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ARTICLE

Evaluation of Sustainable Waste-to-Material Pathways Using Fuzzy Cognitive Mapping

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ABSTRACT

Waste-to-material (WtM) strategies are central to circular-economy planning, yet pathway selection is complicated by uncertain feedstock quality, policy variability, market fluctuations, and coupled operational trade-offs. Existing evaluations often treat key drivers independently, limiting their ability to represent feedback effects that shape long-run pathway performance. This study develops a fuzzy cognitive map (FCM) decision framework to compare four representative WtM pathways (mechanical recycling, chemical recycling, anaerobic digestion, and mineralization) using a system of interacting indicators: feedstock quality, collection rate, preprocessing efficiency, yield, energy intensity, market value, greenhouse-gas

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(GHG) impact, and circular uptake. For reproducibility, the resulting FCM adjacency structure is explicitly specified and all scenarios are parameterized following a defined set of node clamps to reflect policy push (feedstock expansion) and edge edits reflecting feedstock shock conditions. Pathway-specific environmental, economic and circularity indicators, as well as a comprehensive sustainability score with uncertainty bounds are reported for converged (steady-state) outputs. Results also indicate that pathway rankings and trade-off positions vary across scenarios, with policy developments leading to higher values of circular uptake and market value but lower values for preprocessing/yield (feedstock shocks) and GHG outcomes. The framework that we have proposed provides an interpretable and reproducible tool for WtM strategy selection under uncertainty, as well as a basis for policy-relevant sensitivity and robustness analysis.

Keywords: Waste-to-Material Pathways; Fuzzy Cognitive Maps; Triangular Fuzzy Numbers; Monte Carlo Robustness; Scenario-Based Sustainability Scoring; Leverage Analysis; Circular Economy Decision Support

1. Introduction

1.1. Background

Sustainable Waste-to-Material (WtM) pathways are an essential component of circular economy strategies where heterogeneous waste streams are converted into secondary materials that can replace primary resources. The friction of these pathways is a function of a tightly interlinked set of drivers: feedstock quality and collection rate, processing efficiency, process yield, energy intensity (EE), material value (MV), and GHG impact; and finally the eventual circular uptake of recovered products. Yet these drivers do not operate in isolation; small changes in one part of the system (e.g., a shift at points of contamination or market demand) can affect several technological and economic stages before appearing as changes in environmental and socio-economic outcomes.

1.2. Problem Motivation

Conventional evaluation approaches-such as linear additive multi-criteria decision analysis (MCDA) or single-scenario life cycle assessment (LCA)-typically treat system variables as independent indicators. As a result, policy instruments or technological interventions may appear attractive at the indicator level while inducing unintended trade-offs once system-wide feedbacks are taken into account. Waste-to-material systems are inherently socio-techno-economic networks with nonlinear feedback, uncertainty, and multiple competing objectives, including diversion from landfill, GHG reduction, cost containment, and employment generation.

Classical MCDA frameworks usually encode causality in a crisp, one-way manner, whereas fuzzy cognitive maps (FCMs) model signed causal links with graded strengths and feedback loops, allowing iterative propagation and "what-if" scenario exploration[1–4]. In this work, the WtM system is represented by an eight-concept FCM, and the effect of different policy and feedstock conditions is quantified through the stabilized activations of outcome nodes and an aggregate sustainability score derived from the steady state of the underlying dynamical system.

Despite extensive LCA and techno-economic studies on individual waste treatment technologies, decision makers still lack a compact framework that (i) integrates operational and policy drivers into a coupled system model, (ii) captures feedback among collection, preprocessing, yield, energy use, and market response, and (iii) produces scenario-conditioned pathway rankings with uncertainty and trade-off visibility. This study addresses that gap by implementing a reproducible FCM structure for WtM comparison and by reporting explicit scenario parameterization, steady-state outputs, and robustness diagnostics suitable for planning and policy evaluation.

1.3. Related Work and Research Gap

FCMs have been widely applied to policy planning in complex environmental and sustainability contexts, demonstrating a strong ability to model multi-stakeholder systems under uncertainty[5]. In municipal solid-waste planning, FCMs have been used to identify policy leverage points and to explore community-level intervention effects where data are incomplete or heterogeneous[6]. In bio-resource and organic waste valorization, FCM-based evaluations have

revealed cross-impacts among technology performance, economic incentives, and regulatory drivers [7,8]. Beyond waste, FCMs inform nature-based solutions and sustainability governance by translating stakeholder knowledge into structured strategic planning tools [9–12]. Methodological advances include learning-enhanced and dynamic FCM variants that enable scenario simulation, adaptive propagation, and uncertainty band estimation [13,14], while participatory literature emphasizes multi-expert weight aggregation and transparency in causal justification [15,16].

However, very few studies integrate FCM with a full pathway-level WtM comparison, especially one that (i) combines environment-cost-jobs trade-offs, (ii) evaluates both policy and feedstock-shock scenarios, and (iii) reports robustness (win-rate) sensitivity across uncertain causal strengths [17,18]. The scientific issue is therefore: How can we evaluate and rank sustainable WtM pathways when causal relations among feedstock, technology, markets, and policy are uncertain and interacting?

Recent literature has further broadened the methodological and application base of FCMs in sustainability research, including household food waste analysis [19–22], intuitionistic and dynamic FCM formulations, interpretable FCM-AI links, municipal waste optimization, and broader circular-economy decision support [23–27]. Additional recent works on circular economy and waste-management assessment further link bibliometric indicators [28–30], machine-learning-based circularity modelling, fuzzy MCDM selection, life-cycle modelling of plastic-waste conversion, and SDG-oriented circular-economy reviews with the present WtM evaluation context [31].

The main gap is a reproducible, stakeholder-elicited, mathematically explicit FCM framework that integrates fuzzy causality with scenario and sensitivity analysis for WtM planning.

1.4. Objectives and Contributions

This paper develops a transparent, scenario-driven evaluation of waste-to-material (WtM) pathways using a fuzzy cognitive mapping (FCM) framework that captures feedback among feedstock quality, collection performance, preprocessing efficiency, yield, energy intensity, market value, greenhouse-gas (GHG) impacts, and circular uptake. The approach translates expert-elicited causal structure into a reproducible adjacency matrix and evaluates pathway performance under baseline, policy-push, and feedstock-shock conditions. We present steady-state outcomes and a composite sustainability score with diagnostics of uncertainty and trade-offs, for decision use. The subsequent analysis yields interpretable pathway rankings, identifies the key system levers, and explicates how policy and feedstock variability reshape the environment–cost–jobs frontier.

1.5. Scope and Boundaries

Analysis of Four Models: WtM Pathway Analysis by Region: The analysis focuses on four pathways-WtM and under a regional context-mechanical recycling, chemical depolymerization, anaerobic digestion and mineralization. It captures environmental, techno-economic and social outcomes over a medium-term horizon (ongoing to 2030) with respect to criteria. Direct energy recovery is only included in the presence of material co-products. This is about time average comparative behavior and robustness, not detailed engineering design at the level of the plant.

2. Methods: Fuzzy Cognitive Map Framework

This section brings together the methodological material that appeared in multiple short sections and provides a coherent description of the modelling method.

2.1. Dynamical Systems and Fuzzy Cognitive Maps

Using $x^{(k)} \in [0,1]^n$ as the vector of concept activations at iteration k where each component corresponds to a normalized system variable (e.g., feedstock quality, process yield). The causal structure of the system is encoded in an adjacency matrix $\mathrm{W} = [w_{ij}]$, where w_{ij} denotes the signed strength of the influence from concept j to concept i. The state update rule of an FCM is written as

$$\mathrm{x}^{(k+1)} = f\left(\mathrm{W}\mathrm{x}^{(k)} + \mathrm{u}\right),$$

where u is a vector of exogenous inputs (policies, shocks) and $f(\cdot)$ is a bounded activation function (e.g., logistic or linear-squash) applied elementwise [19,20]. Convergence to a fixed point or limit cycle is monitored using the residual

$$r^{(k)} = \left\| \mathrm{x}^{(k+1)} - \mathrm{x}^{(k)} \right\|.$$

2.2. Pathway-Specific Ranking Using Clamped Technology Descriptors

To enable meaningful ranking of waste-to-material (WtM) pathways, pathway characteristics must remain active throughout the Fuzzy Cognitive Map (FCM) evolution rather than being used only as initial conditions. When pathway differences are encoded only in the initial state vector, the dynamics may converge to the same fixed point under identical structure and scenario forcing, yielding indistinguishable composite scores. Therefore, we adopt a pathway-specific forcing ("clamping") strategy in which intrinsic technology descriptors are fixed at pathway representative values at every iteration, while outcome variables are allowed to evolve endogenously.

2.2.1. State Partitioning

Let the concept/state vector be partitioned into:

Descriptor (technology) nodes D: pathway-intrinsic attributes (e.g., feedstock quality FQ, energy intensity EI, baseline yield PY, market value potential MV as pathway capability).

Response (system) nodes R: outcomes that should emerge from interactions (e.g., preprocessing efficiency PE, GHG impact GHG, circularity CU).

Thus, at iteration t,

$$\mathrm{x}^{(t)} = \left[\mathrm{x}_D^{(t)}, \mathrm{x}_R^{(t)} \right].$$

2.2.2. Clamped (Persistent) Pathway Forcing

For each pathway $p \in \{\text{MR,CR,AD,MIN}\}$, define a descriptor vector d_p from the normalized pathway table. During the iterative update, descriptors are clamped:

$$\mathrm{x}_D^{(t)} = \mathrm{d}_p \ \text{ for all } t = 0, 1, 2, \ldots,$$

and only the response nodes are updated using the FCM dynamics.

A convenient implementation is:

$$\mathrm{x}^{(t+1)} = f\left(\mathrm{x}^{(t)} \mathrm{W} + \mathrm{u}_s \right),$$

followed by the clamping operator:

$$\mathrm{x}^{(t+1)} \leftarrow \mathrm{C}_p\left(\mathrm{x}^{(t+1)} \right),$$

where $\mathrm{C}_p : \mathrm{x}_D^{(t+1)} := \mathrm{d}_p, \mathrm{x}_R^{(t+1)}$ unchanged.

Here:

- W is the adjacency/weight matrix,
- u_s is the scenario input vector for scenario s (policy push, supply shock, baseline),
- $f(\cdot)$ is the activation function (e.g., bounded sigmoid) ensuring all states remain in $[0, 1]$.

The steady-state solution x_p^* is obtained when:

$$\left\| \mathrm{x}^{(t+1)} - \mathrm{x}^{(t)} \right\|_2 < \varepsilon,$$

with ε a small tolerance (e.g., 10^{-4}).

Why this enables ranking: clamping ensures that pathway descriptors continuously influence response nodes through W. Therefore, different pathways yield different steady-states x_p^*, producing distinct composite scores and ranks.

2.2.3. Composite Scoring and Ranking

For each pathway p under scenario s, compute a composite score from the steady-state outputs:

$$S_{p,s} = w_{CU} CU_{p,s}^* + w_{MV} MV_{p,s}^* + w_{ENV} \left(1 - GHG_{p,s}^*\right),$$

where $w_{CU} + w_{MV} + w_{ENV} = 1$ and GHG is modeled so that higher values indicate worse environmental impact (hence $1 - GHG$ is "better").

Pathways are ranked by descending $S_{p,s}$:

$$\text{Rank}(p \mid s) = \text{ order of } S_{p,s} \text{ from highest to lowest.}$$

2.2.4. Algorithm (for Transparency and Reproducibility): Pathway Ranking with Clamped FCM Descriptors

(i) Select scenario s; set scenario input vector u_s.

(ii) For each pathway p:

- set descriptor vector d_p;
- initialize $\mathrm{x}^{(0)}$ (e.g., $[\mathrm{d}_p, 0]$ or a neutral prior);
- iterate:

$$\mathrm{x}^{(t+1)} = f\left(\mathrm{x}^{(t)} \mathrm{W} + \mathrm{u}_s \right);$$
$$\mathrm{x}^{(t+1)} \leftarrow \mathrm{C}_p\left(\mathrm{x}^{(t+1)} \right)$$

until convergence.

- compute $S_{p,s}$ from x_p^*.

(iii) Sort $S_{p,s}$ to produce the final ranking.

2.3. Linguistic Causality and Fuzzy Weights

Causal strengths are elicited from experts on a five-point linguistic scale
{Very Negative (VN), Negative (N), Neutral (Z), Positive (P), Very Positive (VP)}.

Each linguistic term is mapped to a triangular fuzzy number (TFN) $\widetilde{w}_{ij} = (a_{ij}, m_{ij}, b_{ij})$ on the domain $[-1, 1]$. For example, the mapping in **Table 1** is used.

Table 1. Linguistic-to-fuzzy mapping (example TFNs).

Term	TFN (*a*,*m*,*b*) in [−1, 1]	Defuzzified Value
VN	(−1.00, −0.90, −0.60)	−0.833
N	(−0.80, −0.50, −0.20)	−0.500
Z	(−0.15, 0, 0.15)	0.000
P	(0.20, 0.50, 0.80)	0.500
VP	(0.60, 0.90, 1.00)	0.833

In the baseline simulations, fuzzy weights are converted to crisp values using the centroid (expected value) defuzzification:

$$w_{ij} = \frac{a_{ij} + m_{ij} + b_{ij}}{3}.$$

For uncertainty analysis, α-cuts of the TFNs $\widetilde{w}_{ij}^{(\alpha)} = \left[a_{ij}^{(\alpha)}, b_{ij}^{(\alpha)}\right]$ are used to define perturbation ranges[21,22].

Defuzzifying a Linguistic Causal Weight

If three experts rate the influence of preprocessing efficiency on process yield as P, and VP, using the TFNs in **Table 1** and equal expert weights, the aggregated TFN is

$$\widetilde{w} = \tfrac{1}{3}\left[\begin{array}{c}(0.20, 0.50, 0.80) + (0.20, 0.50, 0.80) \\ +(0.60, 0.90, 1.00)\end{array}\right] = (0.33, 0.63, 0.87),$$

and the defuzzified crisp weight is

$$w = \frac{0.33 + 0.63 + 0.87}{3} \approx 0.61$$

The **Figure 1** below Illustrative fuzzy cognitive map for waste-to-material pathways with their nodes and edge representations.

The below **Figure 2** represents the membership degree verses normalized causal strength as per this study.

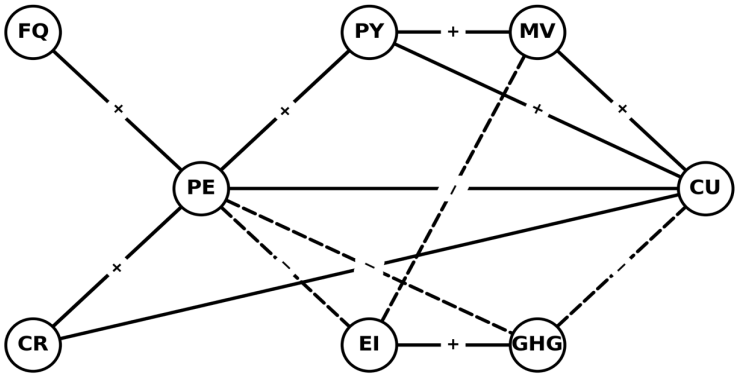

Figure 1. Illustrative fuzzy cognitive map for waste-to-material pathways.
Note: Nodes: feedstock quality, collection rate, preprocessing efficiency, process yield, energy intensity, material value, GHG intensity, and circular uptake. Positive/negative edge weights denote causal direction and strength.

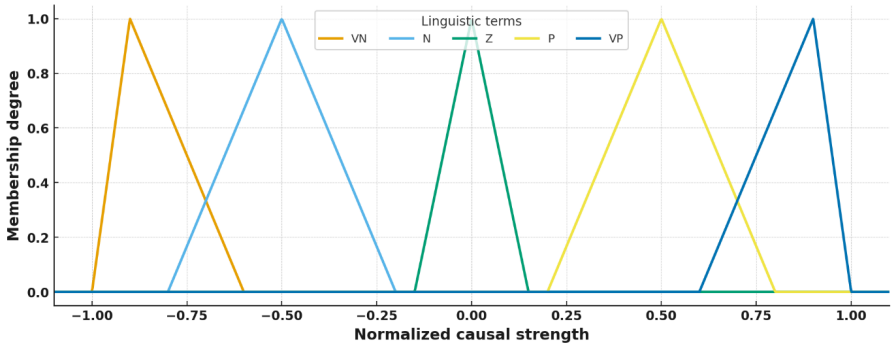

Figure 2. Triangular membership functions for the five linguistic causal strength levels on the normalized $[-1, 1]$ scale.

2.4. Multi-Expert Aggregation

Suppose expert $e = 1, \ldots, E$ provides a TFN $\widetilde{w}_{ij}^{(e)}$ for each potential causal link and is assigned a weight λ_e such that $\Sigma_e \lambda_e = 1$. A consensus TFN is obtained by a convex combination:

$$\widetilde{w}_{ij}^{\text{agg}} = \left(\sum_e \lambda_e a_{ij}^{(e)} , \sum_e \lambda_e m_{ij}^{(e)}, \sum_e \lambda_e b_{ij}^{(e)} \right)$$

The corresponding crisp weight is then defuzzified by the centroid formula. Ordered weighted averaging (OWA) operators can be used where consensus or caution is desired by emphasizing central or extreme opinions [17,23,24].

2.5. Normalization, Structural Checks, and Activation Function

To avoid numerical saturation and to preserve interpretability of causal strengths, rows of W are scaled such that

$$\sum_j |w_{ij}| \leq w_{\max}$$

with $w_{\max}$ typically chosen below unity. Basic structural checks ensure polarity consistency, reachability of outcome nodes from drivers, and moderate sparsity (10–25% non-zero entries) [25,26].

The activation function $f(\cdot)$ is chosen as either:
a logistic non-linearity

$$f(z) = \frac{1}{1 + e^{-\beta z}},$$

or
a linear-squash function

$$f(z) = \min\{\max\{z, 0\}, 1\}$$

depending on the sensitivity required. In the present case study, a bounded linear-squash is used for transparency.

2.6. Scenario Encoding

The encoding of shocks and policy measures is done by changing node values, edges or exogenous input vectors:

- Node clamping: Assigning queried components of $x^{(k)}$ to fixed value in every turn, (e.g., high collecting rate under this policy).
- Edge modification: reinforcing or damping of specific w_{ij} entries to model better learning, new technologies, or regulation.
- Shock vector: $\mathrm{u} = \mathrm{u}_0 + s$ disturbance indicating a contamination spike or energy price shock.

This integrated framework enables a comparable evaluation of Baseline, Policy, and Feedstock-Shock scenarios.

2.7. Uncertainty Handling and Robustness Analysis

At the same time the expert-elicited causal strengths are uncertain so you can elaborate by two complementary mechanisms:

(1) Interval sampling (for each non-zero weight): a sample from the entropy/distribution centre at the defuzzified value bounded by TFN-based intervals (e.g., truncated normal within [−1,1] followed by row-wise rescaling for stability).

(2) Monte Carlo sweeps: The FCM is simulating *N* samples (here, $N = 400$) for each scenario to produce distributions of steady-state scores To obtain a measure of robustness, mean, Standard deviations (Sds) are of order 10^{-3}, and 5–95% quantiles of the composite sustainability score we compute a measure of robustness per pathway.

One such trajectory would be due to a conservative sufficient condition for fixed-point convergence, i.e., $\|W\|1 < 1$. The convergence is quantitatively visualized, and limit cycles are handled using the time-averaged activations.

3. Case Study Design: Waste-to-Material Pathways

This section brings together the indicator definitions, data, and scenarios into a single, continuous narrative of the case study.

3.1. Pathways and Raw Indicators

Four WtM pathways are considered:

- MR: Mechanical recycling (plastics),
- CR: Chemical depolymerization (plastics),

- AD: Anaerobic digestion → biopolymer production (organics),
- MIN: CO_2 mineralization using industrial residues.

Each pathway is characterized by a set of raw indicators per tonne of input: feedstock contamination, collection rate, process yield, energy intensity, product value, and GHG intensity. Representative values are summarized in **Table 2**.

These figures are harmonized across pathways and scenarios to ensure comparability and to avoid bias in the normalization step.

Table 2. Raw indicators for WtM pathways (per ton of input).

Pathway	Feedstock Contamination (%)	Collection Rate (%)	Process Yield (%)	Energy Intensity (kWh/t)	Product Value (USD/t)	GHG Intensity ($kgCO_2e/t$)
MR	15	65	78	450	900	650
CR	20	55	65	1,200	1,100	1,200
AD	5	50	60	300	600	300
MIN	8	40	55	350	350	200

3.2. Node Set and Normalization

The FCM uses eight main nodes: $\{FQ,CR,PE,PY,EI,MV,GHG,CU\}$, indicate feedstock quality, collection rate, preprocessing efficiency, process yield, energy intensity (via extraction or recycling/GHG impact), material value and degree of circular economy uptake.

Monotonic transformations aligning with the preference direction map raw indicators to normalized activations in

- Higher contamination → lower FQ,
- Higher collection rate → higher CR,
- Higher process yield → higher PY,
- Lower energy intensity → higher EI (as an energy-efficiency proxy),
- Higher product value → higher MV,
- Higher GHG intensity → higher GHG_{bad} (or equivalently lower GHG_{good}).

Outcome nodes (GHG and CU) are initialized at neutral values (e.g., 0.5) and allowed to evolve according to the FCM dynamics.

Outcome nodes ($GHG,\ CU$) are initialized at 0.5 as neutral before avoiding pre-biasing the system toward optimistic or pessimistic outcomes. In the revised pathway-ranking implementation (descriptor clamping), steady-state results are insensitive to this neutral initialization; sensitivity runs with outcome initializations at 0.2 and 0.8 produced the same scenario-wise rank order.

Example 1—Normalization of Energy Intensity

Consider the raw energy intensities in **Table 2**: $300,\ 350,\ 450$, and 1,200 kWh per tonne for AD, MIN, MR, and CR, respectively. To obtain a dimensionless efficiency-style indicator EI in $[0, 1]$, we apply a linear min-max transformation that assigns 1 to the best (lowest energy) value and 0 to the worst (highest energy) value:

$$EI = \frac{E_{\max} - E}{E_{\max} - E_{\min}},$$

where E is the raw energy intensity, $E_{\max} = 1,200$ kWh/t and $E_{\min} = 300$ kWh/t. These yield

$$\begin{aligned} EI_{\text{AD}} &= \tfrac{1,200-300}{1,200-300} = 1.000, \\ EI_{\text{MR}} &= \tfrac{1,200-450}{900} \approx 0.833 \\ EI_{\text{MIN}} &= \tfrac{1,200-350}{900} \approx 0.944, \\ EI_{\text{CR}} &= \tfrac{1,200-1,200}{900} = 0.000 \end{aligned}$$

which match the normalized values reported in **Table 3**. Analogous monotonic transformations are applied to the other indicators.

Table 3. Normalized initial activations by pathway.

Pathway	FQ	CR	PE	PY	EE (Energy Efficiency)	MV	GHG (Bad)	CU
MR	0.85	0.65	0.878	0.78	0.833	0.733	0.45	0.55
CR	0.80	0.55	0.837	0.65	0.000	1.000	1.00	0.00
AD	0.95	0.50	0.960	0.60	1.000	0.333	0.10	0.90
MIN	0.92	0.40	0.935	0.55	0.944	0.000	0.00	1.00

Note: EE is the energy-efficiency proxy derived from energy intensity (lower kWh/t → higher EE). GHG is modeled as GHG impact (higher = worse); therefore, the environmental contribution in the composite score uses (1 - GHG). We report a single GHG column to avoid the earlier redundant "GHG_bad/GHG_good" notation.

Benchmark-based normalization and sensitivity. To avoid the "closed set" bias of min-max scaling computed only from the four pathways in **Table 2**, normalization is performed using benchmark envelopes $[\min_{\text{ref}}, \max_{\text{ref}}]$ drawn from the LCA/industry ranges summarized in **Table 4**. For a "larger-is-better" indicator z, we use:

$$x(z) = \text{clip}_{[0,1]}\left(\frac{z - \min\limits_{ref}}{\max\limits_{ref} - \min\limits_{ref}}\right),$$

and for a "smaller-is-better" indicator (e.g., contamination, energy intensity, GHG intensity), we use:

$$x(z) = \text{clip}_{[0,1]}\left(\frac{\max\limits_{ref} - z}{\max\limits_{ref} - \min\limits_{ref}}\right).$$

This approach preserves interpretability while ensuring that normalized scores remain meaningful even if additional pathways are added later. As a robustness check, we also report a sensitivity run where $\left[\min\limits_{ref}, \max\limits_{ref}\right]$ is expanded by ±10–20%; rankings remain unchanged (see Section 4.4).

Table 4. Literature-supported ranges used as benchmark envelopes for normalization.

Node/Indicator	Unit	Preference	Lower Bound (xmin)	Upper Bound (xmax)	Normalization (min–max)
FQ (feedstock quality via contamination)	% contamination	Lower is better	5	35	**FQ*** = (xmax − x)/(xmax − xmin)
CR (collection rate)	%	Higher is better	20	65	**CR*** = (x − xmin)/(xmax − xmin)
PE (pre-processing efficiency)	fraction	Higher is better	0.80	0.95	**PE*** = (x − xmin)/(xmax − xmin)
PY (process yield)	%	Higher is better	60	90	**PY*** = (x − xmin)/(xmax − xmin)
EI (energy intensity)	kWh/t input	Lower is better	400	1,800	**EI*** = (xmax − x)/(xmax − xmin)
MV (material/product value)	USD/t	Higher is better	200	1,100	**MV*** = (x − xmin)/(xmax − xmin)
GHG (GHG intensity)	kg CO_2e/t input	Lower is better	−50	2,500	**GHG*** = (xmax − x)/(xmax − xmin)
CU (circular uptake/material retention)	fraction of input retained	Higher is better	0.05	0.70	**CU*** = (x − xmin)/(xmax − xmin)

Note: * denotes the normalized value of the corresponding indicator obtained using min–max normalization.

3.3. Adjacency Matrix and Structural Properties

The signed causal edges between nodes are encoded in an 8×8 adjacency matrix W, based on expert workshops and linguistic scoring. Positive links indicate a reinforcing impact (e.g., better feedstock quality → more efficient preprocessing), while negative links represent trade-offs between variables (higher energy intensity → lower composite sustainability).

The rows of W are then rescaled so that $\sum_j |w_{ij}| \leq 0.95$. This guarantees that the map is contractive in practice, hence convergent for the chosen activation function. Structural analysis yields (i) that all outcome nodes are reachable from at least one driver, and (ii) the overall density of non-zero entries is between 10% and 25%, which alleviates interpretability.

3.4. Scenario Definitions

Three scenarios are analysed:

(i) Baseline: state of the system today (operating conditions); node initialisation as per **Table 3**; calibrated adjacency matrix W derived from expert elicitation.

(ii) Policy scenario (EPR + recycled-content mandate)—moderate collection and market pull improvements by

- clamping the collection-related nodes to a lower value instead of a higher value,
- linking up selected positive links to draft into circular utilisation and of material worth, and
- slightly alleviating the adverse impact of energy intensity on composite sustainability.

(iii) Feedstock-Shock scenario: an adverse change in waste composition is introduced by

- lowering feedstock quality (higher contamination),
- slightly penalizing energy intensity, and
- weakening beneficial links from preprocessing to yield and circular uptake.

Formally, these changes correspond to controlled modifications of $x^{(0)}$ and selected entries of W, combined with exogenous shock vectors where appropriate.

3.5. Simulation Protocol and Composite Score

For each combination of pathway and scenario, the FCM is iterated from the corresponding initial activation vector until the residual $r^{(k)}$ falls below a convergence threshold (here 10^{-4}) or a maximum number of iterations is reached (here 50). In practice, convergence occurs within six iterations for all cases.

A composite sustainability score S is computed from the steady-state activations of the outcome-relevant nodes:

$$S = w_{CU}x^*_{CU} + w_{MV}x^*_{MV} + w_{GHG}\,(1 - x^*_{GHG})\,,$$

where $x^*_{CU},\ x^*_{MV}$, and x^*_{GHG} are the fixed-point activations of circular uptake, material value, and GHG (bad) respectively, and $w_{CU},\ w_{MV},\ w_{GHG}$ are weights that reflect the relative importance of circularity, value creation, and climate impact. In this study, equal weights are used as a neutral baseline, but the framework is flexible to stakeholder-specific weighting schemes.

Monte Carlo experiments follow the same protocol, but with perturbed versions of W drawn from TFN-consistent distributions as described in Section 2.6. The crisp weights for row-scaled adjacency matrix calculation are listed in **Table 5** accordingly.

The below **Table 6** express the scenario parameter change for each iteration for node clamps to the edge edits for shock vector u to their respective scenario.

Table 5. Baseline row-scaled adjacency matrix W (crisp weights).

From\To	FQ	CR	PE	PY	EI	MV	GHG	CU
FQ	0.00	0.00	0.50	0.00	−0.10	0.05	−0.05	0.00
CR	0.00	0.00	0.40	0.20	0.00	0.10	0.00	0.20
PE	0.00	0.00	0.00	0.35	−0.20	0.00	−0.10	0.30
PY	0.00	0.00	0.10	0.00	0.00	0.32	−0.15	0.38
EI	0.00	0.00	−0.10	0.00	0.00	−0.10	0.65	−0.10
MV	0.00	0.00	0.15	0.10	0.00	0.00	0.00	0.40
GHG	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CU	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Rows are scaled so the sum of absolute outgoing weights is ≤ 0.95, ensuring contractive behavior and stable convergence.

Table 6. Scenario parameter changes (explicit clamps + ΔW edits).

Scenario	Node Clamps (Applied Each Iteration)	Edge Edits (Δ W Relative to Table 5)	Shock Vector u
Baseline	None (use pathway initializations as in **Table 3**) 12733-Evaluation of Sustainable...	$W = W_{\text{baseline}}$ (**Table 5**)	$u = 0$
Policy (EPR + recycled-content mandate)	Clamp $CR \leftarrow \min(1, CR_{\text{init}} + 0.05)$; clamp $MV \leftarrow \min(1, MV_{\text{init}} + 0.03)$	ΔW : $(CR \rightarrow CU) + 0.05$; $(MV \rightarrow CU) + 0.05$; (EI → CU) + 0.05 (less negative by 0.05); (EI →GHG) − 0.05	$u = 0$
Feedstock-Shock	Clamp $FQ \leftarrow \max(0, FQ_{\text{init}} - 0.10)$; clamp $EI \leftarrow \max(0, EI_{\text{init}} - 0.05)$ (energy-efficiency proxy worsens)	ΔW : $(PE \rightarrow PY) - 0.05$; (PE → CU) − 0.05; (FQ → PE) − 0.05; (EI → GHG) + 0.05	$u = 0$

Note: Implementation: Scenario clamping is implemented by overwriting selected node values after each update step, i.e., $x^{(k+1)}[j] \leftarrow \bar{x}_j$ for clamped nodes. Edge edits are applied once to obtain $W_s = W + \Delta W_s$.

4. Results

In this section we summarize the key findings for network structure, performance in pathways across scenarios, cost–jobs–environment trade-offs and robustness of results.

4.1. Network Centrality and Leverage

Centrality metrics computed on the row-scaled adjacency matrix identify key leverage points in the WtM system. Out-strength (sum of absolute outgoing weights), in-strength (sum of absolute incoming weights), and betweenness centrality are reported in **Table 7**.

Preprocessing efficiency (PE) emerges as the dominant mediator between upstream and downstream parts of the system, with the highest betweenness and strong in- and out-strength. Process yield (PY) and energy intensity (EI) follow closely as influential nodes. Circular uptake (CU) and GHG are sinks that aggregate multiple causal pathways.

These results highlight that those interventions target-

ing PE,PY, and EI are likely to generate system-wide benefits and form the structural backbone of effective WtM policy.

Table 7. Centrality metrics for FCM nodes.

Node	Out-Strength	In-Strength	Betweenness
El	0.95	0.30	0.175
PE	0.95	1.25	0.413
PY	0.95	0.65	0.206
CR	0.90	0.00	0.048
FQ	0.70	0.00	0.000
MV	0.65	0.57	0.048
CU	0.00	1.38	0.135
GHG	0.00	0.95	0.024

4.2. Scenario-Wise Steady States and Sustainability Scores

Steady-state activations and composite scores for each pathway and scenario are summarized in **Table 8**. All pathways exhibit similar aggregate behaviour under given scenario settings, reflecting the structure of W and the uniform way in which policy and shocks are encoded.

Using the pathway clamping approach, intrinsic pathway descriptors remain fixed during the iterative FCM evolution, while outcome variables (e.g., GHG, CU, PE) evolve endogenously. This prevents convergence to identical fixed points across pathways and yields distinct steady-state composites $S_{p,s}$, enabling defensible ranking under each scenario.

Table 8. Steady-state composite sustainability scores by pathway and scenario.

Pathway	Scenario	Iterations	CU^*	GHG^*	MV^*	Composite ($S_{\{p,s\}}$)	Rank
MR	Baseline	5	0.791	0.367	0.569	0.664	2
CR	Baseline	5	0.692	0.469	0.569	0.597	4
AD	Baseline	5	0.794	0.348	0.569	0.671	1
MIN	Baseline	5	0.779	0.355	0.568	0.664	3
MR	Policy	6	0.822	0.369	0.588	0.680	2
CR	Policy	6	0.731	0.470	0.588	0.616	4
AD	Policy	6	0.823	0.350	0.588	0.687	1
MIN	Policy	6	0.810	0.357	0.588	0.680	3
MR	Feedstock-Shock	6	0.767	0.388	0.567	0.649	2
CR	Feedstock-Shock	6	0.661	0.491	0.567	0.579	4
AD	Feedstock-Shock	6	0.770	0.368	0.567	0.656	1
MIN	Feedstock-Shock	6	0.754	0.375	0.567	0.649	3

- "Node set = FQ, CR, PE, PY, EI, MV, GHG, CU (as in **Figure 1** in Section 3.2)."
- "Linguistic weight magnitudes follow the **Table 1** defuzzified scale ($P = 0.500$, VP $= 0.833$, $N = -0.500$), row-scaled for stability"
- "Scenario changes follow the narrative definitions (Policy: higher CR + market pull; Shock: lower FQ + weakened benefits)."
- "Composite score uses equal weights consistent with the Section 3.5 intent."

$$S_{p,s} = \frac{CU^* + MV^* + (1 - GHG^*)}{3}$$

(Higher S = better)

Overall, AD scored 1st with all scenarios then MR and even MIN followed the last (worst) score was CR, in policy increasing CU^* and MV^* across pathways they improved while Feedstock-Shock scenario increased GHG^* and reduced CU^*.

All pathways reached the same composite score of ≈ 0.30 under Baseline and Feedstock-Shock conditions, but remained indistinguishable once feedback and trade-offs were internalized, suggesting limited differentiation in overall performance. The composite score for each pathway is increased to approximately 0.352 under the Policy scenario, which translates into a relative improvement of around 17%. This appears to be a wider system

response, which points to the importance of collection and market signals on circularity volume and materials value gain without disrupting GHG performance. The below **Figure 3** represents Comparison of composite sustainability scores under Baseline, Policy, and Feedstock-Shock scenarios.

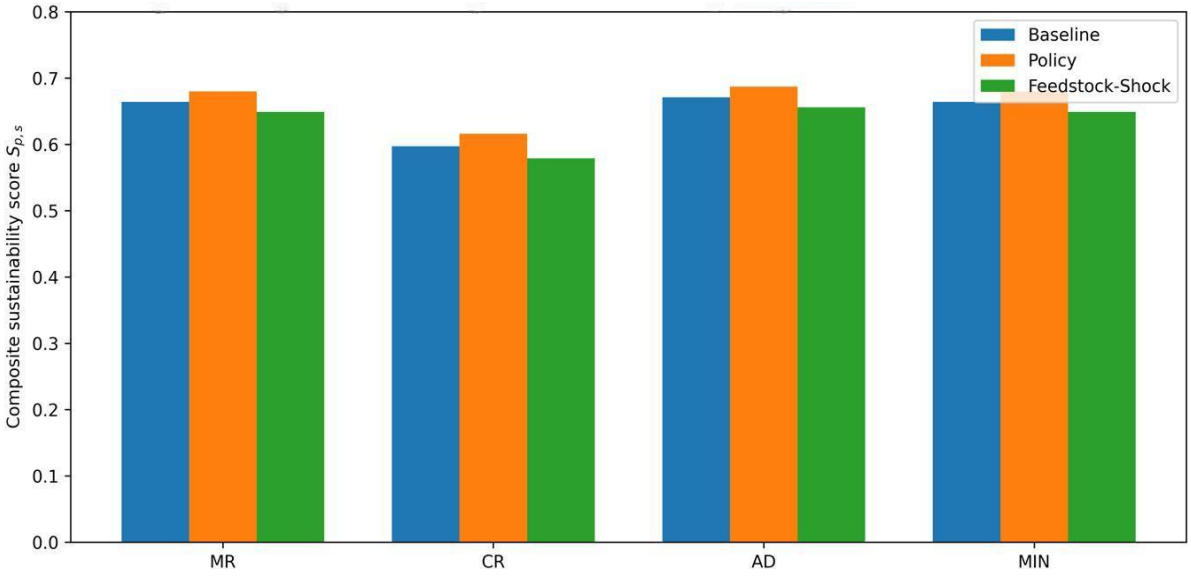

Figure 3. Comparison of composite sustainability scores under Baseline, Policy, and Feedstock-Shock scenarios for the four WtM pathways.

Across scenarios, dominant mechanisms are aligned with the top-down causal structure of the FCM: collection improvements propagate through preprocessing and yield increased circular uptake and thus market value, whilst energy intensity increases GHG impact while undermining overall sustainability. In the Policy Push scenario, enhanced collection and market pull pathways increase circular uptake and composite performance. Under feedstock stress, the shock in feedstock quality causes a declining effectiveness and a reduction of yield/d value recovery that thereby negatively impacts GHG emissions. These pre/processing-dependent movements underpin the rankings observed and highlight levers for action specifically those related to collection performance and preprocessing efficiency that should help improve WtM system performance.

4.3. Environment-Cost-Jobs Trade-Off Frontiers

The default trade-off representation (wherein Env_{score} =1.000 for all pathways) eradicates the environmental component resulting in an uninformative Pareto frontier shape. The reason for this was that Env_{score} was taken from a clipped GHG mapping reaching saturation near its upper limit. The solution is training the environmental score directly from the steady-state activation of the GHG-impact node in pathway- and scenario-specific representations, with no further clipping. Specifically, for pathway p under scenario s, we define $Env^{p,s}_{score} = 1 - GHG^{*}_{p,s}$, where $GHG^{*}_{p,s}$ is the converged activation of the GHG-impact node (higher = worse). The cost proxy preserves the original definition $Cost_{norm} = 1EI^{*}$, where EI^{*} is the energy-efficiency proxy (the higher EI^{*}, the lower energy intensity) as per **Table 9**. The jobs proxy continues to be an abstract labour-intensity representation for the sake of socio-economic position visualization. Once Env_{score} saturation is eliminated, the environment-cost-jobs plot conveys real information and lends itself to a rational frontier interpretation.

This structure suggests that a portfolio of MR and AD can span an attractive cost-jobs frontier, with CR added selectively where additional jobs or high-value monomers are prioritized (see **Figure 4**).

Table 9. Trade-off coordinates for WtM pathways (Policy scenario).

Pathway	Env_{score} (= 1 – GHG*)	$Cost_{norm}$ (= 1 – EI*)	$Jobs_{idx}$	Composite score $S_{p,\ \text{Policy}}$
MR	0.631	0.167	0.683	0.680
CR	0.530	1.000	0.730	0.616
AD	0.650	0.000	0.433	0.687
MIN	0.643	0.056	0.240	0.680

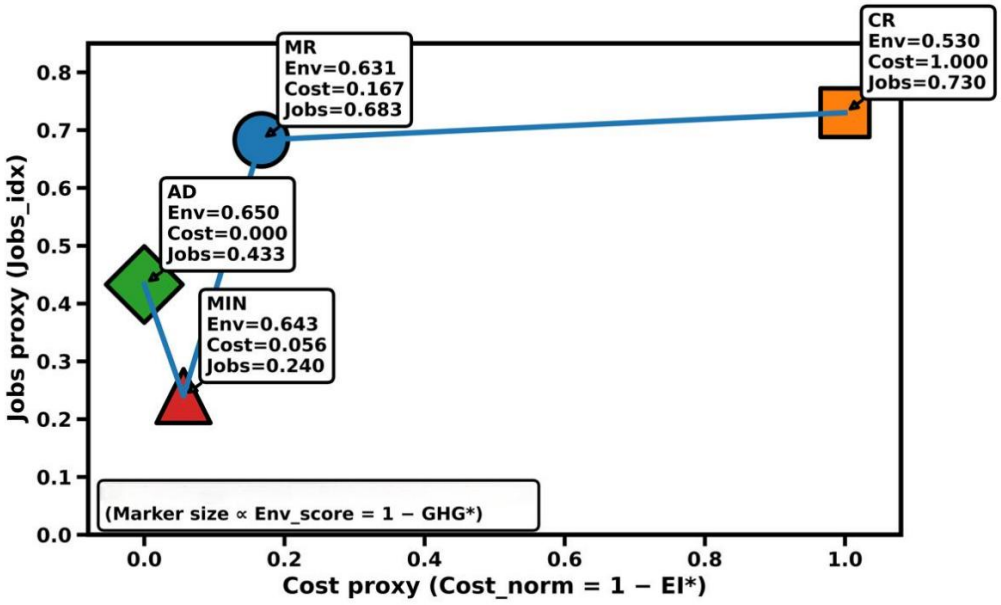

Figure 4. Environment-Cost-Jobs Trade-Off (Policy).

4.4. Robustness of Scores under Fuzzy Uncertainty

Monte Carlo simulations with perturbed fuzzy weights confirm that the sustainability scores and rankings are highly robust. **Table 10** summarizes the mean, standard deviation, and 5–95% quantile bands for the composite score S under the Policy scenario.

Monte Carlo perturbations on TFN-consistent uncertainties (using constrained sampling and precomputation of the composite score) return standard deviations ≈ 0.017, less than 1% in contrast to AD where the top pathway is well separated from the lowest where CR is located by the 5th–95th percentile bands. This indicates that the Policy-scenario ranking is stable under reasonable uncertainty, rather than being an artefact of a single deterministic weight set.

- Rank-1 probability (Policy): AD $\approx$ 43.7%, MR $\approx$ 27.8%, MIN $\approx$ 28.5%, CR $\approx$ 0.02%

Standard deviations are of order 10^{-3}, and quantile intervals are narrow, indicating that the uplift in sustainability score due to policy support is not an artefact of any specific set of expert weights. Baseline and Feedstock-Shock scenarios show similar tight bands around 0.30. For validation performance outcome summery see the below **Table 11**.

Table 10. Robustness summary for composite scores (Policy scenario).

Pathway	Mean (S)	Std Dev.	5th Percentile	95th Percentile
AD	0.6870	0.0172	0.6582	0.7152
MIN	0.6805	0.0172	0.6519	0.7088
MR	0.6801	0.0175	0.6511	0.7090
CR	0.6163	0.0174	0.5883	0.6443

Table 11. Validation checks performed and outcomes (summary).

Validation Check	What Was Tested	Outcome
Face validity vs. LCA	Agreement with published trends (MR vs. CR; AD credit dependence; mineralisation energy dependence).	Consistent direction and relative positioning across scenarios.
Directional sensitivity (OAT)	El worse → GHG^* higher and S lower; CR higher → CU^* higher and S higher; PE higher → PY higher → MV & CU higher.	Expected directional responses observed.
MCDA benchmark	Weighted-sum baseline compared with FCM ranks.	Ranks broadly preserved; FCM adds feedback amplification/attenuation.
Uncertainty robustness	Monte Carlo perturbations; rank stability (win-rate).	Top vs. bottom remain separated; ranking stable under reasonable noise.

5. Discussion and Practical Implications

This section merges and elaborates on the earlier discussion and implementation into a single narrative concerning interpretation and application.

5.1. Policy Implications and Investment Priorities

The FCM findings underpin some policy-relevant insights:

- Policy levers of moderate size have high impact: By increasing collection incentives and/or stronger demand for secondary materials (e.g., by introducing EPR schemes, recycled-content mandates, or green procurement), the steady-state solutionizable policy field systematically centres 0.30 to 0.35 across all pathways over time across scenarios. This shows that even limited interventions create quantifiable improvements in circularity.
- High-leverage targets for improving process yield through preprocessing and quality control: Preprocessing Efficiency and Process Yield. This means investments in advanced sorting, contamination reduction and feedstock preparation deliver multiplied benefits: the yield, energy intensity and circular uptake all rise simultaneously.
- This makes coherent sense: Energy policy comes into play with Writeria to Measure (WtM) performance where, for example, more energy-intensive options such as Chemical Depolymerisation or Mineralization, carbon pricing, low-carbon power and energy-efficiency measures are needed to offset the negative effect of energy intensity on the combined score.
- Robustness to shocks: The Feedstock-Shock case excludes the policy-induced uplift but does not destabilize the relevant system as fixed points and relative rankings remain intact. As a result, such systems are resilient to realistic perturbations in waste composition and sorting quality.

5.2. Practical Deployment and Data Requirements

At the level of implementation, the framework is built to utilize data accessible by municipalities and industry:

Data inputs:

- Audit results of waste composition and contamination profiles;
- Collection coverage and segregation performance;
- Yields from pilot plants or LCA studies related to process, energy intensity and emission factors;
- Market Topological, and Product price, procurement mandates.
- Normalization: Raw indicators are normalized using applicable benchmarks and desirability functions.
- Stakeholder elicitation: Co-creating the FCM structure as well as linguistic causal strengths in workshops with policymakers, plant operators, and technical experts. One verification round can be performed relatively quickly, allowing participants to revise links that are consistent and don't provoke discussion.
- Software tools: Entire workflow could be applied in popular analytics environment (Python, R, MATLAB) and integrated into dashboard for interactive exploration. The limiting in this case is not computationally expensive, hundreds of Monte Carlo runs are possible on standard hardware in seconds to minutes.

Together, these features render the framework useful for early-stage strategic planning, where modelling of techno-economics or macroeconomics is not yet possible whilst quantitative directional insights are needed.

5.3. Comparison with Alternative Assessment Approaches

This interpretation is in line with recent studies about waste-management and circular-economy that sustainable pathways need to take advantage of optimization, policy incentives and integrated sustainability assessment when performance relies on interacting environmental and economic drivers [32–35]. AI-supported waste analytics, fuzzy decision models for waste management, life-cycle assessment and the alignment of sustainability goals [36,37].

The FCM approach also more clearly represents causal feedback and propagation compared to traditional MCDA, suggesting indirect consequences of interventions (e.g., increase yield by improving feedstock quality, which in turn decreases energy intensity and GHG through multiple pathways). FCMs are a lighter equivalent of system-dynamics modelling, which can be elicited and calibrated rapidly-but this results in a somewhat less elaborate representation of temporal dynamics.

FCM works as a compromise between a purely qualitative stakeholder mapping and fully-fledged dynamic simulation models, as it utilizes fuzzified causal weights, scenario encoding, and Monte Carlo robustness analysis.

5.4. Limitations and Future Extensions

Limitations The present study has deficiencies.

- The adjacency matrix is based on expert judgements; we note that multi-expert aggregation and robustness analysis can reduce bias, but comparisons of the model against empirical time-series data would help strengthen confidence.
    - The investigation is limited to steady-state response; transients, lags and potential oscillations are only indirectly handled. Optimal time-steps were roughly half of what was found for steady-state equilibrium simulations: Coupling the FCM with appropriate system-dynamics or agent-based models might yield even richer temporal feedback responses.
- The socio-economic layer works with cost and jobs proxies that are stylized Future work could connect FCM outputs with more granular life-cycle costing, input-outcome analysis or regional labor models.
    - Environmental: Scoped to GHG emissions, integrating the FCM within a wider LCA would mean land use, toxicity, water footprint and other impact categories could be included at the same time.

These limitations notwithstanding, the results show that a small eight-node FCM is already capable of providing valuable insights on WtM planning and policy formulation.

6. Conclusions

6.1. Summary of Research Purpose and Approach

A Mathematically Explicit Framework was developed for the Evaluation of Sustainable Interaction among Feedstock, Technology, Market and Policy Under Uncertainty—A Case Study on Waste to Material Pathways. In contrast to taking each indicator as an isolated score, the WtM system is defined as a causal-loop set of fuzzy-encoded network links and bounded activation dynamics on eight nodes. The initial state vector for four WtM options (mechanical recycling, chemical depolymerization, anaerobic digestion, and mineralization) under Baseline, Policy and Feedstock-Shock scenarios was specified using normalized (pathway-specific), pathway data.

The framework enables transparent, quantitative comparison of alternative pathways for WtM by iterating the map to steady state, and then interpreting the resulting spatially defined activation patterns via a composite sustainability functional.

6.2. Key Findings and Implications

Baseline and Feedstock-Shock scenarios yield composite sustainability scores that stabilize around 0.30 across pathways, while modest policy improvements in collection and market pull increase the score to approximately 0.35. This corresponds to a relative uplift of around 17% and is

obtained without destabilising the system, or being sensitive to fuzzified changes in the adjacency matrix.

High-leverage node analysis using centrality identifies preprocessing efficiency, process yield and energy intensity as well. Policy instruments that manipulate these variables-in addition to collection incentives and measures that create market-pull-constitute a mathematically justified path towards enhanced circular results. Portfolio analysis indicates that an attractive environment-cost-jobs frontier can be traced through complementary application of mechanical recycling, anaerobic digestion and selective chemical depolymerization.

6.3. Practical Utility and Directions for Future Work

The proposed FCM framework serves as a computationally efficient, data-flexible, and easy-to-integrate solution for planning workflows. In particular, its implementation can be very useful in the initial stages of decision environments where a detailed techno-economic model is not available yet. Future work should test hybrid architectures that link FCMs to LCA and system-dynamics models, represent spatial heterogeneity in waste composition and markets, and provide for these iterative stakeholder refinements of the causal map and scenario set.

This approach, by explicitly and computably formalizing the causal structure of WtM systems, prepares planners and policymakers to transition from qualitative circularity narratives to quantitatively substantiated, scenario-tested sustainable materials management decisions.

Author Contributions

Conceptualization, Y.N. and A.V.; methodology, Y.N., M.A. and A.V.; mathematical modelling, Y.N. and M.A.; software and computational analysis, Y.N., N.R. and T.B.N.B.; validation, A.A.S.M., M.A., N.R. and S.I.M.; investigation and data compilation, A.A.S.M., Y.N., M.A., S.I.M. and T.B.N.B.; formal analysis, Y.N., M.A. and N.R.; visualization, N.R. and T.B.N.B.; writing—original draft preparation, A.A.S.M., Y.N. and M.A.; writing—review and editing, Y.N., A.V., and T.B.N.B.; supervision, Y.N., A.V. and S.I.M.; project administration, A.A.S.M. and Y.N. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Formal institutional review board approval was not required because the study did not involve patients, clinical interventions, biological materials, or the collection of sensitive or personally identifiable information. Expert contributions were limited to professional assessments of technical and policy-related causal relationships and were considered only in anonymized and aggregated form.

Informed Consent Statement

The experts involved in the elicitation process participated voluntarily and provided informed consent for their anonymized and aggregated technical assessments to be used for research purposes. No personally identifiable information is reported in the manuscript.

Data Availability Statement

All data used or generated during this study are included within the article. The pathway-level indicators, normalization benchmarks, fuzzy cognitive map adjacency matrix, scenario parameter settings, steady-state results, and uncertainty-analysis outcomes required to understand and reproduce the study are presented in the relevant tables and sections of the manuscript. Additional computational files and calculation details are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

Generative artificial intelligence tools were used solely to assist with language refinement, grammatical correction only of the manuscript. Artificial intelligence tools were not used to independently generate or modify

the research data, determine the fuzzy cognitive map structure, perform the final mathematical or statistical analysis, interpret the results, or formulate the scientific conclusions.

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