

A Fuzzy Dematel Analysis of Circular Economy Implementation Barriers in Indian Automobile Manufacturing

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Abstract

This study develops an empirical-to-causal framework for examining barriers to circular economy (CE) implementation in Indian automobile manufacturing. A 306-response industry survey was first used to establish contextual evidence of CE awareness, practices, training, organizational arrangements and perceived material/design issues. Based on this evidence and prior CE barrier literature, twelve manufacturing-focused barriers were established. A separate expert elicitation stage was then conducted with two experienced automobile-sector professionals. Each expert evaluated 132 directional relationships among the twelve barriers using five linguistic influence levels: No Influence, Very Low, Low, High and Very High. The linguistic assessments were represented using trapezoidal fuzzy numbers and analyzed using Fuzzy DEMATEL. The study isolates clearly the barriers acting as causal drivers and the barriers which acts as net effect, which is a significant outcome and can act as guidance for management to define directions for CE adoption in manufacturing. The results also demonstrate that barrier prominence and causal role are not equivalent.

Keywords: Circular economy; automobile manufacturing; CE barriers; Fuzzy DEMATEL; trapezoidal fuzzy numbers; causal analysis

1. INTRODUCTION

The automobile industry is a particularly relevant setting for circular economy implementation because vehicle manufacturing is a resource intensive activity and if not optimized for resource utilization can lead to severe environmental hazards and non-sustainable development. The existing literature has established that CE implementation is constrained by a combination of technological, organizational, economic, cultural and supply-chain barriers. A systematic review by Govindan and Hasanagic, for example, frames CE implementation barriers and practices across supply-chain stakeholders, while automotive-specific research has identified a set of roadblocks to CE adoption in the Indian automobile sector. Plethora of literature is dedicated on establishing priority amongst the roadblocks or barriers to CE adoption, but priority does not reveal the structure through which barriers reinforce one another.

This distinction is central to the present study. A barrier can have high overall prominence because it both influences and is influenced by many other barriers. Conversely, a barrier may have a relatively modest prominence but still function as an upstream cause. Fuzzy DEMATEL is appropriate for this problem because it represents complex cause-effect relationships and can accommodate ambiguity in expert

judgments. Fuzzy DEMATEL has specifically been proposed for situations where perceived influence relationships are imprecise.

The present study draws on two complementary sources of evidence. First, 306 usable industry responses provide an empirical picture of the current CE situation and help shape a barrier framework relevant to automobile manufacturing. Second, two experienced industry professionals were asked to assess how these barriers influence one another. The purpose of this expert assessment is not to present the relationships as statistically proven causal links, given the limited number of experts. Instead, their responses are used to capture informed industry perceptions of how the barriers are connected and which barriers tend to drive others. The results from the two experts are examined both separately and together to see how consistently they identify the relationships among the barriers. The analysis is therefore guided by four research questions:

1. What CE implementation barriers exist in Indian automobile manufacturing context?
2. How do these barriers influence one another based on the perceptions of experienced industry professionals?
3. Which barriers appear to act mainly as drivers of other barriers, and which barriers are effects of the driving barriers?
4. How can this understanding of the relationships among barriers help managers decide where to intervene?

2. Literature Review

2.1 Circular Economy and Automobile Manufacturing

Circular Economy (CE) in automobile manufacturing goes beyond simply recycling vehicles and materials at the end of their life. It includes reuse, remanufacturing, repair, design for disassembly, material recovery, resource-efficient production and reverse logistics. These activities are closely connected: material and product design affect recovery and reuse, quality requirements influence the use of recovered materials, and reverse logistics determines whether these materials can return to production. Although CE transitions have been widely discussed in the literature, particularly in developed economies, the practical challenges of implementing CE in the Indian automobile manufacturing sector remain less explored.

2.2 Barriers to CE Implementation

The transition to CE is not straightforward. Previous studies have identified several barriers, including limited organisational commitment and awareness, economic uncertainty, technological and supply-chain challenges, and difficulties related to product design and reverse logistics. These challenges are particularly important in automobile manufacturing, where complex products and strict quality and safety requirements make reuse, remanufacturing and material recovery more difficult.

2.3 From Barrier Ranking to Causal Structure

This distinction is important because the barrier that appears most important is not necessarily the one driving the rest of the system. Methods such as Fuzzy TOPSIS and Fuzzy AHP help identify which barriers deserve attention, but they do not show how the barriers are connected or whether a barrier mainly influences others or is influenced by them.

Fuzzy DEMATEL helps address this gap by looking at these relationships directly. It examines how each barrier influences the others and how much influence it receives in return. In this framework, **D** represents the influence given by a barrier and **R** represents the influence received. Their sum, **D + R**,

shows how strongly a barrier is connected to the overall system, while **D – R** indicates whether it behaves more as a driver or as an outcome.

The aim of this study is therefore not simply to produce another ranking of CE barriers. It is to connect the evidence from automobile manufacturing with an understanding of how these barriers influence one another. This provides a clearer picture of the CE implementation challenge for managers.

3. Research Framework

The research framework follows four stages.

- **Stage 1** uses the 306-response survey to establish the manufacturing context.
 - **Stage 2** consolidates twelve barriers from the empirical evidence and prior literature.
 - **Stage 3** uses a separate two-expert elicitation exercise to evaluate the directional influence between every pair of barriers.
 - **Stage 4** applies Fuzzy DEMATEL to obtain prominence, net causal influence and a causal network.
- The logic is deliberately sequential: empirical survey evidence identifies and grounds the barrier set; expert judgment supplies directional structural information; DEMATEL reveals the causal architecture; and the resulting architecture can later become the structural foundation for System Dynamics stocks, flows, feedback loops and intervention scenarios.

4. Empirical Survey Evidence

The empirical component used 306 completed responses from the Indian automobile manufacturing context. Table 1 tabulates survey evidence:

Table 1: Empirical Survey results on 306 automobile manufacturing practitioners/experts

Indicator	Response / Status	Percentage (%)
Awareness of Circular Economy	Aware	78.1
	Not aware	21.9
Current Production Process	Linear	59.5
	Both linear and circular	29.4
	Circular	11.1
CE Training / Workshop Exposure	Yes	67.6
	No	32.4
Separate Waste-Management Department	Yes	73.5
	No	26.5
Scope for Converting Linear to Circular Production	Yes	73.9
	No	26.1

The material-level responses also point toward the need to recover the precious metals and other material in order to make the circular transition possible and sustainable. There are non-recyclable material mentions also, which requires better waste disposal mechanisms. The most frequently mentioned non-recycled items included rubber bushes, plastic dashboards, foam seats, seals/gaskets, hoses, filters and other mixed or contaminated materials. Frequently identified recyclable materials included battery housings, steel frames, aluminium panels, copper wiring scrap and metal components.

Open-ended responses reinforce an operational emphasis. The dominant assembly-efficiency recommendation was the use of automation and better material flow, while sustainability recommendations emphasized increased recycled-material use and circular-production monitoring. Other recurring suggestions included Industry 4.0, robotics, line balancing, removal of non-value-added activities, Kaizen/Poka-Yoke, automated inspection, JIT, inventory tracking, energy monitoring, green logistics and packaging reduction.

These findings were not treated as direct evidence of causal relationships. Instead, they were used to identify the types of barriers that need structural examination and to ensure that the DEMATEL framework remained anchored to the manufacturing setting.

5. CE Barrier Framework

An important feature of this study is the way the CE barrier framework was developed. Instead of starting with a predefined list of barriers taken from the literature, the framework was built from the responses of 306 automobile manufacturing practitioners. The questionnaire did not directly ask respondents to list or rank barriers to CE. Instead, questions were framed around their actual experience—for example, their awareness of CE, existing production practices, training, organizational arrangements, material use and recovery, and the possibility of moving from linear towards circular production. These questions were designed to understand the underlying situation rather than simply ask respondents whether a particular barrier existed. When the responses were examined together, several recurring gaps and difficulties became visible. These were then interpreted and organized into the CE barrier framework used in the study. This approach gives the framework a stronger connection to the realities of automobile manufacturing and complements the barriers identified in earlier literature.

Table2: Barrier framework from empirical study

Code	Barrier
B1	Lack of CE awareness and understanding
B2	Confusion between CE and conventional waste management
B3	Inadequate CE training and workforce capability
B4	Lack of top-management commitment and dedicated CE responsibility
B5	Resistance/difficulty in transition from linear to circular production
B6	Inadequate automation and recycling/recovery technology
B7	Lack of digital/real-time monitoring of circular material flows
B8	High investment and uncertain economic returns from CE
B9	Inefficient reverse logistics and recovery flows
B10	Lack of design for circularity/reprocessing
B11	Complexity and contamination of materials limiting recovery
B12	Quality and safety concerns regarding recycled/refashioned products

The twelve-barrier framework is intentionally manufacturing-focused, Next, we have advanced our study to a two-expert based Fuzzy DEMATEL study.

6. Methodology: Two-Expert Fuzzy DEMATEL

6.1 Expert elicitation

Two experts were used in the final study design. Expert 1 is identified in the questionnaire as a Senior

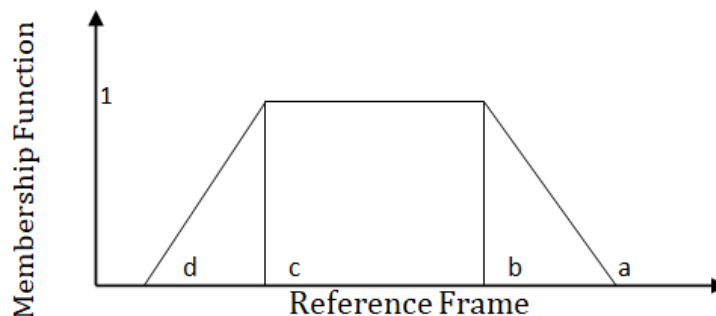
R&D Director with 25 years of professional experience and 8 years of CE/sustainable-manufacturing experience. Expert 2 is identified as a General Manager with 28 years of professional experience and 9 years of CE/sustainable-manufacturing experience. The objective was expert knowledge elicitation rather than statistical generalization.

For twelve barriers, each expert assessed $12 \times 11 = 132$ directional relationships. The diagonal was fixed at zero. Thus, the two completed matrices contain 264 directional judgments in total.

6.2 Fuzzy numbers and linguistic scale

In this study we have used trapezoidal fuzzy numbers.

Figure 1: Trapezoidal Fuzzy number



$$\mu_A(x) = \begin{cases} 0, & x < d \\ (x - d)/(c - d), & d \leq x \leq c \\ 1, & c \leq x \leq b \\ (b - x)/(b - a), & b \leq x \leq a \\ 0, & x > a \end{cases}$$

- Value lying between b & c will be fuzzy Number completely
- Value before a or after d has no relation with Fuzzy number.
- Partial Fuzziness in any value between c& d or b & a

6.3 Aggregation and Defuzzification of Expert Judgements

Let $B = \{B_1, B_2, \dots, B_{12}\}$ denote the set of identified CE barriers. For each ordered pair of barriers (B_i, B_j) , $i \neq j$, Expert k expresses the perceived influence of barrier B_i on barrier B_j using one of the five linguistic terms: **No Influence (NI)**, **Very Low (VL)**, **Low (L)**, **High (H)**, and **Very High (VH)**. Each linguistic assessment is represented by a trapezoidal fuzzy number (TFN).

For a particular relationship $B_i \rightarrow B_j$, let the assessments of Expert 1 and Expert 2 be represented by

$$\tilde{x}_{ij}^{(1)} = (a_{ij}^{(1)}, b_{ij}^{(1)}, c_{ij}^{(1)}, d_{ij}^{(1)})$$

and,

$$\tilde{x}_{ij}^{(2)} = (a_{ij}^{(2)}, b_{ij}^{(2)}, c_{ij}^{(2)}, d_{ij}^{(2)}).$$

Because the two experts are given equal importance in the present study, the aggregated fuzzy assessment is obtained by taking the arithmetic mean of the corresponding vertices:

$$\tilde{x}_{ij} = \frac{1}{2} (\tilde{x}_{ij}^{(1)} + \tilde{x}_{ij}^{(2)})$$

Thus, **aggregation is performed component-wise**, preserving the four-point representation of the trapezoidal fuzzy judgement. The aggregated fuzzy direct-relation matrix can therefore be written as

$$\tilde{\mathbf{X}} = [\tilde{x}_{ij}]_{12 \times 12}$$

where

$$\tilde{x}_{ii} = (0, 0, 0, 0),$$

because a barrier is not considered to exert a direct influence on itself.

The aggregated TFNs are subsequently converted into crisp values to obtain the direct-relation matrix required for the DEMATEL calculations. A simple and transparent **vertex-average defuzzification rule** is used:

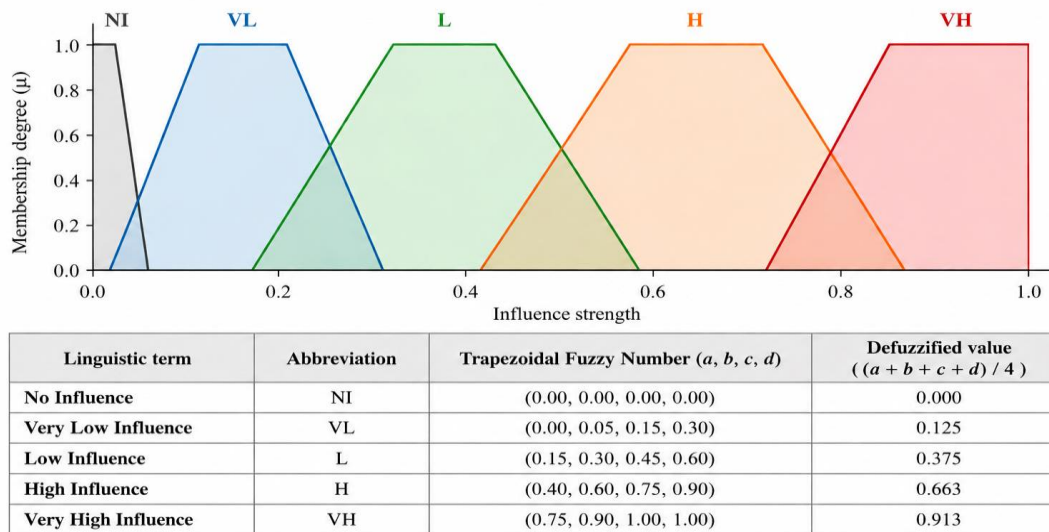
$$x_{ij} = \frac{a_{ij} + b_{ij} + c_{ij} + d_{ij}}{4}$$

where $x_{ij} \in [0, 1]$ represents the crisp strength of the perceived direct influence of barrier B_i on barrier B_j . Accordingly, the crisp direct-relation matrix is

$$\mathbf{X} = [x_{ij}]_{12 \times 12}.$$

The same aggregation and defuzzification procedure is applied consistently when generating the individual expert crisp matrices used for the robustness comparison. This allows the causal structure obtained from the aggregated assessment to be examined alongside the structures obtained independently from the two experts.

Figure 2: Frame of reference for linguistic fuzzy number and de-fuzzified values



6.4 Normalization of the Direct-Relation Matrix

The crisp matrix $\mathbf{X}$ contains the direct influence strengths among the twelve CE barriers. Since the magnitude of the entries must be constrained before calculating indirect relationships, the matrix is normalized using the maximum total direct influence exerted by any barrier.

First, the row sum associated with barrier B_i is calculated as

$$r_i = \sum_{j=1}^{12} x_{ij}.$$

The normalization factor is then defined as

$$s = \max_{1 \leq i \leq 12} \left\{ \sum_{j=1}^{12} x_{ij} \right\}.$$

The normalized direct-relation matrix is obtained as

$$\mathbf{N} = \frac{\mathbf{X}}{s}.$$

Thus, each element of the normalized matrix is

$$n_{ij} = \frac{x_{ij}}{s}.$$

This normalization ensures that the maximum row sum of $\mathbf{N}$ is equal to 1 or less, providing the required basis for incorporating indirect influences through the DEMATEL total-relation matrix.

6.5 Total Relation Matrix

A key advantage of DEMATEL over simple ranking methods is that it considers not only **direct influence** but also the influence transmitted through other barriers.

The first-order influence between barriers is represented by $\mathbf{N}$, while higher-order influences are represented by

$$\mathbf{N}^1, \mathbf{N}^2, \dots$$

Therefore, the complete influence structure can be expressed as

$$\mathbf{T} = \mathbf{N} + \mathbf{N}^1 + \mathbf{N}^2 + \dots.$$

Provided that the series converges, this can be expressed in closed form as

$$\mathbf{T} = \mathbf{N}(\mathbf{I} - \mathbf{N})^{-1}$$

where $\mathbf{I}$ is the 12×12 identity matrix.

The element t_{ij} of $\mathbf{T}$ represents the **total influence of barrier B_i on barrier B_j** , incorporating both the direct relationship and the influence transmitted through other barriers in the system.

A barrier may not appear very influential on its own, but its influence can become much stronger when it affects other barriers indirectly through the wider system.

6.6 Prominence and Net Causal Influence

Once the total relation matrix $\mathbf{T} = [t_{ij}]$ has been obtained, the overall position of each barrier within the causal system is determined from its row and column sums.

For barrier B_i , the total influence **given to other barriers** is calculated as

$$D_i = \sum_{j=1}^{12} t_{ij}$$

whereas the total influence **received from other barriers** is

$$R_i = \sum_{j=1}^{12} t_{ji}.$$

The **prominence** of barrier B_i , representing its overall involvement in the system, is then defined as

$$P_i = D_i + R_i.$$

A higher value of P_i indicates that the barrier is more strongly connected with the other barriers, irrespective of whether it primarily influences or is influenced by them.

The **net causal influence** is calculated as

$$C_i = D_i - R_i.$$

The sign of C_i provides the basis for separating the barriers into causal and effect groups:

$$C_i > 0 \Rightarrow B_i \text{ is a net causal barrier,}$$

$$C_i < 0 \Rightarrow B_i \text{ is a net effect barrier.}$$

A value of C_i close to zero indicates that the barrier has a relatively balanced role in terms of influence given and influence received.

Consequently, the DEMATEL analysis provides two complementary perspectives:

$$D_i + R_i \rightarrow \text{How important/connected is the barrier?}$$

and

$$D_i - R_i \rightarrow \text{Does the barrier mainly drive or receive influence?}$$

This distinction is particularly relevant to the present research because **a barrier with high prominence is not necessarily a causal driver**. A barrier may be highly connected to the CE implementation system while primarily acting as an outcome of other underlying barriers.

6.5 Inter-expert agreement and robustness

Because the study uses two experts, agreement was treated as a substantive methodological check. Exact linguistic agreement was calculated across all 132 directional judgments. Adjacent-category agreement was also calculated, where a difference of one linguistic level was treated as close agreement. Spearman rank correlation of the encoded linguistic categories was used only as a descriptive agreement diagnostic; no inferential p-value is interpreted because the 132 judgments are repeated assessments of the same factor pairs rather than independent observations.

7. Results

7.1 Inter-expert agreement

Across the 132 directional relationships, the experts agreed exactly on 75 judgments (56.8%). All 132 relationships (100.0%) were within one linguistic category. The mean absolute difference in encoded linguistic category was 0.432 category. The descriptive Spearman correlation was approximately 0.622, indicating a meaningful positive association between the experts' directional assessments. **The agreement result is particularly useful because it shows that the experts differed in intensity in some cases but did not exhibit large categorical disagreements.**

Table 3: Inter-expert agreement percentage across barriers

Barrier	Exact Agreement (%)
B1	9.1%
B2	54.5%
B3	36.4%
B4	63.6%
B5	36.4%
B6	72.7%
B7	54.5%

B8	54.5%
B9	72.7%
B10	81.8%
B11	72.7%
B12	72.7%

7.2 Aggregated Fuzzy DEMATEL results

The aggregated DEMATEL model produces a clear separation between overall prominence and net causal role. Table 5 reports the combined results. The highest prominence value is observed for B1, followed by B10 and B6. Prominence should be interpreted as the overall involvement of a barrier in the network, not as a simple priority score.

Table 4: Cause and Effect classification through DEMATEL

Rank	Barrier	D	R	D+R	D-R	Type
1	B1	5.3702	4.8718	10.2420	0.4984	Cause
2	B10	4.9011	5.2162	10.1173	-0.3152	Effect
3	B6	4.7083	4.9992	9.7075	-0.2909	Effect
4	B4	5.6353	4.0242	9.6594	1.6111	Cause
5	B3	4.7678	4.8148	9.5826	-0.0470	Effect
6	B5	5.3001	4.2794	9.5795	1.0207	Cause
7	B7	4.4094	5.1405	9.5498	-0.7311	Effect
8	B12	4.3201	5.1467	9.4668	-0.8266	Effect
9	B8	4.4166	4.4162	8.8328	0.0004	Cause
10	B11	4.1154	4.4309	8.5463	-0.3155	Effect
11	B9	3.5360	4.9926	8.5286	-1.4566	Effect
12	B2	4.6503	3.7980	8.4483	0.8523	Cause

7.4 Cause and effect groups

The aggregated model classifies **five barriers as net causes**:

- B1 (CE awareness)
- B2 (confusion between CE and conventional waste management)
- B4 (top-management commitment and dedicated responsibility)
- B5 (transition difficulty)
- and B8 (investment and uncertain economic returns).

Seven barriers are net effects: B3, B6, B7, B9, B10, B11 and B12.

B4 is the strongest causal driver, with $D-R=1.6111$, followed by B5 (1.0207), B2 (0.8523) and B1 (0.4984). B8 is effectively neutral in the aggregated model ($D-R=0.0004$), so its classification as a cause should be regarded as fragile rather than as a strong causal finding.

Among the effect-side barriers, B9 has the most negative net effect (-1.4566), followed by B12 (-0.8266) and B7 (-0.7311). This indicates that reverse logistics/recovery flows, product quality and safety concerns, and digital monitoring may be more strongly shaped by upstream organizational and transition conditions than they independently drive the system.

7.5 Threshold sensitivity

The mean off-diagonal total-relation value in the aggregated matrix is 0.3957. Using this value as the network threshold retains 68 directed relationships. Changing the threshold to 0.35, 0.375, 0.40, 0.425 and 0.45 retains 103, 88, 63, 42 and 27 relationships, respectively. This confirms that the displayed network density is threshold-sensitive, as expected in DEMATEL. The threshold should therefore be reported explicitly and the causal interpretation should focus on relationships that remain among the stronger links rather than on every edge in the dense network.

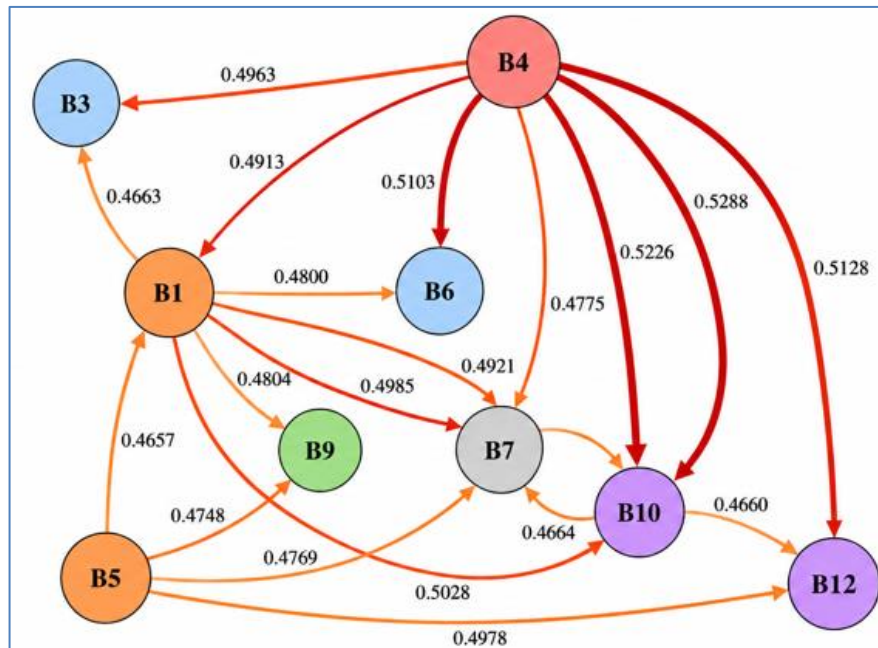
7.6 Strongest structural relationships

At the mean threshold, the strongest total-relation links include B4→B10, B4→B7, B4→B12, B4→B6, B5→B10, B1→B10 and B5→B12. These links suggest that organizational commitment and transition capability have broad downstream consequences, particularly for circular design, monitoring, technology, quality and recovery outcomes.

Table 5: From – To relationship amongst barriers

From Barriers	To Barriers	Total relation
B4	B10	0.5288
B4	B7	0.5226
B4	B12	0.5128
B4	B6	0.5103
B5	B10	0.5028
B1	B10	0.4985
B5	B12	0.4978
B4	B3	0.4963
B1	B12	0.4926
B1	B7	0.4921
B4	B1	0.4913
B1	B9	0.4804
B1	B6	0.4800
B4	B9	0.4775
B5	B7	0.4769
B5	B9	0.4748
B10	B7	0.4664
B1	B3	0.4663
B10	B12	0.4660
B5	B1	0.4657

Figure 3. Cause–effect map based on the aggregated two-expert Fuzzy DEMATEL model



The results reinforce the central proposition of this study: barrier importance and barrier causality are not the same construct. **B1 is the most prominent barrier, but its net causal influence is moderate compared with B4 and B5.**

8. Managerial Implications

1. Establish explicit CE ownership at senior-management level. A dedicated CE responsibility structure can coordinate design, manufacturing, recovery, procurement, quality and logistics rather than treating CE as a waste-management subfunction.
2. Develop a CE transition roadmap for moving from linear to circular production. The roadmap should identify material loops, recovery routes, design changes, process modifications, capability gaps and investment requirements.
3. Convert CE awareness into operational competence. Training should cover circular design, material recovery, reverse logistics, recycled-material quality, digital traceability and business-case evaluation.
4. Clarify the distinction between CE and conventional waste management. This can improve decision-making by shifting attention from disposal toward prevention, reuse, remanufacturing, recovery and value retention.
5. Treat digital monitoring and automation as enabling infrastructure. Monitoring should be connected to material-flow decisions, recovery yields, quality and circular KPIs rather than implemented as isolated Industry 4.0 projects.
6. Address design for circularity upstream. Since B10 is highly prominent but a net effect, design interventions should be linked with upstream management commitment and manufacturing-transition planning.
7. Use causal priorities rather than prominence alone. The strongest immediate managerial attention should be given to B4 and B5, supported by B1 and B2, while downstream interventions should be sequenced accordingly.

9. Conclusion

This study moves the analysis of circular economy barriers in Indian automobile manufacturing from ranking toward causal structure. Using a 306-response empirical context and a separate two-expert directional assessment, twelve manufacturing-focused CE barriers were examined using trapezoidal Fuzzy DEMATEL.

The aggregated model identifies B1, lack of CE awareness and understanding, as the most prominent barrier. However, B4, lack of top-management commitment and dedicated CE responsibility, is the strongest net causal driver, followed by B5, difficulty in transitioning from linear to circular production, and B2, confusion between CE and conventional waste management. Several highly prominent barriers—including circular design, automation/recovery technology and digital monitoring—appear primarily as downstream effects. This demonstrates why prominence and causality should be analyzed together.

The two experts exhibit 56.8% exact agreement and complete adjacent-category agreement, while the common causal core across the individual models consists of B1, B2, B4 and B5. The result therefore provides a defensible starting point for intervention sequencing, while also highlighting the uncertainty surrounding near-neutral barriers such as B8.

References

1. Agrawal, R., Wankhede, V. A., Kumar, A., & Luthra, S. (2021). Analysing the roadblocks of circular economy adoption in the automobile sector: Reducing waste and environmental perspectives. *Business Strategy and the Environment*, 30(2), 1051–1066. <https://doi.org/10.1002/bse.2669>
2. Govindan, K., & Hasanag, M. (2018). A systematic review on drivers, barriers, and practices towards circular economy: A supply chain perspective. *International Journal of Production Research*, 56(1–2), 278–311. <https://doi.org/10.1080/00207543.2017.1402141>
3. Hiete, M., Merz, M., Comes, T., & Schultmann, F. (2012). Trapezoidal fuzzy DEMATEL method to analyze and correct for relations between variables in a composite indicator for disaster resilience. *OR Spectrum*, 34(4), 971–995. <https://doi.org/10.1007/s00291-011-0269-9>
4. Si, S.-L., You, X.-Y., Liu, H.-C., & Zhang, P. (2018). DEMATEL Technique: A Systematic Review of the State-of-the-Art Literature on Methodologies and Applications. *Mathematical Problems in Engineering*, 2018, 3696457.
5. Kirchherr, J., Piscicelli, L., Bour, R., Kostense-Smit, E., Muller, J., Huibrechtse-Truijens, A., & Hekkert, M. (2018). Barriers to the circular economy: Evidence from the European Union (EU). *Ecological Economics*, 150, 264–272.
6. Tura, N., Hanski, J., Ahola, T., Ståhle, M., Piiparinen, S., & Valkokari, P. (2019). Unlocking circular business: A framework of barriers and drivers. *Journal of Cleaner Production*, 212, 90–98.
7. Agyemang, M., Kusi-Sarpong, S., Khan, S. A., Mani, V., Rehman, S. T., & Kusi-Sarpong, H. (2019). Drivers and barriers to circular economy implementation. *Management Decision*, 57(4), 971–994.
8. Dey, P. K., Malesios, C., De, D., Budhwar, P., Chowdhury, S., & Cheffi, W. (2020). Circular economy to enhance sustainability of small and medium-sized enterprises. *Business Strategy and the Environment*, 29, 2145–2169.
9. Rizos, V., Behrens, A., Kafyeke, T., Hirschnitz-Garbers, M., & Ioannou, A. (2016). Implementation of circular economy business models by small and medium-sized enterprises (SMEs): Barriers and enablers. *Sustainability*, 8(11), 1212.

10. Zhang, T., Chu, J., Wang, X., Liu, Y., & Cui, P. (2011). Development pattern and enhancing system of automotive components remanufacturing industry in China. *Resources, Conservation and Recycling*, 55(6), 613–622.
11. Saripalle, M., & Gupta, P. (2025). Driving productivity: a comparison of the Indian automobile manufacturers and component suppliers. *Asian Journal of Technology Innovation*, 33(3), 1106-1136.
12. Murugan, M., & Marisamynathan, S. (2022). Analysis of barriers to adopt electric vehicles in India using fuzzy DEMATEL and Relative importance Index approaches. *Case Studies on Transport Policy*, 10(2), 795-810.
13. Singh, P., Bhushan, S., & Banwet, D. (2023, December 14–16). Application of Fuzzy Analytical Hierarchy Process for ranking the Circular Economy Barriers in Automobile Industry [Conference presentation]. 26th Annual International Conference of the Society of Operations Management (SOM 2023), IIM Shillong, Meghalaya, India.