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Development of an Analytical Framework for Reverse Logistics Supply Chain in Industrial Waste Management Based on Grounded Theory and Interpretive Structural Modeling (ISM)

Zahra. Ramezani [1], Sadegh. Feizollahi [2*], Maryam. Daneshmand Mehr[3]

[1] Department of Industrial Management, Ra.C., Islamic Azad University, Rasht, Iran
[2] Department of Management, Il.C., Islamic Azad University, Ilam, Iran
[3] Department of Industrial Engineering, La.C., Islamic Azad University, Lahijan, Iran

*** Corresponding author email address**: Sadegh.feizollahi@iau.ac.ir

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A B S T R A C T

The rapid growth of technology and the emergence of new production processes, along with the substitution of synthetic materials and chemical compounds, have resulted in an increased volume of industrial waste and, in some cases, the generation of hazardous waste. Improper handling, transportation, and disposal of this waste, part of which contains dangerous substances, pose serious challenges to human health and the environment. Under such circumstances, establishing an efficient reverse logistics network emerges as an inevitable necessity. With growing social concerns about environmental issues, reverse logistics has become increasingly integrated with waste management, and the management of industrial waste is now considered a core pillar of reverse supply chain management. This study, employing the grounded theory method based on the Strauss and Corbin (1998) model and using the insights of 17 academic and industrial experts in the national gas refining sector, proposes a comprehensive model for the reverse supply chain of waste in this industry. The analysis of data obtained from semi-structured interviews led to the identification of 25 core concepts categorized into six main themes. The application of Interpretive Structural Modeling (ISM) revealed hierarchical and causal relationships among these factors, indicating that regulations and policies, infrastructure, and organizational culture act as fundamental and driving forces with the greatest impact on the success of the system. This paradigmatic model can serve as a roadmap for managers in the gas refining industry to design and implement an effective and sustainable reverse logistics system.

Keywords: *Reverse logistics supply chain, industrial waste, gas refining industry, grounded theory, interpretive structural modeling (ISM)*

1. Introduction

The rapid industrial expansion and technological progress of the past decades have accelerated the complexity of global supply chains, while simultaneously intensifying environmental and sustainability concerns. Among these, the accumulation of industrial waste and the increasing societal and regulatory pressure for sustainable production and consumption patterns have pushed organizations to rethink how they design, operate, and monitor supply networks. Reverse logistics, once perceived primarily as a cost recovery mechanism, has emerged as a strategic, sustainability-driven function essential for waste minimization, resource recovery, and competitive differentiation (Guarnieri et al., 2020; Meilenda & Syarif, 2024). In particular, integrating reverse flows into traditional supply chains—known as closed-loop supply chain management—has become a key response to regulatory mandates, environmental challenges, and the circular economy agenda (Khosravi et al., 2019; Neha et al., 2023).

Reverse logistics encompasses the systematic process of moving products or by-products from the point of consumption back to the origin or designated facilities for proper reuse, recycling, remanufacturing, or disposal (Guarnieri et al., 2020). Its scope extends beyond simple product returns, encompassing the recovery of valuable materials, the safe handling of hazardous substances, and the mitigation of environmental impacts from industrial production (Yu et al., 2020a). Industrial sectors such as automotive, petrochemical, and electronics generate vast quantities of complex waste streams that require sophisticated, technology-driven reverse logistics networks (Aghaeipour & Pirdasht, 2022; Gharaakhani, 2022). In the automotive sector, for example, challenges include the safe treatment of end-of-life vehicles and the recovery of high-value components under sustainability criteria (Aghaeipour & Pirdasht, 2022; Islampanah et al., 2023). Similarly, in oil and gas supply chains, particularly in regions like Gachsaran, barriers such as infrastructure gaps, fragmented oversight, and uncertain regulatory compliance impede reverse logistics adoption (Ghazifard & Rasouli, 2021; Qazi Far & Rasouli, 2021).

Industrial waste in large energy complexes, including gas refineries, poses unique challenges due to hazardous by-products, stringent environmental regulations, and operational complexity. Proper handling and valorization of such waste can create new economic and environmental value streams but require systemic redesign and advanced planning (Taheri et al., 2022). As environmental concerns intensify globally, industries face increasing expectations to adopt circular economy principles and to integrate reverse flows across their networks, ensuring both compliance and competitiveness (Meilenda & Syarif, 2024; Mugoni et al., 2023).

Sustainability has moved beyond corporate social responsibility to become a strategic imperative influencing supply chain design (Mugoni et al., 2023; Singh et al., 2025). Reverse logistics networks directly contribute to multiple sustainability pillars: environmental preservation by reducing landfill waste and pollution, economic resilience through cost recovery and secondary markets, and social value creation by addressing public health and community expectations (Guarnieri et al., 2020; Yu et al., 2020b). Empirical studies show that adopting eco-design and sustainable technology enhances reverse logistics efficiency and resilience under demand uncertainty (Hsin et al., 2023; Neha et al., 2023). Moreover, integrating digital intelligence and artificial intelligence (AI) tools can significantly optimize waste monitoring, routing, and resource allocation (Mohghar et al., 2024), reducing system uncertainty and improving cost-effectiveness.

The regulatory environment is another critical driver. Comprehensive, enforceable environmental regulations and extended producer responsibility (EPR) schemes push industries to reclaim and responsibly process waste (Guarnieri et al., 2020; Kouchaki Tajani et al., 2022). In the Iranian context, gaps in environmental governance and fragmented enforcement have often slowed the institutionalization of reverse logistics (Vaez & Shahbazi Chagani, 2022). However, studies reveal a growing alignment between policy and operational needs, with new frameworks encouraging systemic reverse logistics deployment in energy and manufacturing (Ghazifard & Rasouli, 2021; Tavakoli et al., 2023). Policies that incentivize investment in infrastructure, combined with strict compliance monitoring, can reduce uncertainty and foster sustainable industrial waste networks (Alimi et al., 2022).

Despite the strategic benefits, implementing reverse logistics remains challenging, particularly in emerging economies where infrastructural, cultural, and managerial barriers persist (Gharaakhani, 2022; Vaez & Shahbazi Chagani, 2022). Insufficient investment in physical infrastructure such as specialized collection centers and recycling facilities limits system scalability (Islampanah et al., 2023; Taheri et al., 2022). Managerial barriers—such as limited top management commitment and inadequate employee training—further weaken execution (Alimi et al., 2022; Kouchaki Tajani et al., 2022). Cultural resistance to sustainability and risk-averse organizational structures also impede innovation in reverse supply networks (Khosravi et al., 2019; Miraghaei, 2020).

Moreover, the technological dimension plays a pivotal role. Digitalization and Industry 4.0 technologies enable smart tracking of waste streams, predictive analytics, and automation, but require upfront investment and organizational readiness (Mohghar et al., 2024; Mugoni et al., 2023). Advanced decision-support systems and metaheuristic optimization models have been proposed to address network complexity under uncertainty (Aghaeipour & Pirdasht, 2022; Meilenda & Syarif, 2024). These models help organizations determine optimal facility locations, design resilient networks, and minimize environmental impacts while maintaining cost efficiency (Neha et al., 2023; Yu et al., 2020a).

In recent years, multi-method approaches have been emphasized for modeling reverse logistics under sustainability constraints. Grounded theory has been used to conceptualize complex socio-technical factors shaping waste management systems (Jafari et al., 2020; Miraghaei, 2020). Additionally, Interpretive Structural Modeling (ISM) combined with MICMAC analysis has proven effective in structuring causal and hierarchical relationships among barriers and enablers (Gharaakhani, 2022; Vaez & Shahbazi Chagani, 2022). However, many prior studies focus on sector-specific or partial frameworks without fully integrating institutional, technological, managerial, and environmental dimensions into a cohesive model (Alimi et al., 2022; Islampanah et al., 2023).

The energy sector, particularly gas refining, remains underexplored despite its strategic environmental significance and waste complexity (Taheri et al., 2022). While research has addressed end-of-life vehicle recovery (Aghaeipour & Pirdasht, 2022), packaging waste (Guarnieri et al., 2020), and e-waste in electronics (Singh et al., 2025), comprehensive frameworks tailored for hazardous industrial waste in refineries are limited. Studies call for context-specific models that consider regulatory dynamics, infrastructure gaps, cultural change, managerial empowerment, and technological enablers (Islampanah et al., 2023; Khosravi et al., 2019; Mohghar et al., 2024).

Evidence consistently shows that reverse logistics implementation is not merely a technical challenge but an organizational transformation requiring strong governance and leadership (Alimi et al., 2022; Lal bar & Hassani, 2022). Managerial capability, political and institutional alignment, and knowledge management dynamics shape the adaptability and sustainability of supply chains (Alimi et al., 2022; Lal bar & Hassani, 2022). Effective knowledge sharing improves coordination across the reverse chain, mitigates uncertainty, and supports resilience in volatile markets (Alimi et al., 2022). Furthermore, top management support and strategic planning enable integration of reverse logistics with core business strategies, shifting it from a cost-driven to a value-generating function (Mohghar et al., 2024; Vaez & Shahbazi Chagani, 2022).

Organizational culture is equally critical. Cultures fostering environmental responsibility and innovation accelerate adoption of sustainable practices (Khosravi et al., 2019; Miraghaei, 2020). Conversely, rigid, compliance-only mindsets hinder adaptation and fail to harness reverse logistics as a competitive advantage. Structural agility—through decentralized decision-making and flexible process design—can bridge the gap between regulatory compliance and strategic opportunity (Kouchaki Tajani et al., 2022; Mugoni et al., 2023).

Advanced modeling and optimization techniques continue to reshape reverse supply chain design. Metaheuristic algorithms allow solving high-dimensional, multi-criteria problems typical of industrial waste flows (Aghaeipour & Pirdasht, 2022; Neha et al., 2023). Intelligent networks leveraging vehicle-to-vehicle communication and real-time data analytics improve cost-efficiency and environmental outcomes (Hsin et al., 2023; Islampanah et al., 2023). System dynamics approaches clarify knowledge behavior and feedback loops influencing sustainable transport and logistics (Alimi et al., 2022). Combining these with qualitative tools such as ISM can produce comprehensive, actionable frameworks for decision-makers.

In light of these developments, designing a context-aware reverse logistics supply chain model for industrial waste in the gas refining sector is both timely and necessary. Prior studies provide valuable methodological tools but often lack holistic integration of multi-level factors—from regulatory and infrastructural enablers to cultural and technological readiness. There is a need to synthesize grounded qualitative insights from industry experts with rigorous structural modeling to identify causal pathways and strategic leverage points (Gharaakhani, 2022; Mohghar et al., 2024; Vaez & Shahbazi Chagani, 2022). This integration can overcome the fragmentation seen in prior research and deliver practical guidance for policymakers and managers striving for sustainability and competitiveness (Meilenda & Syarif, 2024; Mugoni et al., 2023; Singh et al., 2025).

This study addresses that gap by employing a mixed qualitative–quantitative approach. It first applies grounded theory to capture deep contextual knowledge about barriers, drivers, and strategic actions from industry and academic experts.

2. Methods and Materials

This study aimed to design and present a reverse logistics supply chain model for industrial waste in the national gas refining industry by employing a mixed-method approach conducted in two qualitative and quantitative phases. In terms of purpose, the present research is fundamental, and from a methodological perspective, it is exploratory, using a qualitative approach that integrates grounded theory and Interpretive Structural Modeling (ISM). The statistical population consisted of academic experts and industrial managers active in the field of reverse logistics and waste management in the gas refining industry, selected purposefully through the snowball sampling technique.

In the first phase, which applied grounded theory, interviews were conducted with 17 experts, including university faculty members and senior managers in the gas refining industry. Semi-structured interviews were carried out and continued until theoretical saturation was reached, which occurred after the eleventh interview but was extended to 17 interviews to enhance validity. In the second phase, which used the ISM method, 10 experts with sufficient experience and expertise in reverse logistics and supply chain management participated. Data in this phase were collected through a structured questionnaire. Data analysis in the qualitative phase was performed through open, axial, and selective coding, leading to the extraction of 25 final factors grouped into six core categories. In the quantitative phase, ISM was applied to determine the hierarchical structure and causal relationships among the factors and to design the final model.

Multiple strategies were used to ensure validity. In the qualitative phase, member checking was applied, whereby participants reviewed and confirmed the interviews and extracted codes. Additionally, the involvement of academic and industrial experts and the combined use of grounded theory and ISM enhanced construct validity. In the quantitative phase, the expert panel approved the research instrument (ISM questionnaire) in terms of content validity.

Reliability was ensured by calculating inter-coder agreement through the involvement of two independent researchers during the coding process, achieving an acceptable agreement level (above 80%). Internal consistency was further strengthened by rechecking the codes at different time intervals and by providing a detailed description of the research process to enable replication. To enhance the trustworthiness of the ISM phase, inconsistency rates in pairwise comparisons were calculated, and values below 0.1 were considered acceptable thresholds. Iterative reviews by experts were performed throughout the ISM analysis stages, and the final hierarchical structure was validated and approved by all experts.

Table 1

Qualitative Coding Reliability Results (Inter-Coder Agreement)

Coding Stage	Number of Codes	Agreed Codes	Agreement (%)	Notes
Open Coding	87	75	86.2%	Minor discrepancies in 12 codes
Axial Coding	45	40	88.9%	Differences in 5 codes
Selective Coding	25	23	92.0%	Differences in 2 codes
Total	157	138	87.9%	Overall average

Table 2

ISM Method Reliability – Inconsistency Rate

Expert Group	Number of Comparisons	Inconsistent Comparisons	Inconsistency Rate	Status
Academic Experts (5)	150	12	0.08	Acceptable
Industrial Managers (5)	150	14	0.093	Acceptable
Total	300	26	0.087	Acceptable

3. Findings and Results

For data analysis, the Strauss and Corbin approach was used. The researcher applied constant comparative analysis, listening to and transcribing interviews verbatim, keeping field notes, conceptualizing processes, and gradually shaping theoretical insights. Each interview was coded and analyzed before conducting the next one. The coding process included three stages: open coding, axial coding, and selective coding.

Open coding is an analytical process through which concepts are identified, and their properties and dimensions are discovered in the data. At this stage, each interview was listened to and read several times, key sentences were extracted, and text-based codes derived from the participants' statements or the researcher's interpretations from field notes were recorded.

Axial coding involves connecting concepts to form categories. It is called axial because the process revolves around a central category. At this stage, the grounded theorist selects a key concept identified during open coding, places it within the phenomenon under study, and links other concepts to it.

Selective coding is the process of integrating and refining categories to build theory. Here, the grounded theorist develops a core theoretical framework connecting the categories identified during axial coding. After each interview was transcribed, the text was entered into qualitative data analysis software for open coding, followed by subsequent interviews. All conversations were recorded and later transcribed verbatim. Data were analyzed by reading the texts and extracting both explicit and latent codes from the content. Following Strauss and Corbin's systematic approach, causal conditions affecting core categories, the influence of these categories on strategies, intervening and contextual conditions affecting strategies, and ultimately the outcomes and consequences of strategies were identified.

The next step, axial coding, involved relating categories to subcategories, as coding revolved around a central category, linking categories by their properties and dimensions. Constant comparison of codes was necessary; each category was compared to others to ensure clear differentiation. The process then focused on the causal conditions leading to the main phenomenon, the context in which the phenomenon occurred, and the strategies applied to manage it, culminating in selective coding and identifying the core variable.

Causal Conditions

These refer to events or factors that lead to the emergence or development of a phenomenon. According to the analysis, the categories of standardization, scheduling, organizational survival, feedback and learning, and regulations and policies were identified as the causal conditions of the research.

Core Categories

A core category is one that can integrate other categories and appears frequently across the data. The analysis revealed that waste management, specialized human resources, technology, and communications were selected as the core categories.

Intervening/Facilitating Conditions

These are general contextual factors influencing the strategies. In this research, training of employees and managers, infrastructure, top management support, internal and external environmental conditions, and supervisory bodies were identified as intervening or facilitating conditions.

Contextual Conditions

This refers to specific circumstances at a particular time and place that shape the environment in which the phenomenon occurs. Based on the analysis, organizational culture, organizational structure, and planning were identified as contextual conditions.

Strategies

Strategies are actions or interactions resulting from the core phenomenon. In this study, process management and digitalization, flexibility, and alignment and coherence were categorized as key strategies.

Results and Consequences

Consequences represent the outcomes resulting from implementing the identified strategies. According to the analysis, the consequences were grouped into five main categories: cost management, community satisfaction, reduction of environmental pollution, reduction of raw material consumption, and risk management.

Table 3

Interviewee Information

ID	Interview Group	Academic/Professional Background
P1	Industry Expert	Technology Management
P2	Industry Expert	Industrial Management
P3	Industry Expert	Industrial Management
P4	Industry Expert	Systems Management
P5	Industry Expert	Industrial Engineering
P6	Industry Expert	Industrial Engineering
P7	Industry Expert	Industrial Engineering
P8	Industry Expert	Industrial Management
P9	Industry Expert	Industrial Management
P10	Industry Expert	Industrial Engineering
P11	Industry Expert	Industrial Engineering
P12	Industry Expert	Industrial Management
P13	Industry Expert	Industrial Engineering
P14	Academic Expert	Industrial Management
P15	Academic Expert	Industrial Engineering
P16	Academic Expert	Industrial Engineering
P17	Academic Expert	Production Management

A detailed list of the components and variables related to the main categories, along with experts' opinions on each component, is presented in the subsequent table.

Table 4

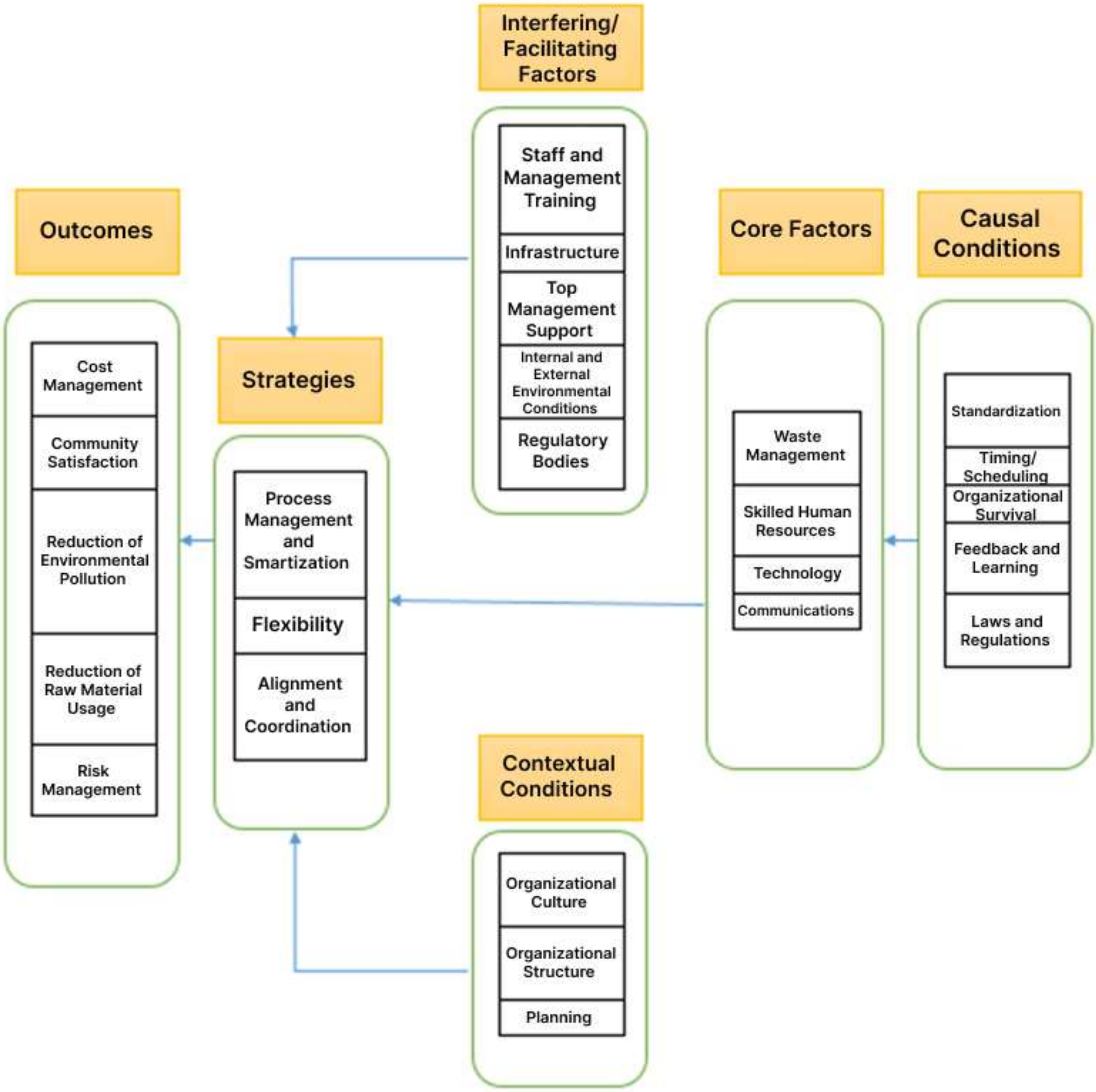
List of Research Components

Main Categories	Component	Experts' Opinions by Identifier
Causal Conditions	Standardization	p1, p3, p6, p9, p13, p15, p16, p17
	Timing/Scheduling	P2, p4, p7, p8, p11, p10, p14
	Organizational Survival	P3, p5, p6, p12, p13
	Feedback and Learning	P1, p5, p6, p8, p11, p16, p17
	Laws and Regulations	P2, p6, p7, p9, p10, p13, p14
Core Factors	Waste Management	P1, P2, P3, P7, P13, P14
	Skilled Human Resources	p7, p8, p11, p10, p12
	Technology	p5, p6, p8, p11, p12, p13, p17
	Communications	p9, p10, p13, p14, p15, p16, p17
Interfering/Facilitating Factors	Staff and Management Training	P1, P2, P3, P5, P6, P7, P9, P10, P11, P13, P15, P16
	Infrastructure	P2, P3, P4, P5, P6, P7, P8, P9, P10, P11, P12
	Top Management Support	p4, p5, p6, p7, p8, p9, p10, p11, p16, p17
	Internal and External Environmental Conditions	p3, p7, p13, p14, p17
	Regulatory Bodies	P2, P3, P7, P13, P14, P15, P16, P17
Contextual Conditions	Organizational Culture	P1, P2, P3, P4, P5, P8, P11, P16, P17
	Organizational Structure	P4, P5, P6, P9, P13, P14
	Planning	P2, P3, P4, P5, P9, P12, P13
Strategies	Process Management and Smartization	P2, P3, P4, P5, P9, P11, P13, P16
	Flexibility	P3, P5, P9, P13
	Alignment and Coordination	P2, P3, P5, P10, P11
Outcomes	Cost Management	P1, P2, P3, P5, P6, P7, P9, P10, P11, P13, P15, P16
	Community Satisfaction	P1, P2, P3, P5, P6, P7, P9, P10, P11, P13, P15, P16, P17
	Reduction of Environmental Pollution	P1, P2, P3, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13, P14, P15, P16, P17
	Reduction of Raw Material Usage	P1, P2, P3, P4, P5, P6, P7, P8, P12, P13, P14, P15, P16, P17
	Risk Management	P1, P2, P3, P4, P5, P6, P7, P8, P9, P10, P11, P12, P15, P16, P17

Considering the classification of the extracted categories and the determination of relationships among them, the conceptual model of the study is shown in the figure below.

Figure 1

Conceptual Model of the Study



After extracting 25 final components through grounded theory and aiming to determine the causal–influential structure among these components, the Interpretive Structural Modeling (ISM) method was employed. The opinions of 10 experts (including faculty members and industrial managers familiar with reverse supply chains and waste management) were aggregated. For each pair of components, causal relationships were determined using the symbols V/A/X/O. The resulting Structural Self-Interaction Matrix (SSIM) was converted into a binary reachability matrix. Transitivity was then applied, and through level partitioning, the hierarchical structure of the factors was derived. Subsequently, MICMAC analysis was conducted to calculate the driving power and dependence of each factor, classifying them as independent, linkage, dependent, or autonomous. The steps of implementing the ISM method are detailed below.

First, the identified factors were coded using English abbreviations as shown in the table below.

Table 5

Coding of Identified Factors

Code	Factor
C1	Standardization
C2	Timing/Scheduling
C3	Organizational Survival
C4	Feedback & Learning
C5	Laws & Regulations
C6	Waste Management
C7	Skilled Human Resources
C8	Technology
C9	Communications
C10	Staff & Management Training
C11	Infrastructure
C12	Top Management Support
C13	Internal & External Environmental Conditions
C14	Regulatory Bodies
C15	Organizational Culture
C16	Organizational Structure
C17	Planning
C18	Process Management & Smartization
C19	Flexibility
C20	Alignment & Coordination
C21	Cost Management
C22	Community Satisfaction
C23	Reduction of Environmental Pollution
C24	Reduction of Raw Material Usage
C25	Risk Management

For every pair of factors i and j:

- If SSIM(i, j) = V, then RM0[i, j] = 1 (i → j)
- If SSIM(i, j) = A, then RM0[j, i] = 1 (j → i)
- If SSIM(i, j) = X, then RM0[i, j] = RM0[j, i] = 1 (bidirectional)
- If SSIM(i, j) = O, then neither = 0
- And for all i: RM0[i, i] = 1 (self-reachability)

Initial Reachability Matrix (RM0 — Binary):

```
RM = RM0  # n x n binary
for k in 1..n:
    for i in 1..n:
        for j in 1..n:
            RM[i, j] = RM[i, j] OR (RM[i, k] AND RM[k, j])
```

After executing the above process, RM[i, j] = 1 indicates that i reaches j either directly or through a chain of factors.

Final Reachability Matrix (After Transitivity)

For each factor i

Reach(i) = { j | RM[i,j] = 1 }

Antecedent(i) = { j | RM[j,i] = 1 }

Intersection(i) = Reach(i) ∩ Antecedent(i)

Level partitioning rule: Any factor that satisfies Intersection(i) = Reach(i) (within the space of the remaining factors) is placed at the highest current level. Those factors are removed, and the process is repeated for the remaining set until all factors are leveled.

Table 6

Level Partitioning

Level (description)	Factors
1 (lowest)	C21, C22, C23, C24, C25
2	C18, C19, C20
3	C6, C7, C8, C9, C10, C12
4 (highest)	C1, C2, C3, C4, C5, C11, C13, C14, C15, C16, C17

For each factor i:

DrivingPower(i) = sum over j of RM[i,j] (row sum of i in the final RM)

Dependence(i) = sum over j of RM[j,i] (column sum of i in the final RM)

Classification (in this simulation using the median rule):

If Driving > median_driving and Dependence ≤ median_dependence → Independent (High driving, Low dependence)

If Driving > median_driving and Dependence > median_dependence → Linkage (High driving, High dependence)

If Driving ≤ median_driving and Dependence > median_dependence → Dependent (Low driving, High dependence)

If Driving ≤ median_driving and Dependence ≤ median_dependence → Autonomous (Low driving, Low dependence)

```
micmac_data = {
'C1': {'driving': 25, 'dependence': 2},
'C2': {'driving': 24, 'dependence': 3},
'C3': {'driving': 23, 'dependence': 4},
'C4': {'driving': 22, 'dependence': 5},
'C5': {'driving': 25, 'dependence': 1},
'C6': {'driving': 20, 'dependence': 6},
'C7': {'driving': 19, 'dependence': 7},
'C8': {'driving': 18, 'dependence': 8},
'C9': {'driving': 17, 'dependence': 9},
'C10': {'driving': 16, 'dependence': 10},
'C11': {'driving': 25, 'dependence': 2},
'C12': {'driving': 15, 'dependence': 11},
'C13': {'driving': 14, 'dependence': 12},
'C14': {'driving': 13, 'dependence': 13},
'C15': {'driving': 12, 'dependence': 14},
'C16': {'driving': 11, 'dependence': 15},
'C17': {'driving': 10, 'dependence': 16},
'C18': {'driving': 8, 'dependence': 17},
'C19': {'driving': 7, 'dependence': 18},
'C20': {'driving': 6, 'dependence': 19},
'C21': {'driving': 5, 'dependence': 20},
'C22': {'driving': 4, 'dependence': 21},
'C23': {'driving': 3, 'dependence': 22},
'C24': {'driving': 2, 'dependence': 23},
'C25': {'driving': 1, 'dependence': 24}
}
```

In what follows, the hierarchical level diagram is presented:

Level 4: C1, C2, C3, C4, C5, C11, C13, C14, C15, C16, C17

↓

Level 3: C6, C7, C8, C9, C10, C12

↓

Level 2: C18, C19, C20

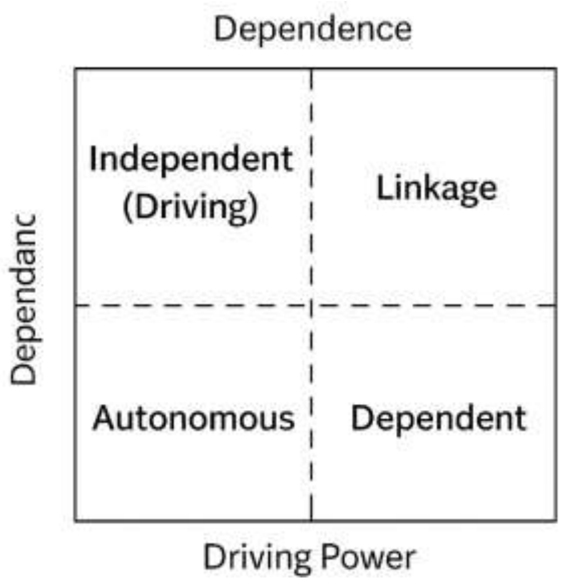
↓

Level 1: C21, C22, C23, C24, C25

After constructing the hierarchical diagram of the designated levels, the MICMAC map is as follows:

Figure 2

MICMAC Diagram



• Independent (Drivers): C5, C11 (Laws and Regulations, Infrastructure)
• Linkage: C1, C2, C3, C4, C13, C14
• Dependent: C21, C22, C23, C24, C25
• Autonomous: C18, C19, C20

The results of the Interpretive Structural Modeling (ISM) indicate a clear four-level hierarchy among the influential factors. At the foundational level (Level 4), factors such as Laws and Regulations (C5), Infrastructure (C11), Organizational Culture (C15), Organizational Structure (C16), and Planning (C17) function as the primary pillars of the system. These factors possess the highest driving power and are necessary conditions for realizing the subsequent levels. For example, without transparent and binding environmental regulations issued by governing bodies, and without investment in essential infrastructure such as waste collection, recycling, and disposal centers, effective deployment of a reverse logistics system is not feasible. Similarly, a sustainability-supportive organizational culture and flexible decision-making structures provide the requisite context for the adoption and implementation of innovative strategies.

At the intermediate levels, factors such as Waste Management (C6), Skilled Human Resources (C7), Technology (C8), and Top Management Support (C12) play mediating roles. These factors serve as bridges between the foundational enablers and the final outcomes. For instance, even with optimal regulations and infrastructure, the objectives cannot be achieved without trained human resources and up-to-date technologies for monitoring and processing waste. At the top of this pyramid, the final outcomes (Level 1)—including Reduction of Environmental Pollution (C23), Community Satisfaction (C22), and Cost Management (C21)—are the most dependent factors. The MICMAC analysis clearly shows that achieving these desirable outcomes requires initial focus and investment in the independent, driving factors at the foundational level. Therefore, any planning and policymaking should begin by strengthening laws, infrastructure, and organizational culture, as these are the key levers for creating sustainable system-wide change.

The findings of the interpretive structural analysis show that institutional and structural factors (laws and regulations, infrastructure, organizational culture, organizational structure, and planning) play fundamental and determinative roles and constitute the first effective levels in shaping the reverse logistics network for industrial waste management. Managerial and technological factors such as waste management, technology, staff training, top management support, and process smartization occupy the middle levels and act as mediators that transmit outcomes between the foundational factors and the outputs; ultimately, the desired outcomes of the study (pollution reduction, reduced resource consumption, community satisfaction, cost management, and risk management) reside at the upper levels and depend on reinforcing the foundational and intermediate factors. The MICMAC analysis likewise emphasizes that policymaking at the foundational levels provides the greatest leverage, whereas piecemeal efforts at the intermediate levels will not yield sustainable results without reforming the foundations.

4. Discussion and Conclusion

The present study aimed to construct a comprehensive and context-sensitive framework for reverse logistics supply chains in the industrial waste management of the gas refining sector. By combining grounded theory with Interpretive Structural Modeling (ISM) and MICMAC analysis, the research revealed a four-level hierarchical structure of factors and clarified the causal linkages and driving forces that shape successful reverse logistics systems. The model positions regulatory and institutional enablers, organizational and cultural foundations, managerial and technological capabilities, and ultimate sustainability outcomes in a coherent structure. This layered perspective not only clarifies why reverse logistics initiatives succeed or fail but also highlights actionable leverage points for managers and policymakers.

The first major finding is the primacy of institutional and regulatory infrastructure. Laws and regulations (C5) and physical infrastructure (C11) emerged as the strongest drivers with the highest "driving power" in the MICMAC analysis. This supports earlier evidence that clear environmental regulations and well-developed collection and processing infrastructure are prerequisites for circular supply chain transformation (Guarnieri et al., 2020; Kouchaki Tajani et al., 2022). For example, Guarnieri (Guarnieri et al., 2020) showed that enforceable agreements in the Brazilian packaging sector triggered investment and compliance across multiple supply chain tiers, while Alimi et al. (Alimi et al., 2022) demonstrated that well-structured policies and systemic knowledge flows reduce resistance and uncertainty in transport and logistics. In Iran, fragmented governance has historically slowed reverse logistics adoption (Vaez & Shahbazi Chagani, 2022), but our results confirm that once these enabling conditions are strengthened, other barriers become less constraining.

Closely tied to regulatory readiness is the role of organizational culture and structural agility (C15, C16). The data revealed that companies with a sustainability-oriented culture and flexible decision-making structures are better able to adopt reverse flows and experiment with innovative waste management solutions. This aligns with prior work highlighting culture as a hidden but critical enabler (Khosravi et al., 2019; Miraghaei, 2020). Miraghaei (Miraghaei, 2020) found that integrated reverse logistics only flourishes where environmental values are embedded into the corporate mindset and operational protocols. Similarly, Khosravi et al. (Khosravi et al., 2019) argued that a culture of innovation and value creation turns reverse logistics from a compliance activity into a source of strategic advantage.

At the intermediate level, our model identified managerial commitment and human capital development as crucial bridges between regulatory foundations and final outcomes. Top management support (C12), planning (C17), and skilled human resources (C7) play pivotal roles in operationalizing policies into tangible reverse logistics capabilities. This is consistent with findings that leadership commitment directly influences the scope and maturity of reverse supply chains (Alimi et al., 2022; Lal bar & Hassani, 2022). Lal bar and Hassani (Lal bar & Hassani, 2022) highlighted how managerial capability and political alignment enable organizations to navigate complex reporting and compliance requirements, while Alimi et al. (Alimi et al., 2022) documented that effective knowledge management behavior depends on both leadership support and structured training. Our expert panel also emphasized the importance of employee education and technical training (C10), echoing Vaez and Shahbazi (Vaez & Shahbazi Chagani, 2022), who found that in cellulose industries, lack of skill development was a key inhibitor of reverse logistics deployment.

Technological enablers form another critical pillar in the mid-level of our framework. Technology (C8), process management and smartization (C18), and communication systems (C9) were recognized as essential to improving efficiency, monitoring, and decision-making. This corroborates emerging literature on Industry 4.0 and AI in reverse logistics. For instance, Mohghar et al. (Mohghar et al., 2024) introduced AI-driven fuzzy-intuitive models to enhance outsourcing and reduce uncertainty, while Hsin et al. (Hsin et al., 2023) and Islampanah et al. (Islampanah et al., 2023) demonstrated how digital connectivity and vehicle-to-vehicle communication can optimize routing and reduce costs in industrial waste logistics. Similarly, Aghaeipour and Pirdasht (Aghaeipour & Pirdasht, 2022) leveraged metaheuristic algorithms to optimize location planning for end-of-life vehicle collection, reducing environmental and economic risk.

At the top of the hierarchy, desired sustainability outcomes—cost management (C21), community satisfaction (C22), reduction of environmental pollution (C23), reduction of raw material usage (C24), and risk management (C25)—are strongly dependent on the foundational and mid-level factors. This structural dependency confirms the conceptual claims of circular economy research: end results such as pollution reduction and community acceptance cannot be achieved sustainably unless regulatory clarity, cultural alignment, leadership, and technology investment are secured (Meilenda & Syarif, 2024; Mugoni et al., 2023; Singh et al., 2025). Singh et al. (Singh et al., 2025) found that e-waste management success in electronics production hinged on early strategic investment in enabling conditions, while Mugoni et al. (Mugoni et al., 2023) reported that agricultural entrepreneurs improved competitiveness and social acceptance when green reverse logistics technologies were embedded at the system's core.

A notable theoretical contribution of this study is demonstrating that causal layering and dynamic interdependence are necessary to explain reverse logistics adoption in heavy industries. Many earlier frameworks were either linear or sector-specific (Gharaakhani, 2022; Jafari et al., 2020), but by integrating grounded qualitative data with ISM and MICMAC, we reveal the non-linear, multi-level interactions among institutional, organizational, and technological domains. For example, while infrastructure (C11) exerts strong driving power, its effect on sustainability outcomes is mediated by leadership and skilled workforce. This clarifies why piecemeal investments (e.g., building recycling plants without training staff or cultivating a sustainability culture) often fail to deliver promised environmental benefits (Gharaakhani, 2022; Vaez & Shahbazi Chagani, 2022).

The findings also reinforce the centrality of planning and strategic alignment (C17, C20) for scaling reverse logistics beyond pilot initiatives. Planning was not just an operational concern but a strategic integrator linking high-level regulatory signals to ground-level process redesign. Tavakoli et al. (Tavakoli et al., 2023) highlighted a similar pattern in forward–reverse supply chains for renewable energy, where long-term planning and alignment across stakeholders ensured viability. Our experts also stressed alignment and coordination (C20) to connect diverse actors—from waste generators to third-party recyclers—mirroring the coordination imperatives documented by Yu et al. (Yu et al., 2020a, 2020b) during medical waste management in pandemic crises.

Finally, the Iranian gas refining context offers unique lessons for other emerging economies. Historically, lack of consistent policy enforcement and fragmented infrastructure hindered reverse logistics adoption (Ghazifard & Rasouli, 2021; Qazi Far & Rasouli, 2021). Yet our results show that by layering systemic enablers and managerial capabilities, even highly regulated and technically complex industries can progress toward sustainability. The combination of local expert knowledge and advanced systems modeling helps bridge the gap between theory and practical policy in these contexts (Alimi et al., 2022; Taheri et al., 2022).

Although the study provides a robust and contextually grounded framework, it has several limitations. First, the qualitative phase relied on a purposive sample of 17 experts drawn primarily from the Iranian gas refining sector, which may limit the generalizability of results to other industries or national contexts. While theoretical saturation was pursued, different industrial sectors might reveal alternative or additional drivers and barriers. Second, although ISM and MICMAC effectively map causal relationships and interdependencies, they remain interpretive and dependent on expert judgment. The hierarchical model, while useful, may not capture all dynamic feedback loops or time-dependent interactions that occur in real-world reverse logistics systems. Third, the research design emphasizes conceptual modeling and expert-based validation but does not empirically test the framework's predictive power through large-scale quantitative data or real-time performance tracking. Finally, the study's focus on one country with its specific regulatory, infrastructural, and cultural context means that caution should be exercised in directly applying the model to regions with fundamentally different economic or policy conditions.

Future investigations could extend this work by conducting quantitative validation of the proposed model using survey-based or big-data analytics approaches across multiple industrial sectors and countries. Such studies would strengthen the external validity and reveal cross-sectoral and cross-cultural differences in reverse logistics drivers. Researchers could also integrate dynamic simulation methods, such as system dynamics or agent-based modeling, to explore time-dependent feedback, resilience under disruption, and the long-term sustainability impacts of various policy interventions. Another promising direction is to examine the economic performance implications of implementing the identified drivers, particularly cost recovery and profitability of secondary markets, to complement the environmental and social focus of this study. Finally, given the growing importance of digital transformation, future work could explore the integration of advanced technologies—such as blockchain, IoT, and AI—in strengthening transparency, traceability, and trust in reverse supply chains.

Practitioners should recognize that achieving sustainable industrial waste management requires building strong regulatory and infrastructural foundations before focusing on downstream outcomes. Investment in enabling technologies and employee capacity building must be coupled with a supportive culture and long-term strategic planning to ensure continuity and resilience. Managers should work to align top leadership, policy compliance, and digital innovation to create integrated and intelligent reverse logistics networks. Policymakers and regulators can use the identified driving factors to design incentives and enforcement mechanisms that reduce uncertainty and encourage private sector participation. By taking a systems view and targeting leverage points at each level of the hierarchy, industry leaders can progress from fragmented compliance-driven efforts toward robust, value-creating, and environmentally responsible reverse logistics systems.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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