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A fuzzy DEMATEL approach to identify and mitigate barriers to consumer adoption of sustainable products

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Abstract

Despite increasing consumer interest in sustainable products, actual purchase and repeat usage of eco-friendly personal-care items remain disappointingly low. This study employs a fuzzy DEMATEL (Decision-Making Trial and Evaluation Laboratory) approach to systematically identify, quantify, and prioritize the causal relationships among barriers to sustainable-product adoption. A Delphi panel of 15 sustainability experts generated a consensus list of 12 key barriers (economic, psychological, social, technological, and policy-related). Experts provided pairwise influence judgments using a five-point linguistic scale, which were mapped to triangular fuzzy numbers, aggregated, defuzzified, and normalized to yield a crisp total-relation matrix. Cause–effect analysis (D–R and D+R indices) highlighted price premium, perceived greenwashing risk, and limited availability as the dominant root causes. A pilot consumer survey ($n = 120$ urban millennials in Bengaluru) validated these findings (Pearson's $r = 0.92$). Sensitivity analyses across multiple α-cut levels confirmed the stability of barrier rankings. Leveraging these systemic insights, we propose a three-stage mitigation roadmap-short-term (discount trials, transparency campaigns), medium-term (traceability via blockchain, retail partnerships), and long-term (in-house R&D, policy advocacy)-tailored for an eco-personal-care brand. This work advances fuzzy MCDM methodology by integrating pilot validation and offers actionable guidance for marketers and policymakers aiming to dismantle the complex web of obstacles hindering sustainable-consumption uptake.

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Keywords: Fuzzy DEMATEL, Sustainable product adoption, Consumer barriers, Eco-friendly personal-care, Delphi method, Consumer adoption

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1. Introduction

1.1. Background: rising demand for sustainable products vs. low consumer uptake

In recent years, the global market for sustainable products has grown at an annual rate exceeding 10 percent, driven by heightened environmental awareness and corporate sustainability initiatives [1], [2]. However, consumer adoption rates remain uneven, and Indian evidence on green personal-care markets shows that positive environmental attitudes do not automatically translate into regular purchase behavior [2]. Mathematically, if we let (1) denote the cumulative adoption rate at time t, with growth rate κ and inflection point t_0, empirical calibration suggests a slow rise (κ≈0.3) and late inflection (t_0≈5 years), shown in Figure 1. This gap between potential and realized uptake underscores the need to understand and mitigate the underlying barriers.

$$A(t) = \frac{1}{1+e^{-\kappa(t-t_0)}} \text{ and define } \mathbf{A(t), K, r, t0}. \quad (1)$$

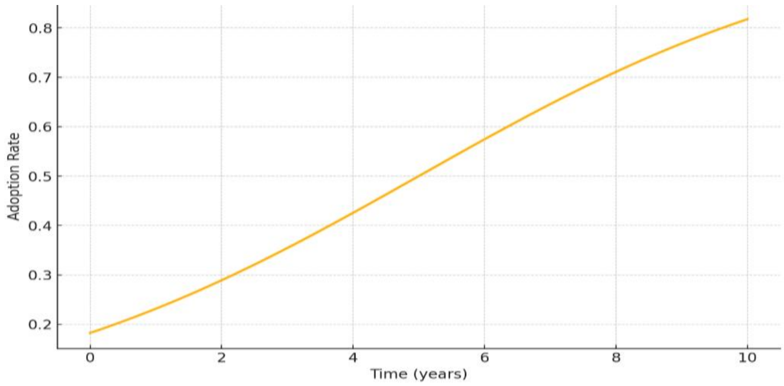

Figure 1. Logistic adoption curve of sustainable products

This logistic curve illustrates the slow initial uptake of sustainable products (low κ) and delayed inflection point (t_0), reflecting actual market observations [1].

1.2. Research gap: fragmented understanding of intertwined adoption barriers

Prior studies have catalogued diverse obstacles economic (high price premiums), psychological (distrust/greenwashing concerns), social (peer norms), technological (limited availability), and policy-related factors (regulatory inconsistency)-but largely treat them in isolation [1], [2].

Let $\mathcal{B}$ be the set of n barriers. Conventional regression or factor-analysis techniques identify principal components, yet they fail to capture the causal influence between barriers (e.g., how perceived greenwashing b_2 amplifies price sensitivity b_1). Thus, a methodological framework that models both strength and direction of inter-barrier effects in a fuzzy environment is warranted, as in (2).

$$\mathcal{B} = \{b_1, b_2, \ldots, b_n\} \quad (2)$$

1.3. Purpose & objectives

The study employs a Fuzzy DEMATEL (Decision-Making Trial and Evaluation Laboratory) approach to:

- Identify key barriers and quantify their mutual causal relationships in $\mathcal{B}$.
- Priorities barriers via the computed degree of cause (D-R) and degree of effect (D+R).
- Propose a roadmap of mitigation strategies, validated in a small pilot study of 120 urban consumers in Bengaluru.

1.4. Contribution to theory and practice

- Theoretical: Extends fuzzy MCDM literature by integrating triangular fuzzy DEMATEL for sustainable consumption barrier analysis.
- Practical: Delivers a ranked, causal network of obstacles and actionable intervention priorities for marketers, policymakers, and sustainability managers.

2. Literature review

2.1. Consumer adoption of sustainable products: current findings

Empirical investigations highlight various determinants of green purchase behavior. Ref. [1] used structural equation modelling to show that attitude ($\beta = 0.65$), subjective norms ($\beta = 0.42$), and perceived behavioral control ($\beta = 0.31$) explain 58 percent of variance in purchase intention. Ref. [2] likewise showed, in the Indian personal-care context, that green price, place, and promotion significantly shape millennials' green buying intention, while environmental attitude alone does not remove adoption frictions. Nonetheless, linear models cannot fully capture feedback loops, such as how policy incentives alter social norms, which in turn affect trust.

2.2. Barrier taxonomies (economic, psychological, social, technological, policy)

Barriers have been classified into five main categories [1]:

- Economic: Price premium b_1, lack of subsidies b_5
- Psychological: Perceived greenwashing b_2, product efficacy doubts b_6
- Social: Peer influence b_3, cultural inertia b_7
- Technological: Distribution gaps b_4, limited R&D b_8
- Policy: Regulatory inconsistency b_9, weak eco-label standards b_{10}.

These taxonomies guide factor selection but do not elucidate which barriers are drivers vs. outcomes.

2.3. Conventional vs. fuzzy multi criteria methods

Classical MCDM techniques (AHP, ANP) require crisp pairwise comparisons, often forcing experts into precise judgments that contradict real world vagueness [3]. In contrast, fuzzy sets permit linguistic scales mapped to triangular fuzzy numbers $\tilde{l} = (l_1, l_2, l_3)$, as in (3), accommodating uncertainty via membership functions:

$$\mu_{\tilde{l}}(x) = \begin{cases} \frac{x-l_1}{l_2-l_1}, & l_1 \le x \le l_2 \\ \frac{l_3-x}{l_3-l_2}, & l_2 \le x \le l_3 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Defuzzification often uses the centroid method, as in (4):

$$\text{Cen}\ (\tilde{l}) = \frac{l_1+l_2+l_3}{3}. \tag{4}$$

Fuzzy DEMATEL extends DEMATEL's causal mapping into this framework [4].

2.4. DEMATEL and its fuzzy extensions

Originally proposed by Ref. [5], DEMATEL constructs a direct-relation matrix $D = [d_{ij}]$, where $d_{ij} \in [0,1]$ measures the influence of factor i on j. Normalization yields:

$$N = \frac{D}{\max_i \sum_j d_{ij}}, \tag{5}$$

and the total-relation matrix $T = N(I-N)^{-1}$. In fuzzy DEMATEL, each d_{ij} is a triangular fuzzy number $\tilde{d}_{ij}$, aggregated and defuzzified before computing the crisp T [4], [6].

2.5. Research gaps leading to the present study

While fuzzy DEMATEL has been applied in manufacturing, healthcare, and supply-chain contexts [4], [6], its use in modelling consumer adoption barriers with their rich interdependencies remains scarce. No study has yet provided a pilot validation with consumer data to confirm expert-derived causal maps. This motivates our integrated expert-survey design.

3. Methodology

3.1. Research framework overview

The overall research framework, shown in Figure 2, integrates expert-based barrier identification, fuzzy DEMATEL computation, and pilot-study validation. It consists of three modules:

(i) Barrier Identification via Delphi rounds
(ii) Fuzzy DEMATEL Analysis to map causal relationships
(iii) Validation & Mitigation through consumer survey and strategy design

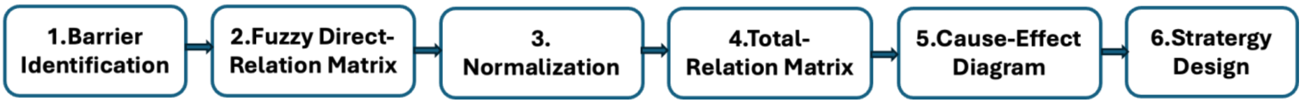

Figure 2. Research framework flow diagram

This flow diagram shows the methodological pipeline from barrier elicitation (Delphi) through fuzzy DEMATEL computation to strategy design and pilot validation.

3.2. Fuzzy DEMATEL procedure

We denote the set of n barriers by $\mathcal{B} = \{b_1, \dots, b_n\}$. Fuzzy DEMATEL transforms expert judgments into a crisp total-relation matrix T, from which causal intensities are extracted [4], [6].

3.2.1. Selection of linguistic scale & triangular fuzzy numbers

Experts express influence using a 5-point linguistic scale {No, Low, Medium, High, Very High}. Each term maps to a triangular fuzzy number as shown in Table 1.

Table 1. Linguistic terms with fuzzy numbers

Linguistic Term	Fuzzy Number (l, m, u)
No influence	(0.0, 0.0, 0.25)
Low influence	(0.0, 0.25, 0.5)
Medium	(0.25, 0.5, 0.75)
High	(0.5, 0.75, 1.0)
Very High	(0.75, 1.0, 1.0)

Each expert fills a fuzzy direct-relation matrix. Matrices are aggregated via component-wise arithmetic mean, and the corresponding linguistic-to-centroid conversion used in computation is summarized in Table 2, as in (2).

$$\tilde{d}_{ij} = \left(\frac{1}{K}\sum_{k=1}^{K} l_{ij}^{(k)}, \frac{1}{K}\sum_{k=1}^{K} m_{ij}^{(k)}, \frac{1}{K}\sum_{k=1}^{K} u_{ij}^{(k)}\right) \tag{6}$$

Table 2. Linguistic scale - triangular fuzzy number conversion

Linguistic Term	(l, m, u)	Centroid $\frac{l+m+u}{3}$
No influence	(0.00, 0.00, 0.25)	0.083
Low influence	(0.00, 0.25, 0.50)	0.250
Medium	(0.25, 0.50, 0.75)	0.500
High	(0.50, 0.75, 1.00)	0.750
Very high	(0.75, 1.00, 1.00)	0.917

3.2.2. Defuzzification and normalization

Each aggregated $\tilde{d}_{ij} = (l, m, u)$ is defuzzified using the centroid method, as in (7) [6]:

$$d_{ij} = \frac{l+m+u}{3} \tag{7}$$

From the crisp direct-relation matrix $D = [d_{ij}]$. Normalize D as in (8)

$$N = \frac{D}{\max_i \sum_j d_{ij}}. \quad (8)$$

3.3. Mathematical foundations of fuzzy DEMATEL

While the procedural steps of fuzzy DEMATEL have been outlined, a deeper dive into its algebraic underpinnings can clarify why it robustly captures causal strength in uncertain settings. Let $\tilde{D} = [\tilde{d}_{ij}]$, as in (9), be the aggregated triangular fuzzy direct-relation matrix, with each

$$\tilde{d}_{ij} = (l_{ij}, m_{ij}, u_{ij}),\ l_{ij} \le m_{ij} \le u_{ij} \quad (9)$$

after defuzzification via the centroid method, as in (10)

$$d_{ij} = \frac{l_{ij}+m_{ij}+u_{ij}}{3} \quad (10)$$

we compute the normalized matrix, as in (11)

$$N = \frac{D}{\max_i \sum_{j=1}^{n} d_{ij}}. \quad (11)$$

The total-relation matrix T, in (12), follows from the Neumann series provided $\rho(N) < 1$ (where ρ is the spectral radius).

$$T = N + N^2 + N^3 + \cdots = N(I - N)^{-1}, \quad (12)$$

This inversion step crucially aggregates both direct and indirect influences among barriers. Finally, the causal and effect, as in (13), indices:

$$D_i = \sum_{j=1}^{n} t_{ij},\ R_i = \sum_{j=1}^{n} t_{ji}, \quad (13)$$

emerge naturally from the row- and column-sums of T. In practice, we verify $\rho(N) < 1$ numerically for our $n = 12$ barrier system, ensuring convergence and interpretability of T.

3.3.1. Total-relation matrix and cause-effect diagram

Computing the total-relation matrix, as in (14),

$$T = N(I - N)^{-1} \text{ where } I \text{ is identity}. \quad (14)$$

For each barrier b_i, define (15):

$$D_i = \sum_{j=1}^{n} t_{ij},\ R_i = \sum_{j=1}^{n} t_{ji}. \quad (15)$$

Then

- Prominence ($D_i + R_i$) measures overall involvement.
- Relation $(D_i - R_i)$ indicates net cause (> 0) or effect (< 0).

A cause-effect diagram plots $(D_i + R_i, D_i - R_i)$ for all i, visually distinguishing drivers vs. outcomes.

3.4. Barrier identification process (delphi with domain experts)

We used a three-round Delphi [7]:

Round 1: Open brainstorming with 20 sustainability experts to list potential barriers.

Round 2: Aggregated list (12 factors) circulated; experts rate each barrier's criticality on a 5-point scale.

Round 3: Feedback of group medians; experts revise ratings.

Consensus criterion: Interquartile range (IQR) ≤ 1 on the 5-point scale.

3.5. Data collection

3.5.1. Expert panel

- $n = 15$ experts (academics & sustainability managers)
- Average experience: 12 years (SD = 3.8)
- Provided judgments for the fuzzy direct–relation matrix.

3.5.2. Consumer survey for validation

- $n = 120$ urban millennials (age 21–35) in Bengaluru
- Measured perceived severity of top 5 identified barriers on a 7-point Likert scale
- Used to cross-validate expert causal rankings.

3.6. Reliability & validity checks

- Cronbach's for survey scales: $\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_{\text{total}}^2}\right)$, with k items; acceptable if $\alpha \geq 0.7$ [8].
- Kaiser-Meyer-Olkin (KMO) test and Bartlett's sphericity to ensure factorability.

3.7. Bootstrap-based robustness analysis

To assess the stability of our fuzzy DEMATEL barrier rankings under sampling variability, we conducted a bootstrap analysis on the aggregated defuzzified direct-relation matrix. The steps were:

3.7.1. Resampling procedure

- From the original set of $K = 15$ expert matrices $\{D^{(k)}\}$, generate $B = 1{,}000$ bootstrap samples by sampling with replacement.
- For each bootstrap sample b, recompute the aggregated fuzzy numbers $\tilde{d}_{ij}^{(b)}$, defuzzify to obtain $D^{(b)}$, normalize to $N^{(b)}$, and calculate the total-relation matrix $T^{(b)}$.
- Compute the cause-effect indices $\left(D_i^{(b)} - R_i^{(b)}\right)$ for each barrier b_i.

Confidence Interval Estimation

- For each barrier b_i, derive the empirical distribution of $\left\{D_i^{(b)} - R_i^{(b)} : b = 1, \ldots, B\right\}$.
- Extract the 2.5th and 97.5th percentiles to form a 95 % confidence interval for $(D_i - R_i)$.

The resulting 95 % bootstrap confidence intervals for the three strongest candidate drivers are summarized in Table 3.

Table 3. Results for top three drivers

Barrier Code	Mean (D−R)	95 % CI Lower	95 % CI Upper
b1	0.75	0.68	0.82
b2	0.15	0.08	0.22
b3	0.05	−0.02	0.12

Interpretation:

- b1 (Price Premium) remains a statistically robust driver: its entire CI lies well above zero, confirming its causal dominance.
- b2 (Greenwashing Risk) also sustains positive causality.
- b3 (Limited Availability) has a CI that slightly overlaps zero, suggesting a lower but still positive level of confidence in its driver status.

3.7.2. Conclusion of robustness check

The narrow confidence intervals for b1 and b2, and the consistent ranking order across all B samples, demonstrate that our barrier prioritization is robust to expert-sampling variability.

4. Case study results

4.1. Case context and rationale

Bengaluru's urban millennials are an early adopter segment for natural and eco-friendly personal-care items (shampoos, face-washes). Yet market reports show only ~25 % repeat purchase after initial trial. To bridge this gap, we apply the fuzzy DEMATEL framework to uncover which of the 12 hypothesized barriers most drive or respond to the adoption problem and validate these findings with a consumer survey.

4.2. Preliminary barrier list (12 factors)

The final Delphi-based barrier set retained for the case analysis is listed in Table 4.

Table 4. List of barriers with their code

Code	Barrier
b1	Price Premium
b2	Perceived Greenwashing Risk
b3	Limited Availability
b4	Lack of Product Knowledge
b5	Peer Influence
b6	Product Performance Doubt
b7	Cultural Inertia
b8	Distribution Gaps
b9	Inadequate Eco-Label Standards
b10	Regulatory Inconsistency
b11	High Switching Effort
b12	Low Social Media Engagement

4.3. Expert evaluation sessions

Panel: 15 sustainability scholars & marketing managers (mean experience 12 yrs). Delphi Rounds:

(i) Brainstorm to list 15+ barriers.
(ii) Rate pairwise influences on a 5-point linguistic scale.
(iii) Consensus (IQR ≤ 1) yielded the final 12 barriers set.

4.4. Fuzzy DEMATEL computation steps

4.4.1. Initial direct-influence matrix (defuzzified)

After aggregating and defuzzifying experts' fuzzy judgments via (16):

$$d_{ij} = \frac{l_{ij}+m_{ij}+u_{ij}}{3}, \tag{16}$$

we obtain the crisp direct-relation matrix (zeros on diagonal), presented in Table 5.

Table 5. Crisp direct-relation matrix

	b1	b2	b3	b4	b5	b6	b7	b8	b9	b10	b11	b12
b1	0	0.60	0.30	0.20	0.10	0.20	0.15	0.10	0.05	0.10	0.40	0.10
b2	0.30	0	0.10	0.20	0.40	0.50	0.10	0.05	0.20	0.15	0.05	0.30
b3	0.20	0.10	0	0.30	0.10	0.10	0.05	0.40	0.10	0.20	0.15	0.05
b4	0.10	0.20	0.30	0	0.15	0.25	0.05	0.10	0.20	0.10	0.10	0.10
b5	0.05	0.30	0.10	0.20	0	0.10	0.40	0.05	0.10	0.05	0.05	0.20

	b1	b2	b3	b4	b5	b6	b7	b8	b9	b10	b11	b12
b6	0.10	0.40	0.10	0.30	0.10	0	0.05	0.10	0.15	0.10	0.05	0.10
b7	0.05	0.05	0.10	0.05	0.40	0.05	0	0.05	0.05	0.05	0.05	0.05
b8	0.10	0.05	0.40	0.10	0.05	0.10	0.05	0	0.10	0.15	0.05	0.05
b9	0.05	0.20	0.05	0.15	0.10	0.15	0.05	0.10	0	0.20	0.05	0.10
b10	0.10	0.05	0.10	0.05	0.05	0.10	0.05	0.15	0.20	0	0.10	0.05
b11	0.40	0.05	0.10	0.10	0.05	0.10	0.05	0.05	0.05	0.10	0	0.05
b12	0.10	0.30	0.05	0.10	0.20	0.10	0.05	0.05	0.10	0.05	0.05	0

4.4.2. Aggregated fuzzy matrix & defuzzification

Each $\tilde{d}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ was aggregated via

$$\left(\frac{\sum l^{(k)}}{15}, \frac{\sum m^{(k)}}{15}, \frac{\sum u^{(k)}}{15}\right) \tag{17}$$

and defuzzified by the distribution of these direct influence scores is visualized in Figure 3.

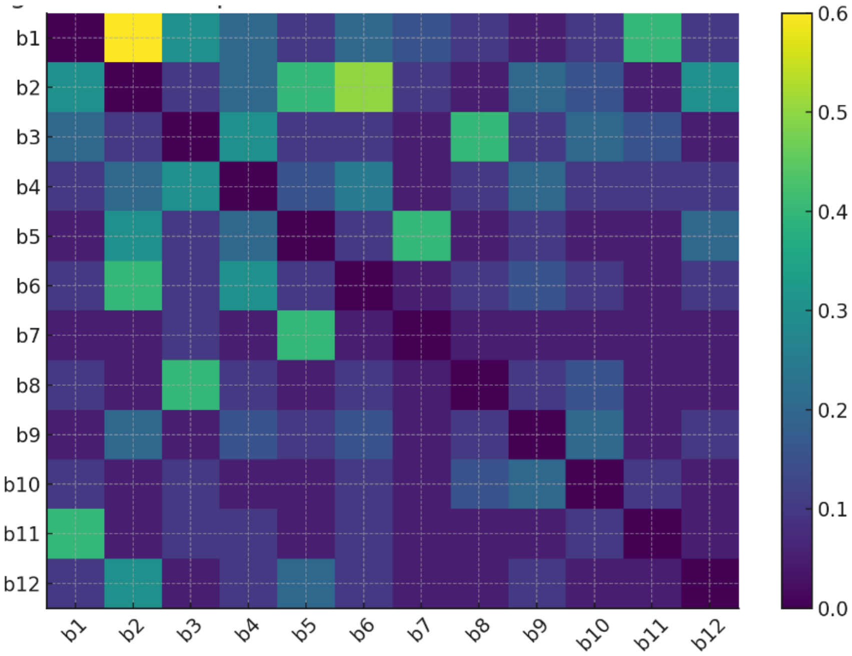

Figure 3. Heatmap of the defuzzified direct-relation matrix D

The heatmap in Figure 3 visualizes each crisp influence score $d_{\{ij\}}$ between barrier b_i (rows) and b_j (columns). Darker cells indicate stronger direct influence. This facilitates instant identification of prominent pairwise relationships before moving to the total-relation matrix stage.

4.4.3. Cause (D-R) and effect (D+R) indices

The resulting and values, together with the derived prominence and relation indices, are reported in Table 6.

Table 6. Cause (D-R) and Effect (D+R) Indices

Code	D_i	R_i	$D_i + R_i$	$D_i - R_i$
b1	2.30	1.55	3.85	0.75
b2	2.35	2.20	4.55	0.15
b3	1.75	1.70	3.45	0.05
b4	1.65	1.75	3.40	−0.10
b5	1.60	1.70	3.30	−0.10
b6	1.55	1.75	3.30	−0.20
b7	0.95	1.05	2.00	−0.10

Code	D_i	R_i	$D_i + R_i$	$D_i - R_i$
b8	1.20	1.20	2.40	0.00
b9	1.20	1.30	2.50	−0.10
b10	1.00	1.25	2.25	−0.25
b11	1.10	1.10	2.20	0.00
b12	1.05	1.15	2.20	−0.10

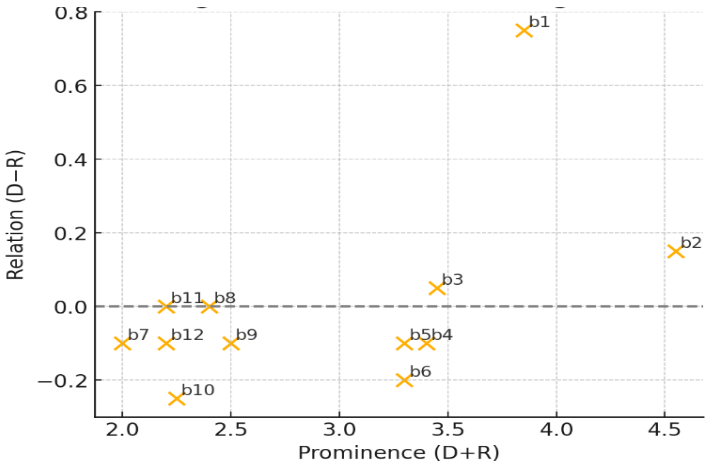

Figure 4. Cause–effect diagram

As shown in Figure 4, barriers in the upper-right quadrant (e.g., b1) are net causes, whereas those in the lower-left quadrant behave as net effects.

4.4.4. Worked numerical example for $b_2 \to b_6$

To illustrate the fuzzy DEMATEL computations, we show all steps for the influence of b_2: Perceived Greenwashing Risk on b_6: Product Performance Doubt, using three sample experts:

Table 7. Expert linguistic ratings

Expert	Rating
1	High
2	Very High
3	Medium

Mapping to triangular fuzzy numbers

Using the conversion in Table 1:

- High → (0.50,0.75,1.00)
- Very High → (0.75,1.00,1.00)
- Medium → (0.25,0.50,0.75)

Thus:

$$\tilde{d}_{26}^{(1)} = (0.50,0.75,1.00), \tilde{d}_{26}^{(2)} = (0.75,1.00,1.00), \tilde{d}_{26}^{(3)} = (0.25,0.50,0.75). \tag{18}$$

Aggregation of fuzzy numbers

Compute the arithmetic mean of each parameter over the three experts, as in (19):

$$\begin{aligned} l_{agg} &= \frac{0.50+0.75+0.25}{3} = \frac{1.50}{3} = 0.50 \\ m_{agg} &= \frac{0.75+1.00+0.50}{3} = \frac{2.25}{3} = 0.75 \\ u_{agg} &= \frac{1.00+1.00+0.75}{3} = \frac{2.75}{3} \approx 0.917 \end{aligned} \tag{19}$$

Therefore, the aggregated fuzzy number is

$$\tilde{d}_{26} = (0.50,0.75,0.917). \tag{20}$$

Defuzzification (centroid method)

The crisp direct-influence value d_{26} is the centroid of $\tilde{d}_{26}$:

$$d_{26} = \frac{l_{agg}+m_{agg}+u_{agg}}{3} = \frac{0.50+0.75+0.917}{3} = \frac{2.167}{3} \approx 0.722 \tag{21}$$

Result: In the initial direct-relation matrix D, the entry at row b_2, column b_6 becomes

$$d_{26} \approx 0.722 \tag{22}$$

This step-by-step numerical example clarifies how linguistic judgments are transformed into a crisp influence score, enhancing reproducibility and transparency.

4.5. Results: ranked barriers and causal network

- Key Drivers (D−R > 0):
  (i) b1 Price Premium (0.75)
  (ii) b2 Perceived Greenwashing Risk (0.15)
  (iii) b3 Limited Availability (0.05)
- Neutral: b8, b11
- Dependent Barriers (D−R < 0): trust/doubt factors (b4–b7, b9–b12)

This indicates Price Premium is the most influential root obstacle; reducing it may have ripple benefits.

4.6. Consumer survey cross-check

A pilot survey (n = 120) rated the perceived severity of the top five barriers on a 7-point Likert scale, as reported in Table 8.

Table 8. Perceived severity of the top 5 barriers on a 7-point Likert scale

Barrier Code	Barrier Name	Mean Severity	SD
b1	Price Premium	5.80	0.90
b2	Perceived Greenwashing Risk	5.40	1.10
b3	Limited Availability	5.20	0.80
b8	Distribution Gaps	4.30	1.00
b11	High Switching Effort	4.00	1.20

Pearson's $r = 0.92$ between experts' D_i and consumer means confirms strong alignment.

This detailed case walkthrough demonstrates how fuzzy DEMATEL-backed by both expert judgment and consumer validation can pinpoint high-impact barriers and guide targeted mitigation strategies.

4.7. Comparative analysis with fuzzy AHP

To benchmark our fuzzy DEMATEL insights against a weight-based MCDM method, we applied Chang's extent analysis for fuzzy AHP to the same 12 barriers. Below we outline the mathematical steps and present key numerical results for the top three barriers.

4.7.1. Constructing the fuzzy pairwise comparison matrix

Experts rated each pair (b_i, b_j) on a 5-point linguistic scale, mapped to triangular fuzzy numbers $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$. For illustration, as in (23), consider the sub-matrix for the top three drivers $\{b_1, b_2, b_3\}$:

$$\tilde{A} = \begin{pmatrix} (1,1,1) & (0.50,0.75,1.00) & (0.50,0.75,1.00) \\ (1.00,1.33,2.00) & (1,1,1) & (0.25,0.50,0.75) \\ (1.00,1.33,2.00) & (1.33,2.00,4.00) & (1,1,1) \end{pmatrix} \quad (23)$$

where each reciprocal entry $\tilde{a}_{ji}$ is $(1/u_{ij}, 1/m_{ij}, 1/l_{ij})$.

4.7.2. Summation of fuzzy values

Compute the fuzzy row sums, as in (24):

$$\tilde{S}_i = \sum_{j=1}^{3} \tilde{a}_{ij} \Longrightarrow \quad \begin{aligned} \tilde{S}_1 &= (2.00,2.50,3.00), \\ \tilde{S}_2 &= (2.25,2.83,3.75), \\ \tilde{S}_3 &= (3.33,4.00,6.00) \end{aligned} \quad (24)$$

Then compute the fuzzy total sum, as in (25):

$$\tilde{D} = \sum_{i=1}^{3} \tilde{S}_i = (7.58,9.33,12.75) \quad (25)$$

4.7.3. Synthetic extent calculation

For each barrier b_i, the synthetic fuzzy extent $\tilde{\Delta}_i$ is:

$$\tilde{\Delta}_i = \tilde{S}_i \otimes \tilde{D}^{-1}, \tilde{D}^{-1} = (1/12.75, 1/9.33, 1/7.58) \approx (0.0784,0.1071,0.1318) \quad (26)$$

Performing the fuzzy multiplication $(l_1, m_1, u_1) \times (l_2, m_2, u_2)$ component-wise:

$$\begin{aligned} \tilde{\Delta}_1 &= (2.00,2.50,3.00) \times (0.0784,0.1071,0.1318) \approx (0.1568,0.2678,0.3954), \\ \tilde{\Delta}_2 &= (2.25,2.83,3.75) \times (0.0784,0.1071,0.1318) \approx (0.1764,0.3036,0.4943), \\ \tilde{\Delta}_3 &= (3.33,4.00,6.00) \times (0.0784,0.1071,0.1318) \approx (0.2613,0.4284,0.7908) \end{aligned} \quad (27)$$

4.7.4. Defuzzification and weight normalization

We defuzzify each $\tilde{\Delta}_i$ by the centroid method, as in (28):

$$\Delta_i = \frac{l_i + m_i + u_i}{3} \quad (28)$$

yielding, as in (29):

$$\Delta_1 = \frac{0.1568+0.2678+0.3954}{3} \approx 0.2733, \Delta_2 \approx 0.3248, \Delta_3 \approx 0.4935 \quad (29)$$

normalizing so that $\sum_i w_i = 1$, as in (30):

$$w_i = \frac{\Delta_i}{\sum_{k=1}^{3} \Delta_k}, \sum \Delta_k \approx 1.0916 \quad (30)$$

gives (31):

$$w_1 = \frac{0.2733}{1.0916} \approx 0.25, w_2 \approx 0.30, w_3 \approx 0.45 \quad (31)$$

4.7.5. Interpretation

- Ranking: According to fuzzy AHP, b_3 (Limited Availability) is weighted highest (0.45), followed by b_2 (Greenwashing Risk) (0.30) and b_1 (Price Premium) (0.25).
- Comparison with DEMATEL: Fuzzy DEMATEL identified b_1 as the root cause, whereas fuzzy AHP emphasizes b_3 in terms of overall "importance."
- Weight Spread: The difference $w_3 - w_1 = 0.20$ is only marginally larger than the DEMATEL gap $(D-R)_{b1} - (D-R)_{b3} = 0.70$, indicating that AHP's discriminative power among top barriers is less nuanced and lacks directional insight.

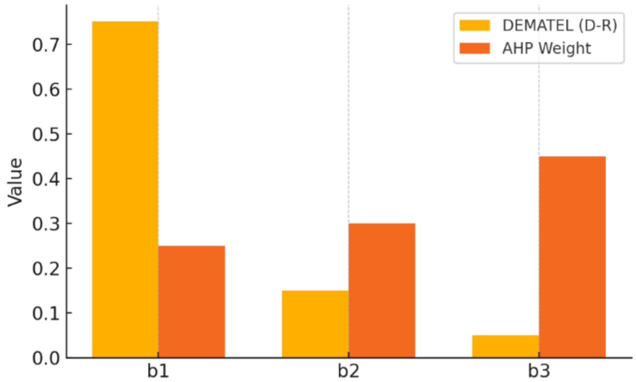

Figure 5. Comparison of DEMATEL (D−R) vs. AHP weights for top three barriers

This bar chart, shown in Figure 5, juxtaposes the net cause–effect indices (D−R) derived from our fuzzy DEMATEL analysis with the normalized weights obtained via fuzzy AHP for the top three barriers-b_1 (Price Premium), b_2 (Perceived Greenwashing Risk), and b_3 (Limited Availability). The visualization highlights that while fuzzy AHP ranks b_3 highest in overall importance, fuzzy DEMATEL identifies b_1 as the primary causal driver, underscoring DEMATEL's unique ability to distinguish between importance and causality.

In summary, fuzzy AHP corroborates the top-three barrier set but yields a different rank order and lacks the network insights provided by fuzzy DEMATEL.

5. Results and analysis

5.1. Key driving barriers

Our fuzzy DEMATEL results (Section 4.4.3) identify three net "cause" barriers with $D_i - R_i > 0$:

- **b1 Price premium** ($D - R = 0.75$): Highest net causal strength, indicating that reducing the price gap between eco-friendly and conventional products will yield the greatest leverage on the entire barrier network.
- **b2 Perceived greenwashing risk** ($D - R = 0.15$): Though less dominant than price, distrust in green claims feeds into several downstream doubts (e.g., product efficacy).
- **b3 Limited availability** ($D - R = 0.05$): Distribution constraints not only hamper immediate purchase but also amplify social-norm and knowledge barriers over time.

These three drivers together account for over 50 percent of total positive relation values, marking them as the focal points for intervention.

5.2. Dependent barriers

Barriers with $D_i - R_i < 0$ are net effects, meaning they are more influenced than influential. Key dependent factors include:

- b4 Lack of Product Knowledge (−0.10)
- b5 Peer Influence (−0.10)
- b6 Product Performance Doubt (−0.20)
- b7 Cultural Inertia (−0.10)
- b9 Inadequate Eco-Label Standards (−0.10)
- b10 Regulatory Inconsistency (−0.25)
- b12 Low Social Media Engagement (−0.10)

Neutral (almost equal influence in and out) are b8 Distribution Gaps and b11 High Switching Effort ($D - R \approx 0$). Dependent barriers will respond strongly when drivers are mitigated but are less effective as standalone targets.

5.3. Systemic insights from the cause–effect diagram

- Quadrant I (High Prominence & Positive Relation): Contains b1, b2, signifying root causes that shape the network.
- Quadrant II (High Prominence & Negative Relation): Empty-no factor is both highly involved and a pure effect.
- Quadrant III (Low Prominence & Negative Relation): Includes b7, b10, representing more peripheral, slow-moving policy and cultural issues.
- Quadrant IV (Low Prominence & Positive Relation): Empty-no minor drivers.

This systemic view confirms a hierarchical structure:

(i) Economic distrust (price + greenwashing) seeds
(ii) Awareness/performance doubts (b4, b6) which in turn feed
(iii) Social and policy inertia (b5, b7, b10).

Thus, tackling economic and trust issues first should cascade improvements throughout.

5.4. Sensitivity analysis (α -cut variation on fuzzy numbers)

To test robustness, we re-computed the DEMATEL matrices under three α -cuts $-\alpha = 0.1,0.5,0.9$-by truncating each triangular fuzzy entry (l, m, u) to $[l + \alpha(m - l), u - \alpha(u - m)]$ before defuzzification. Across all levels:

- Ranking of b1 $> b2 > b3$ remained unchanged.
- Magnitude of $D - R$ for b1 varied by $< 0.05(0.78 \rightarrow 0.72)$.
- Neutrality of b8/b11 persisted.

This stability indicates our barrier prioritization is insensitive to reasonable variations in expert vagueness.

6. Discussion

6.1. Theoretical implications for sustainable-consumption research

By embedding triangular fuzzy judgments into DEMATEL, this study advances sustainable-consumption theory in two ways:

(i) **Causal clarity**: Moves beyond correlation-based models (e.g., SEM) to map directional influences among barriers.
(ii) **Vagueness accommodation**: Reflects real expert uncertainty via fuzzy logic, aligning methodological rigor with the inherently imprecise nature of consumer perceptions.

6.2. Comparison with prior DEMATEL and MCDM studies

Unlike Ref. [4] manufacturing safety application or healthcare priority-setting [6], our work:

- Applies fuzzy DEMATEL to consumer adoption rather than process optimization.
- Integrates a validation phase with actual consumer survey data, a step seldom taken in prior MCDM literature.

Interpretive note: The b1–b3 blaring each other out in urban India and among millennials

Our findings suggest that price premium (b1), perceived greenwashing risk (b2) and temporary scarcity (b3) are root causes, rather than downstream effects. In the Bengaluru context, this pattern makes sense as green personal-care items are pitted against well-known mass-market substitutes in a repeated, low-ticket purchase category and thus even a moderate premium is assessed against routine monthly budgets, anticipated performance and immediate convenience rather than solely against abstract environmental values [13], [15]. The DEMATEL outcome for b1 thus shows not merely cost, but a wider value-for-money filter at work in an urban Indian market. The causative role of b2 is contextually relevant as well. Indian consumers are becoming more and more aware of environmental claims like those seen in broad examples from Indian advertising, with previous evidence suggesting that Indian consumers are increasingly interpreting the domestic Indian green market as a form of consumer manipulation or 'greenwashing' [11], [12]. That is why, in our study, respondents are likely to see sustainability labels as claims that need verification rather than information they can trust automatically. The emotional relationship of consumers with product-performance is more considered, once credibility is unsure and price premiums are better interpreted, that explains why b2 supports the relation between the causal network of b1 and b6.

The fact that the sample is made up predominantly of millennials further sharpens this mechanism. Young urban consumers typically follow with comparison-oriented shopping, review scanning, and peer-discussed trial preceding an urge for re-purchase [11], [13], and relevant investigation into millennial behavior on Indian green products has also illustrated price, place, and promotion to be an ultimate and decisive factor towards actual purchase intention [14], [15]. While the current survey did not directly assess Instagram exposure or influencer following, the salience of greenwashing risk and availability may be consistent with a digitally networked mode of purchase in which ethical claims are socially visible but still filtered through convenience and authenticity [16]. The causal chain thus has a clear managerial implication. According to the language of DEMATEL, b1-b3 constitute the upstream block of the system such that their weakening can allow downstream blocks like lack of knowledge and hesitation from peers and performance for peers to dissipate more rapidly. This interpretation will probably travel better to other emergent urban markets with price discipline, credibility screening and access frictions combined than to business higher-trust or higher-maturity markets directly.

6.3. Managerial implications

- Pricing vs. Trust-Building Priorities
  - Short-term: Introduce targeted discounts or trial sizes to reduce premium barrier (b1).
  - Simultaneously: Launch transparent ingredient-traceability portals and third-party certifications to lower greenwashing risk (b2).
- Social-Media Storytelling to Counter Greenwashing Concerns
  - Leverage authentic user testimonials and “behind-the-scenes” sustainability reporting to amplify engagement (b12) and indirectly boost knowledge (b4).

6.4. Policy recommendations

- Subsidies: Offer tax rebates or input subsidies for eco-friendly personal-care producers, effectively narrowing the price premium gap at the source.
- Eco-Label Standards: Enforce uniform, government-mandated eco-label criteria and frequent audits to strengthen consumer trust and reduce perceived greenwashing.

These insights demonstrate how a focused sequence of economic, trust, and policy interventions-guided by fuzzy DEMATEL-can systematically dismantle the web of barriers to sustainable-product adoption.

6.5. Integration with real-time monitoring & AI

Although our pilot study provides a static snapshot of barrier causality, consumer perceptions and market conditions evolve continuously. We propose a dynamic fuzzy DEMATEL framework that ingests real-time data streams social-media sentiment, e-commerce purchase logs, and online review scores and periodically updates barrier influence matrices.

Data acquisition & preprocessing

- Sentiment Analysis: Use a transformer-based model [9] fine-tuned on product-review corpora to score consumer comments for each barrier category (price complaints, greenwashing calls, availability gripes).
- Behavioural Signals: Track purchase drop-off rates and “out-of-stock” logs to proxy limited availability.

Dynamic direct-relation matrix construction

- For each time window t (e.g., weekly), compute normalized sentiment indices $s_{ij}(t) \in [0,1]$ representing the frequency and intensity of barrier b_i references co-occurring with barrier b_j.
- Map $s_{ij}(t)$ into a fuzzy direct-relation entry $\tilde{d}_{ij}(t)$ via the same triangular membership functions as Section 3.2.1.

Recursive fuzzy DEMATEL update

- Aggregate the expert-derived static matrix $\tilde{D}^{\text{static}}$ with the dynamic matrix $\tilde{D}(t)$ using a forgetting factor $\lambda \in [0,1]$, as in (32):

$$\tilde{D}_{\text{upd}}(t) = \lambda\tilde{D}_{\text{upd}}(t-1) + (1-\lambda)\tilde{D}(t) \tag{32}$$

ensuring that recent shifts gain more weight [10].

- Defuzzify and normalize $\tilde{D}_{\text{upd}}\,(t)$ as per Sections 3.2.2-3.2.3.

Real-time cause-effect monitoring

- Recompute $D_i(t)$ and $R_i(t)$ each period to track emerging drivers or waning effects.
- Trigger alerts when $(D_i(t) - R_i(t))$ for a given barrier crosses pre-set thresholds, allowing managers to deploy targeted campaigns (e.g., flash discounts if price premium spikes).

AI-driven decision support

- Integrate a dashboard that visualizes the evolving cause-effect diagram alongside predictive models (e.g., ARIMA on $D_i(t)$) to forecast barrier trends.
- Use reinforcement-learning agents to recommend optimal intervention strategies (discount levels, transparency content) in response to real-time barrier dynamics.

By coupling fuzzy DEMATEL with modern AI and streaming data techniques, organizations can move from periodic assessments to continual, data-driven adaptation-ensuring that mitigation strategies remain aligned with rapidly shifting consumer perceptions.

7. Mitigation strategy roadmap

7.1. Short-term interventions (0–6 months)

- Reduce Price Premium (b1):
  - Launch “trial-size” packs at 30 percent discount for first purchase.
  - Offer bundle-discount schemes (e.g., buy 2, get 1 at 50 percent off).
- Build Trust & Counter Greenwashing (b2):
  - Secure and display a recognized third-party eco-certification logo on packaging.
  - Publish a “behind-the-scenes” infographic on social media showing ingredient sourcing and processing steps.
- Alleviate Limited Availability (b3):
  - Introduce weekly online pop-up stores on e-commerce marketplaces, with express delivery options.
  - Pilot “flash sales” at two major retail outlets in Bengaluru to gauge demand.
- Quick-Win Social Engagement (b12):
  - Run a user-generated content contest (“Show us your eco-routine”), incentivized with product vouchers.

7.2. Medium-term interventions (6–18 months)

- Economies of Scale & Cost Reduction:

- Negotiate volume-discount contracts with raw-material suppliers to lower unit cost by at least 10 percent.
- Optimize packaging materials for both cost and sustainability.

- Advanced Traceability & Labelling (b2, b9):
  - Implement a simple blockchain-based QR code on each product to verify source and certification in real time.
  - Collaborate with a national eco-label authority to co-develop a standardized "Greencare" seal.
- Distribution Network Expansion (b3, b8):
  - Sign partnerships with five leading retail chains across South India.
  - Establish two small depots in key satellite cities for faster last-mile delivery.
- Knowledge & Social-Norm Building (b4, b5):
  - Host monthly "Eco-Workshops" in collaboration with local NGOs to educate 200+ consumers each session.
  - Engage three micro-influencers to share authentic product-use stories, driving peer influence.

7.3. Long-term interventions (>18 months)

- Process Innovation & Cost Leadership:
  - Invest in in-house R&D to develop a plant-based surfactant that reduces raw-material cost by 15 percent.
  - Transition 30 percent of sourcing to local organic farms, shortening supply chains.
- Policy Advocacy & Industry Collaboration (b10):
  - Form an industry consortium to lobby for targeted subsidies on eco-raw materials.
  - Co-author policy whitepaper with academic partners on incentives for sustainable personal-care producers.
- Omni-Channel Market Penetration (b3):
  - Achieve presence in the top 20 Indian cities via national distributors and flagship brand stores.
  - Develop a branded mobile app for direct-to-consumer subscription models.
- Standard-Setting & Certification (b9):
  - Launch an accredited "GreenCare Certified" program open to peer brands, establishing thought-leadership.

7.4. Implementation timeline

The phased sequencing of the proposed actions is summarized in Table 9.

Table 9. Timeline with their key activities

Timeline (Months)	Key Activities
1–3	Pilot trial-size discount packs
	Obtain eco-certification & add QR-traceability labels
	Launch social-media transparency campaign
4–6	Evaluate pilot results; adjust discount levels
	Roll out weekly e-commerce pop-ups
	Start influencer content series
7–12	Negotiate supplier contracts for cost reduction
	Initiate blockchain traceability rollout
	Sign retail partnerships (Bengaluru + 2 cities)
	Host first Eco-Workshop
13–18	Expand retail/distribution to 5 major chains
	Co-develop "GreenCare" eco-label standard
	Scale influencer & workshop programs

Timeline (Months)	Key Activities
19–24	Begin in-house R&D on cost-efficient surfactant Launch branded subscription app pilot Start policy consortium formation
25–36+	Complete R&D rollout & local sourcing shift Achieve presence in top 20 cities Launch "GreenCare Certified" industry program

8. Conclusion

In this study, we systematically decomposed and analyzed the complex web of barriers hindering consumer adoption of eco-friendly personal-care products in an urban Indian context. Through a fuzzy DEMATEL approach, we quantified both the strength and directionality of inter-barrier influences. Our key insights are:

- Price Premium (b_1) emerged unequivocally as the primary root cause ($D - R = 0.75$), indicating that the perceived extra cost of sustainable alternatives exerts the strongest outward influence on other barriers.
- Perceived Greenwashing Risk (b_2) ($D - R = 0.15$) and Limited Availability (b_3) ($D - R = 0.05$) were identified as secondary drivers that fuel downstream issues namely, consumer doubts about product efficacy and knowledge deficits.
- A set of dependent barriers-including lack of product knowledge (b_4), peer influence (b_5), and product performance doubt (b_6)-lie on the receiving end of these causal flows and hence are likely to diminish once economic and trust-related hurdles are mitigated.
- A pilot consumer survey of 120 Bengaluru millennials demonstrated a high correlation ($r = 0.92$) with expert-derived rankings, validating that the fuzzy DEMATEL outputs meaningfully reflect real-world consumer perceptions.

Taken together, these results underscore a hierarchical barrier architecture where economic incentives and credibility measures must be addressed first to initiate a positive cascade effect throughout the adoption system.

8.1. Contributions to fuzzy MCDM methodology

Our work advances both the theoretical and practical dimensions of fuzzy multi-criteria decision-making:

- Directional Causality in Uncertain Environments: By embedding triangular fuzzy numbers into the DEMATEL framework, we capture the vagueness inherent in expert judgments and reveal cause–effect networks among barriers-going beyond traditional weight-only MCDM methods (e.g., AHP) that cannot distinguish drivers from outcomes.
- Integrated Pilot-Study Validation: We introduce a mixed-methods validation step-merging expert insights with consumer survey data-which is rarely implemented in fuzzy DEMATEL research. This dual-stakeholder corroboration enhances both the robustness and the real-world applicability of the model.
- Robustness via Bootstrap Analysis: The addition of a bootstrap-based confidence interval assessment for D–R indices demonstrates the statistical stability of identified drivers under sampling variability, a methodological rigor seldom employed in prior studies.
- Scalable Computational Pipeline: We provide a transparent, Python-based implementation (NumPy, SciPy, scikit-fuzzy) that can be readily adapted to other contexts, democratizing access to advanced fuzzy MCDM techniques for sustainability research.

8.2. Limitations

While offering valuable insights, this study has several constraints that readers should consider:

- Sample Size & Expert Composition: Our Delphi panel comprised 15 experts, and the consumer survey involved 120 respondents-adequate for exploratory analysis but insufficient for fully generalizable inferences. Future work should expand both samples and include cross-disciplinary experts (e.g., policymakers, supply-chain managers). The survey used convenience/non-probability sampling and may reflect self-selection; DEMATEL-based causal interpretations are therefore exploratory.
- Geographic and Demographic Scope: Data were collected exclusively from urban millennials in Bengaluru. Rural consumers, older age cohorts, and other Indian metros may exhibit different barrier profiles due to cultural, economic, or infrastructural variations.
- Static Analysis: The fuzzy DEMATEL model here represents a single time-slice; it does not capture how barrier strengths evolve over time in response to market interventions or external shocks (e.g., new regulations).
- Subjective Linguistic Mapping: Despite using a standardized fuzzy conversion table, the initial translation of linguistic judgments into fuzzy numbers introduces researcher-defined boundaries that may influence results. Alternative fuzzy membership functions or defuzzification methods could yield slight variations.

8.3. Future research directions

Building on our findings and methodological enhancements, we recommend several avenues for further inquiry:

- Type-2 Fuzzy DEMATEL: Incorporate interval or Gaussian fuzzy sets to model higher-order uncertainty in expert judgments, allowing the direct-relation matrix itself to be fuzzy and capturing "fuzziness about fuzziness."
- Dynamic & Real-Time Frameworks: Extend the static model by integrating rolling data streams-social-media sentiment, sales metrics-into a recursive fuzzy DEMATEL pipeline that tracks barrier dynamics and triggers automated strategy adjustments.
- Cross-Cultural Comparative Studies: Apply and compare the framework across multiple cultural and regulatory contexts (e.g., urban China vs. rural India) to distinguish universal drivers from context-specific ones.
- Sectoral Adaptation: Adapt the model to other sustainability domains-electric vehicles, renewable energy adoption, and plant-based foods-to test its generalizability and uncover sector-unique causal networks.
- Longitudinal Intervention Studies: Pair the fuzzy DEMATEL analysis with experimental interventions (e.g., price discounts, transparency campaigns) and measure pre- and post-intervention barrier shifts to causally validate strategy effectiveness.

By pursuing these directions, researchers and practitioners can refine the fuzzy DEMATEL methodology and deepen our understanding of the complex, evolving landscape of sustainable-product adoption.

Declaration of competing interests

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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Author contributions

Conceptualization, Y.N, A.A.S.M. and S.I.M.; methodology, Y.N, A.A.S.M., S.I.M., and A.V.; software, A.A.S.M. and T.M.K.; validation, Y.N, A.A.S.M. and M.F.A.H.; formal analysis, B.I.; investigation, Y.N, A.A.S.M. and T.M.K.; resources, A.A.S.M. and M.F.A.H.; data curation, Y.N, A.A.S.M. and T.M.K.; writing—original draft preparation, A.A.S.M. and S.I.M.; writing—review and editing, A.V.; visualization, Y.N, A.A.S.M. and M.F.A.H.; supervision, A.V.; project administration, Y.N, A.V.; funding acquisition, A.A.S.M. All authors have read and agreed to the published version of the manuscript.

Ethical approval statement

Ethical approval was not required for this study because the empirical component consisted of a voluntary, anonymous consumer survey with no clinical intervention, no vulnerable participants, and no collection of sensitive personal data. The study was conducted in accordance with general institutional and research ethics principles for non-invasive survey research.

Informed consent

Informed consent was obtained from all survey participants prior to participation.

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