overlooked important differences among the determinants and offered limited analytical detail. As a result, cluster selection considered both the Silhouette Index and the meaningfulness and practical usefulness of the resulting clusters. Therefore, the four-cluster solution, which had the next-highest Silhouette Index, was selected as it offered a more meaningful segmentation while preserving acceptable cluster quality. These clusters provide a more comprehensive understanding of circular economy determinants and were selected for further interpretation. The cluster dendrogram thus obtained is depicted in figure 2.

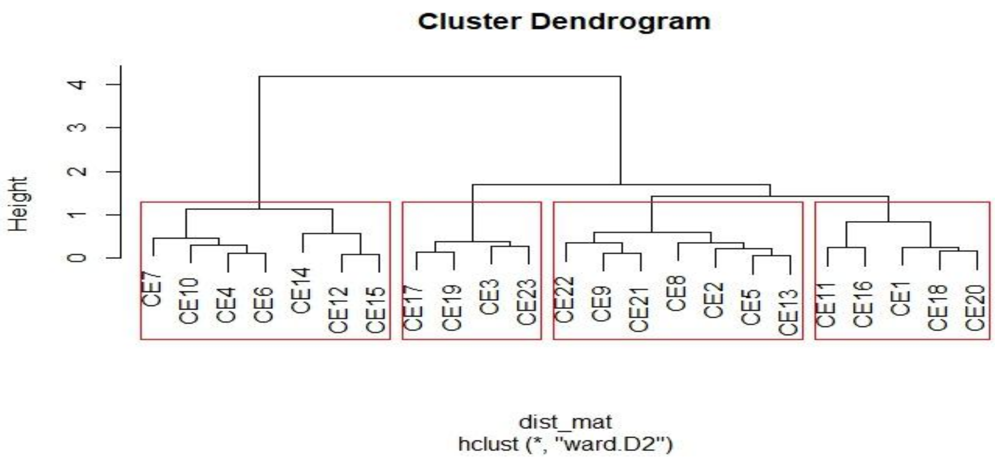

Figure 2. Clustering dendrogram illustrating four clusters.

Table 8 depicts the distribution of determinants across the identified clusters.

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Table 8. Determinants grouped within each cluster

Cluster	CE Determinants
Cluster 1	CE7, CE10, CE4, CE6, CE14, CE12, CE15
Cluster 2	CE17, CE19, CE3, CE23
Cluster 3	CE22, CE9, CE21, CE8, CE2, CE5, CE13
Cluster 4	CE11, CE16, CE1, CE18, CE20

To assess the robustness of the hierarchical clustering solution, a sensitivity analysis was conducted in RStudio. All matrix elements were perturbed by adding random noise generated from a normal distribution with a mean of 0 and a standard deviation of 0.01. The perturbed matrix was subsequently with diagonal values set to 1 and correlation coefficients limited to the range of −1 to 1. The procedure was repeated 100 times, and each perturbed matrix was clustered using Ward's method. The Adjusted Rand Index (ARI) was used to compare the simulated cluster assignments with the original clustering solution. The analysis yielded a mean ARI of 0.862 (SD = 0.141), suggesting that the clustering results remained highly consistent under small perturbations. These findings demonstrate that the identified clusters are robust and not significantly influenced by minor changes in expert assessments.

4.2. Discussion

The four clusters collectively describe how different factors—strategic, regulatory, market, and macro-institutional—work together to promote a circular ESC. This section explains the relationships among the identified determinants within and across the four clusters and highlights their overall role in shaping circular industrial practices.

Cluster 1: Strategic and Technological Capabilities. Determinants included in this cluster are Innovation, Management commitment and leadership, Competitive advantage Digital technologies/ Technological advancement, Supply chain integration, Environmental management systems and Organizational agility and collaboration.

The use of innovation and digital technologies in SC processes strengthens CE practices and improves competitiveness. *Digital technologies* like Industry 4.0 enable dynamic tracking and resource optimization contributing to improved sustainability along the value chain [52]. This is strengthened by Vertical and horizontal *integration in the SC* which helps ensure efficient material and information flow, efficient resource consumption, and coordinated reverse logistics [35]. The use of artificial intelligence, blockchain, and the Internet of Things promotes circular business models, better resource utilization, and extended product life [53]. Innovative product design methods, including disassembly and modular design, help improve material retrieval and reuse at end-of-life [54]. Complementing this, *Organizational agility and collaboration* enable firms to respond to changes and support joint decision-making and innovation across the supply network [55]. Thus, *innovative practices*, *digital technologies, SC integration and Organizational agility* support and strengthen *competitive advantage.* However, this necessitates *strong management commitment and leadership* that can help navigate barriers to their implementation enabling effective integration across the SC [56], [57]. Hence, *Environmental management systems* offer a clear structure to the management of organizations to minimize ecological impact and maintain regulatory compliance at all stages [58]. These determinants, together with technological capabilities, improve the strategic and operational readiness of firms for CE implementation.

Cluster 2: Regulatory and Resource-Efficiency Factors. Determinants included in this cluster are Environmental standards and certification, Information sharing along value network, Extended Producer Responsibility (EPR), and Potential to optimize resource usage.

Environmental standards and certification establish clear benchmark for sustainability compliance and help evaluate the extent of CE adoption [39]. *EPR* further strengthens this by holding producers responsible for end-of-life products and encourages designs of electronic components that are durable, recyclable, and compliant with certification norms [59]. This ecosystem of Environmental standards and EPR works best when supported by relevant *information sharing* among stakeholders who need to openly communicate about their responsibilities and expectations. Information sharing also ensures better traceability and decision-making for material recovery [60]. These determinants work together to improve *resource efficiency* by lowering the use of new materials, increasing recovery, and enhancing lifecycle performance while maintaining output [61].

Cluster 3: Market and Network Drivers. This cluster includes determinants such as Global sustainability goals and commitment, Knowledge sharing and training, Job creation opportunities, Stakeholder collaboration, Economic Incentives and subsidies, Consumer demand and awareness and Reverse logistics infrastructure.

Organizational alignment with the *United Nations SDGs and ESG standards* guides firms to invest in *training and knowledge-sharing*, helping to spread practices needed for CE adoption [31], [62]. Growing *consumer awareness and demand* for sustainable electronic items urges firms to engage in circular practices [39]. *Economic incentives* like subsidies and tax breaks make such commitment commercially viable**.** *Collaboration* between formal industry, informal recycling sectors, NGOs, and government agencies enhances these capabilities and supports effective *reverse logistics* for electronic waste valorization such as collection, sorting, and processing [60]. This in turn stimulate *job creation opportunities* in recycling, refurbishing, and remanufacturing activities.

Cluster 4: Macro-Institutional and Contextual Enablers. Determinants which are included in this cluster include Awareness campaigns, Cultural enablers, Government policies and regulations, Investment recovery, and Population and Urbanization.

Government regulations such as the E-Waste (Management) Rules, 2022 and eco-labelling standards support circular practices by setting clear regulatory framework and incentives [39]. These regulatory efforts are strengthened by an organizational *culture* that has environmental ethos embed as it plays an important role in adopting circular practices beyond regulatory requirements. Such commitment within the organization supports the transition to circular SCs by addressing initial constraints and complexities [63]. Apart from regulatory and cultural enablers, *Population growth and urbanization* in India drive higher consumption of electronics, increasing e-waste and the need for circular practices, while supporting scalable *investment recovery* [26]. To make this happen, *awareness campaigns* that encourage behavioral change among consumers and firms are essential so as to increase participation in responsible disposal and recycling [21]. These initiatives are essential for educating both the public and recycling workers about proper e-waste disposal practices especially in emerging economies like India [38]. Economic gains from recycling and material recovery motivate firms to follow regulations and invest in awareness and cultural transformation, showing that CE practices provide both economic and environmental advantages [62].

Together, these clusters support each other. The effectiveness of firm responses to regulatory (Cluster 2) and market pressures (Cluster 3) depends on digital and strategic capabilities (Cluster 1), shaped by the broader institutional environment (Cluster 4). In addition to confirming the importance of determinants identified in previous studies, the clustering analysis offers further empirical insights by showing how these determinants are related to one another. Rather than functioning as separate factors, the determinants clustered into four meaningful groups related to capabilities, regulation, markets, and institutional support. This structure suggests that CE adoption is driven by interconnected capability domains rather than independent determinants. Consequently, the clustering results add to the existing literature by offering a more integrated view of how CE determinants are related within India's electronics supply chain.

4.3. Implications

To facilitate successful CE implementation in India’s electronics supply chain, managers should adopt a balanced approach that simultaneously strengthens technological, regulatory, market, and macro-level collaborative initiatives. Organizations aiming to accelerate the adoption of circular products and processes should invest in innovation, foster top management support, leverage digital technologies, enhance supply chain integration, strengthen environmental management practices, and develop organizational agility. Complementing these initiatives, managers should reinforce environmental compliance, strengthen information exchange among value chain stakeholders, ensure the effective implementation of EPR frameworks, and support investments aimed at enhancing resource efficiency. The effective advancement of CE implementation also requires companies to support sustainability goals, enhance capacity building through training and knowledge sharing, generate green employment opportunities, foster multi-stakeholder collaboration, and encourage the adoption of circular business models through incentives, consumer awareness, and reverse logistics infrastructure. Finally, strengthening CE adoption requires practitioners to work collaboratively with governments and civil society organizations to increase awareness, promote sustainable consumption and production behaviors, support conducive policy measures, leverage investment recovery opportunities, and address the pressures associated with population growth and urbanization.

5. Conclusion

The study depicts that the integrated application of PF MCDM and AHC framework helps understand expert judgements and stratify related determinants in an intricate decision setting. The four coherent clusters- strategic and technological capabilities, regulatory and resource efficiency factors, market drivers, and macro-level enablers, reveal that CE adoption in ESC is shaped by multiple connected determinants, not isolated factors. By presenting a holistic perspective of CE approaches in India's electronics sector, this study provides a useful framework to policy makers, industry practitioners and researchers.

In addition to contributing to the domain, the study also outlines limitations and suggests directions for future research. While the use of small number of experts is a standard MCDM practice, it may restrict diverse range of stakeholders' viewpoints. Although the expert panel offered valuable domain expertise, it mainly represented academic and industry viewpoints. Future studies could include a wider range of stakeholders, such as policymakers, environmental regulators, recycling operators, producer responsibility organizations, and NGOs, to provide a more comprehensive assessment of CE determinants. The evaluation of criteria is based on expert opinions. However, such assessments are subjective and may be influenced by individual viewpoints and cognitive biases. Although linguistic terms facilitate expert evaluation, they may introduce some ambiguity and may limit the accuracy of collected data. Other fuzzy approaches like interval-valued or hesitant fuzzy sets, and alternate MCDM methods like MULTIMOORA, GLDS etc. can be utilized to improve robustness and applicability of the results. Different clustering approaches like Divisive Hierarchical Clustering (DHC) or Density-Based clustering can be explored to understand multifaceted relationships among the determinants. The results can be further validated by involving a larger number of experts in the study. Also, the electronics industry encompasses diverse subsectors such as consumer electronics, industrial electronics, and ICT manufacturing, which may differ in terms of operational characteristics. Further research can examine differences across sub-sectors and conduct cross-country comparisons to find out sector-specific or nation-specific variations for CE adoption.

6. Declarations

6.1. Author Contributions

Conceptualization: S.B. and V.G.; Methodology: V.G.; Software: S.B.; Validation: S.B. and V.G.; Formal Analysis: S.B. and V.G.; Investigation: S.B.; Resources: V.G.; Data Curation: V.G.; Writing Original Draft Preparation: S.B. and V.G.; Writing Review and Editing: V.G. and S.B.; Visualization: S.B.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The primary data used in this study are available on request from the corresponding author. The complete data tables, of which only representative excerpts are presented in this study due to space limitations, are publicly available at https://doi.org/10.5281/zenodo.21266677.

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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