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Research Paper

An integrated BWM–THOR II–DEMATEL–QFD framework for scrap steel reverse logistics: linking strategy desirability with implementation feasibility in the Turkish automotive sector

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ABSTRACT

Circular economy practices have elevated the role of reverse logistics in resource-intensive industries, where the recovery of high-value materials such as scrap steel is central to resource efficiency and environmental performance. This study develops an integrated multi-criteria framework addressing three questions typically treated in isolation: which reverse logistics strategy is most appropriate, which barriers shape its implementation, and which actions should be prioritised. The framework combines the Best–Worst Method (BWM) for criterion weighting, THOR II for ranking alternatives, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) for distinguishing driving from dependent barriers, and Quality Function Deployment (QFD) for translating the diagnosis into prioritised solutions. The empirical application draws on five senior practitioners in the Turkish automotive industry, supported by two academic consultants during criteria validation; the same panel contributed to all four quantitative stages. THOR II is implemented with criterion-specific indifference, preference, and discordance thresholds derived from the empirical dispersion of each criterion, departing from the uniform-threshold practice shown to yield non-robust rankings. Economic and regulatory criteria carry the highest priorities, and in-house operation emerges as the leading strategy across all dominance scenarios, with outsourcing and the digital lean model as complements and public–private partnership ranking last. The informal scrap economy, the absence of a clear regulatory framework, and gaps in technology, incentives, and operational knowledge are the most influential driving barriers; prioritised actions converge on strategic embedding, regulatory clarity, and digital monitoring. The contribution is the demonstration that strategy desirability in emerging manufacturing economies cannot be separated from implementation feasibility.

1. Introduction

The circular economy has moved from a policy aspiration to a strategic imperative for resource-intensive industries (Geissdoerfer et al., 2017). Within this transition, reverse logistics (RL) (the collection, sorting, reuse, remanufacturing, and recycling of post-consumer materials) operates as the analytical backbone of circular material flows (Barnes et al., 2003; Ghoushchi & Hushyar, 2020). The automotive sector is widely regarded as a priority context for RL because vehicles contain large volumes of recoverable materials and their life cycles generate distinct environmental and economic externalities (Sarkar et al., 2018). In Türkiye, the automotive industry is among the largest sectors by output and employment (OSD, 2022), and exposure to the European Green Deal, the EU Carbon Border Adjustment Mechanism, and the Turkish National Circular Economy Action Plan has made the recovery of scrap steel a competitive prerequisite rather than a discretionary sustainability measure.

The challenge that this study addresses is that the desirability of an RL strategy and the feasibility of implementing it are governed by different conditions. A strategy can rank first on cost, regulatory alignment, or environmental performance and still fail in practice when the institutional, organisational, and informational conditions for its execution are absent. In emerging manufacturing economies (and the Turkish automotive sector is a representative case) this gap between desirability and implementation is widened by an informal scrap economy that diverts material from formal flows, by regulatory frameworks whose incentive structures are still consolidating, and by the technological and managerial capacity required to internalise recovery operations (Bhatia et al., 2020; Pourmehdi et al., 2021; Soares et al., 2022; Waqas et al., 2020).

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The existing literature treats these two questions, which strategy is desirable, and what makes it feasible, largely in separation. Three research streams can be distinguished. The first stream optimises the physical configuration of recovery networks through mixed-integer programming and its multi-objective extensions (Antuchevičienė et al., 2020; He et al., 2024; Mora et al., 2014; Shankar et al., 2018), but typically takes institutional and organisational conditions as given. The second stream catalogues the barriers that prevent RL adoption and analyses their causal structure through ISM, DEMATEL, or SEM (Kaviani et al., 2020; Pourmehdi et al., 2021; Soares et al., 2022; Solati et al., 2023; Waqas et al., 2020), but rarely connects the barrier diagnosis back to the question of which strategy to pursue. The third stream applies MCDM methods to strategy or barrier ranking, most commonly through sequential AHP–TOPSIS pipelines (Prakash & Barua, 2016; Sirisawat & Kiatcharoenpol, 2018; Tavana et al., 2021), but seldom validates why a hybrid is necessary and frequently assumes criterion independence by construction. The three streams produce internally consistent answers to different questions, but the analytical link that would connect strategy desirability to implementation feasibility (and both to a deployable set of solution measures) has not been built.

The central proposition of this study is that, in emerging manufacturing economies, *strategy desirability cannot be separated from implementation feasibility*: the desirability of a strategy is conditioned on the removability of the barriers it faces, and that conditioning is itself the integrative analytical idea that an RL decision-support framework should operationalise. The study addresses three sequential questions for scrap steel reverse logistics in the Turkish automotive industry: (i) which strategy is most appropriate under economic, regulatory, environmental, and digitalisation criteria; (ii) which implementation barriers shape its feasibility and how those barriers are causally related; and (iii) which solution measures should be prioritised to address the upstream barriers identified in (ii). To answer these in a single coherent chain, the paper develops a four-stage integrated framework that combines the Best–Worst Method (BWM; Rezaei, 2015) for criterion weighting, THOR II (Esteves et al., 2022) for non-compensatory strategy ranking, DEMATEL (Tzeng et al., 2007) for barrier causality analysis, and Quality Function Deployment (QFD) for solution prioritisation. The methods are used in a logically dependent sequence rather than in parallel, and the application of THOR II to RL strategy selection, together with the use of DEMATEL-derived barrier weights as the prioritisation criteria of the QFD stage, are themselves methodological steps that have not previously been taken in the RL literature.

The study makes three concrete contributions. Theoretically, it formalises the feedback link between strategy desirability and barrier removability that the network-design and barrier-identification streams have until now treated separately, and articulates the central proposition above as a testable claim in the RL literature on emerging economies. Methodologically, it constructs a four-stage decision-support architecture in which each method addresses one of the three sequential questions and feeds the next, and introduces criterion-specific indifference, preference, and discordance thresholds in THOR II (derived from the empirical dispersion of each criterion's evaluation vector) as a refinement of the conventional uniform-threshold practice. Contextually, it reveals that in the Turkish automotive context the most influential barriers are upstream institutional conditions rather than operational difficulties, and that technology-led strategies dominate only when the institutional layer matures, a result that has direct implications for RL strategy design in comparable emerging manufacturing economies.

The remainder of the paper is organised as follows. Section 2 reviews the three literature streams and positions the study against them. Section 3 describes the integrated four-stage framework and the data collection protocol. Section 4 presents the empirical results, the sensitivity analyses, and the analytical interpretation. Section 5 discusses the findings against the central proposition. Section 6 closes with the theoretical, methodological, managerial, and policy implications, together with the limitations of the study and directions for future research.

2. Literature review

Reverse logistics has matured along three distinct research streams: the design of physical recovery networks, the identification of barriers to RL adoption, and the application of multi-criteria decision-making (MCDM) methods to RL strategy and barrier problems. Each stream addresses a different layer of the same problem and has developed its own conceptual vocabulary. The present review covers these three streams in turn and closes with a synthesis that positions the current study against them.

2.1. Reverse logistics network design

The first stream focuses on the physical configuration of recovery networks: facility location, capacity allocation, and the flow of recovered materials between collection, dismantling, processing, and disposal nodes. The dominant analytical instrument is mixed-integer linear programming (MILP), often extended to multi-objective formulations that balance economic, environmental, and service-quality goals. End-of-life vehicles have been a particularly productive setting: Shankar et al. (2018) develop a strategic closed-loop supply chain model for ELV reclamation in India, Mora et al. (2014) optimise an ELV recovery network in Italy with cost-minimisation objectives, and He et al. (2024) and Xia et al. (2024) extend the formulation to uncertainty-aware multi-objective programming for ELV recovery in China. In the steel industry, Antuchevičienė et al. (2020) propose a robust multi-objective sustainable reverse supply chain plan for Iranian steel, while Vahdani et al. (2013) develop a bi-objective interval fuzzy possibilistic chance-constrained MILP for iron and steel under uncertainty.

Earlier foundational contributions established the structural vocabulary that the stream still relies on: Cruz-Rivera and Ertel (2009) study ELV collection in Mexico through an uncapacitated facility location problem, and Alumur et al. (2012) formulate a multi-period reverse logistics network for consumer electronics in Germany. More recent work has incorporated stochastic and hybrid extensions, with Shahparvari et al. (2021) developing chance-constrained robust stochastic programming for Iranian automotive networks and Govindan et al. (2020) proposing a hybrid FANP–FDEMATEL–MOMILP for circular supplier selection and closed-loop supply chain design.

Within the Turkish and broader automotive literature, the same configurational emphasis is observable. Ayvaz et al. (2021) develop a multi-objective fuzzy reverse logistics network for end-of-life vehicles considering economic, environmental, and social sustainability, Qi and Hongcheng (2008) argue for cost-driven recovery configurations, and Xu (2020) studies pricing and collection decisions in a closed-loop supply chain through a game-theoretic lens. Further applications include Pedram et al. (2017) on an automotive tyre case and Sadrnia et al. (2014) on an automotive wiring-harness network optimised through MILP coupled with a genetic algorithm.

The stream has achieved substantial gains in computational tractability and modelling sophistication. Its principal limitation, recurrently noted within the studies themselves, is that the resulting network configurations rest on parameter values (return volumes, recovery margins, regulatory continuity) that are treated as exogenous. Implementation feasibility, in particular, is rarely part of the analytical frame: the network solves a configuration problem on the assumption that the institutional and organisational conditions for the configuration to operate are already in place.

2.2. Barriers to reverse logistics adoption

The second stream takes the opposite view of the same problem: rather than designing a network and assuming its conditions, it begins with the conditions and asks why RL systems fail to materialise in practice. The empirical bulk of this stream comes from emerging economies, where the gap between the configurational optimum and the implementable system is sharpest. Bhatia et al. (2020) apply Grey-DEMATEL to the Indian automotive closed-loop supply chain and identify managerial barriers (the absence of incentive structures for recycled-material use and the bias of financial incentives toward the linear economy) as the most prominent. Soares et al., (2022) use the same method on Brazilian end-of-life vehicle management and find that the absence of specific legislation drives managerial and financial obstacles downstream.

In the steel and metal sector, Pourmehdi et al. (2021) combine ISM with FANP to analyse Industry 4.0 integration barriers in Iranian steel reverse logistics, identifying the absence of Industry 4.0 expertise and the lack of training programmes as the top-ranked challenges; their hierarchical model shows that poor data quality is a dependent outcome rather than an independent problem. Solati et al. (2023) prioritise policy, knowledge, and economic barriers in the iron and steel making industry, while Vargas et al. (2016) document the financial and organisational barriers facing micro and small enterprises in Brazil's metal industry.

Several barrier studies make their causal structure explicit. Waqas et al. (2020) apply ISM and MICMAC to the Pakistani manufacturing sector and identify regulatory barriers (the absence of government policy incentives, the lack of enforceable laws on product return, and the political volatility of the regulatory regime) as root causes driving organisational, financial, and technological obstacles. The earlier Waqas et al. (2018) Delphi–SEM study finds that lack of initial capital, the absence of skilled professionals, and company-level policies against RL are the most consistently binding constraints. Hu et al. (2021) employ DEMATEL on tyre recycling in China and identify unified product standards and tax incentive policies as the most urgent regulatory levers, while Molla et al. (2022) and Sitinjak et al. (2023) reach similar conclusions for India and Indonesia respectively, with inadequate regulation, insufficient infrastructure, and the lack of financial incentives consistently dominating.

The Turkish and broader automotive literature on barriers converges on a comparable structure. Kaviani et al. (2020) combine BWM and WINGS to evaluate Iranian automotive RL barriers and identify economic barriers as the most important. González-Torre et al. (2010) use SEM on the Spanish automotive sector to disentangle internal and external eco-innovation barriers, and Subramanian et al. (2014) document, through a multiple-case study of Chinese auto-parts manufacturers, that government regulation, technological capability, and managerial commitment jointly determine RL success. Sonar et al. (2022), Prajapati et al. (2019), and Derse (2024) reinforce these findings using DEMATEL–ISM, SWARA–WASPAS, and fuzzy DEMATEL–FUCOM–SWARA respectively, with information sharing, strategic embedding, training, and institutional support emerging as the dominant leverage points. Pinho Santos and Proença (2022) place the discussion in the broader frame of circular supply chains, arguing that government regulation, innovation strategies, and planned partnerships are the central enablers.

A consistent feature of this stream is the distinction between driving and dependent barriers, supported by ISM-, DEMATEL-, or SEM-based causal modelling. Across heterogeneous national settings, regulatory and informational barriers emerge repeatedly as upstream drivers, while operational and coordination barriers appear downstream as their accumulated symptoms. The limitation of the stream is also consistent: barrier identification rarely connects back to strategy choice. The catalogue of obstacles is established, but how it should shape the selection of one RL strategy over another is typically left outside the analytical frame.

2.3. Mcdm-based strategy selection and barrier prioritisation

The third stream uses MCDM methods to formalise both strategy choice and barrier prioritisation. AHP and TOPSIS, frequently in their fuzzy variants, dominate the empirical record. Sirisawat and Kiatcharoenpol (2018) apply Fuzzy AHP and Fuzzy TOPSIS to prioritise solutions for RL barriers in the Thai electronics industry, while Prakash and Barua (2016) and Prakash et al. (2015) use Fuzzy AHP for barrier analysis in the Indian electronics sector, identifying coordination with third-party logistics providers, customer perception of RL, and the absence of return-monitoring systems as the most binding constraints. Dutta et al. (2021) apply Grey-DEMATEL with fuzzy integrals across multiple Indian sectors and find that the difficulty of managing the quality of circular goods, together with the absence of top-management responsibility, are the prominent barriers. U-Dominic et al. (2021) develop an IF-DEMATEL–EDAS model for Nigerian manufacturing and rank low product quality, the risk of storing hazardous materials, and low technical expertise as the priority barriers.

Strategy-side applications cover facility location, recovery-mode selection, and third-party provider selection. Ocampo et al. (2019) combine Fuzzy DEMATEL, Fuzzy ANP, and Fuzzy AHP for collection and distribution centre location in Philippine furniture manufacturing and find that government policy interacts most strongly with all other criteria. Wang et al. (2019) develop an integrated AHP–EW and Grey MABAC model for construction machinery collection-mode selection in China, identifying manufacturer take-back as the optimal configuration. Govindan et al. (2019) use ELECTRE I, Revised Simos, and SMAA for third-party reverse logistics provider selection in Indian automotive remanufacturing, while Tavana et al. (2021) integrate Fuzzy BWM with COPRAS, MULTIMOORA, and TOPSIS for supplier selection in asphalt manufacturing and show that simpler ranking methods can produce results highly correlated with more complex approaches when the underlying weights are derived through BWM.

Hybrid integration is widespread but methodologically uneven. The majority of studies follow sequential AHP–TOPSIS pipelines in which AHP determines criterion weights and TOPSIS ranks alternatives, with few justifying why a hybrid is necessary and fewer still validating the integration by comparing the hybrid against its constituent methods. Methods that explicitly model criteria interdependence (DEMATEL, ANP, WINGS) appear in a minority of studies; the remainder assume criterion independence by construction. BWM (Rezaei, 2015) is a recent entrant in this literature, preferred for its lower elicitation burden, but is typically used in isolation rather than as part of an integrated chain. ELECTRE-family outranking methods, despite their theoretical advantages for non-compensatory decision problems with veto effects, remain under-represented in the RL literature. QFD applications in RL contexts are rare, and the THOR family (although offering an axiomatic outranking formulation with explicit non-compensation) has not been applied to reverse logistics in any prior published study.

2.4. Research gap and positioning

Reading the three streams together reveals a recurring division of labour. Network-design studies optimise physical configuration on the assumption that institutional and organisational conditions are settled. Barrier studies catalogue why those conditions are not settled, but typically stop short of connecting the diagnosis back to strategy choice. MCDM applications either rank strategies under independence assumptions that conceal the very interactions barrier studies identify, or rank barriers without translating the ranking into a deployable set of interventions. The result is a literature in which the three streams produce internally consistent answers to different questions but rarely engage with the question that the others are answering.

Recent contributions in 2023–2024 have further extended this discussion. Zolfani, Görener, and Toker (2023) developed a hybrid fuzzy MCDM framework to prioritise resource-recovery business-model solutions in emerging economies, illustrating how multi-method MCDM architectures can support strategic recovery decisions. Kannan et al. (2023) proposed a bi-objective optimisation model for eco-efficient reverse logistics network design, contributing to the systems-level understanding of recovery infrastructure. In the automotive end-of-life literature, Li et al. (2024) reviewed circular-economy approaches to electric-motor recycling, highlighting the interaction between strategic and technological choices in upstream recovery decisions. These contributions, together with the digital and circular-economy framings discussed earlier, position the present study within current debates on integrated reverse logistics decision-making in resource-intensive sectors.

The present study sits at the intersection of the three streams. A four-stage decision-support architecture is constructed in which each method addresses one of the three questions and feeds the next: BWM produces the criterion weights, THOR II uses them to rank strategy alternatives under non-compensatory preference logic, DEMATEL diagnoses the cause–effect structure of the implementation barriers facing the leading strategy, and QFD translates that diagnosis into a prioritised set of solution measures. The integration is constitutive rather than additive: removing any one stage would leave a recognisable gap in the chain. The application of THOR II to RL strategy selection, and of QFD to RL solution prioritisation under DEMATEL-derived barrier weights, are themselves methodological contributions to the third stream. The choice of scrap steel reverse logistics in the Turkish automotive industry, a sector in which scrap is a high-volume strategic input, where exposure to EU emission and recycling obligations translates compliance into a competitive prerequisite, and where the institutional environment is still consolidating, provides a context in which the connection between strategy desirability and implementation feasibility is empirically observable. Table 1 positions the present study against representative work in each of the three streams.

3. Methodology

This study develops an integrated multi-stage decision-support framework that combines the Best–Worst Method (BWM), THOR II, the Decision-Making Trial and Evaluation Laboratory (DEMATEL), and Quality Function Deployment (QFD) to address three sequential questions for scrap steel reverse logistics in the Turkish automotive industry: which strategy is most appropriate, which barriers shape its implementation, and which actions should be prioritised to overcome them. The methodological flow, together with the feedback configurations identified as directions for future work, is presented in Fig. 1.

The four methods are used in a logically dependent sequence rather than in parallel. BWM produces the criterion weights that are required as input to THOR II for ranking the strategy alternatives; the leading strategy then frames the implementation question that DEMATEL diagnoses; the cause–effect structure obtained from DEMATEL, in turn, defines the prioritisation criteria of the QFD stage, which translates the diagnosis into deployable solution measures. Removing any one stage would leave a substantive gap in the analytical chain: omitting BWM would leave THOR II without grounded weights; omitting THOR II would reduce the problem to barrier analysis without a strategic anchor; omitting DEMATEL would treat barriers as an unstructured list and obscure the distinction between drivers and symptoms; and omitting QFD would leave the analysis at the level of diagnosis without a prioritised set of interventions.

3.1. Data collection and expert panel

The empirical input to the framework was obtained from a panel of five senior decision-makers working in the Turkish automotive industry. The panel was finalised after an initial outreach to ten candidates, five of whom were able to participate across all four quantitative stages (BWM, THOR II, DEMATEL, QFD). Selection criteria were a minimum of five years of professional experience, active involvement in strategic or operational decision-making, and direct familiarity with reverse logistics and scrap material management. The functional roles covered production planning, supply chain management, sustainability, recycling, and materials-related decision processes. The same five experts contributed to every quantitative stage, which preserved judgement consistency and allowed the outputs of each method to be transferred meaningfully to the next.

The evaluation criteria, strategy alternatives, implementation barriers, and solution measures were initially compiled from the literature review and then validated through consultation with two academics specialising in reverse logistics and sustainable supply chain

Table 1
Synthesis of representative studies across the three streams of reverse logistics research.

Study	Method(s)	Sector / Context	Focus	Integration across streams
Shankar et al. (2018)	MILP	Automotive (ELVs), India	Network design	Stream 1 only
Mora et al. (2014)	MILP	Automotive (ELVs), Italy	Network design	Stream 1 only
He et al. (2024)	Fuzzy MINLP	Automotive (ELVs), China	Network design under uncertainty	Stream 1 only
Antuchevičienė et al. (2020)	Multi-objective optimisation	Steel, Iran	Network design	Stream 1 only
Vahdani et al. (2013)	Fuzzy chance-constrained MILP	Iron and steel	Network design	Stream 1 only
Ayvaz et al. (2021)	Multi-objective fuzzy MILP	Automotive (ELVs)	Network design	Stream 1 only
Bhatia et al. (2020)	Grey-DEMATEL, AHP	Automotive, India	Barrier causal analysis	Streams 2 + 3
Soares et al. (2022)	Grey-DEMATEL	Automotive (ELVs), Brazil	Barrier causal analysis	Streams 2 + 3
Pourmehdi et al. (2021)	ISM, FANP	Steel, Iran	Barriers (Industry 4.0)	Streams 2 + 3
Solati et al. (2023)	FAHP, FTOPSIS	Iron and steel, Iran	Barriers + solutions	Streams 2 + 3
Waqas et al. (2020)	ISM, MICMAC	Manufacturing, Pakistan	Barrier causal analysis	Stream 2
Kaviani et al. (2020)	BWM, WINGS	Automotive, Iran	Barriers	Streams 2 + 3
Sonar et al. (2022)	DEMATEL, ISM	Automotive supply chain	Barriers	Streams 2 + 3
Sirisawat & Kiatcharoenpol (2018)	Fuzzy AHP, Fuzzy TOPSIS	Electronics, Thailand	Barrier-solution prioritisation	Stream 3
Prakash & Barua (2016)	Fuzzy AHP	Electronics, India	Barrier prioritisation	Stream 3
Ocampo et al. (2019)	Fuzzy DEMATEL/ANP/AHP	Furniture, Philippines	Facility location	Stream 3
Govindan et al. (2019)	ELECTRE I, Revised Simos, SMAA	Automotive remanufacturing, India	3PRLP selection	Stream 3
Dutta et al. (2021)	Grey-DEMATEL, fuzzy integrals	Multiple sectors, India	Barrier-strategy prioritisation	Streams 2 + 3
Derse (2024)	Fuzzy DEMATEL, FUCOM, SWARA	Green/reverse logistics	Driver-barrier analysis	Streams 2 + 3
Present study	**BWM, THOR II, DEMATEL, QFD**	**Scrap steel automotive, Türkiye**	**Strategy + barriers + solutions**	**Streams 1 + 2 + 3**

Note: 'Integration across streams' refers to the analytical scope of the study, not to the technical sophistication of the methods used within any single stream.

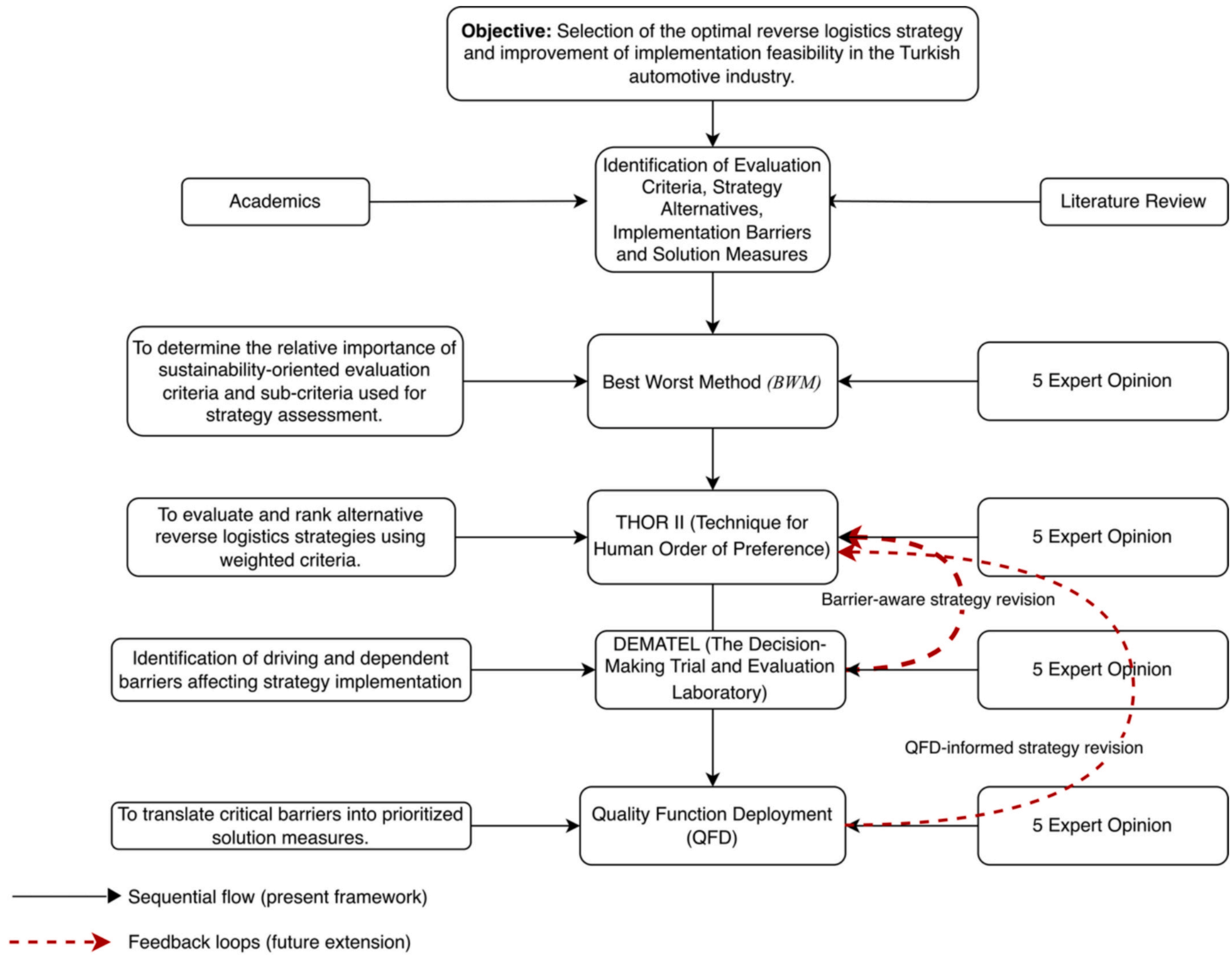

Fig. 1. Integrated BWM–THOR II–DEMATEL–QFD framework for scrap steel reverse logistics in the Turkish automotive sector. Note: Solid arrows represent the sequential information flow and methodological dependencies of the present study. Dashed arrows indicate two feedback configurations discussed in Section 5.2 as directions for future work: barrier-aware strategy revision (DEMATEL feedback into THOR II) and QFD-informed strategy revision (QFD feedback into THOR II).

management. The academic consultation was limited to the conceptual validation of the constructs and did not involve any quantitative assessment.

3.2. *Evaluation criteria, strategy alternatives, barriers, and solution measures*

3.2.1. *Evaluation criteria*

Thirty-three sub-criteria, organised under seven thematic groups (economic, social, legal/regulatory, environmental, internal management, external market, and digitalisation & technology) were used to evaluate the strategy alternatives. The full list of criteria and the corresponding sources are reported in Table 2.

3.2.2. *Strategy alternatives*

Five reverse logistics strategies are considered, defined along a common set of dimensions to ensure conceptual comparability. The three classical governance modes (in-house operation, joint venture, and outsourcing) have been examined in recent MCDM-based reverse logistics studies, including in the Chinese iron and steel scrap-recycling industry (Gu et al., 2021) and in emerging-economy manufacturing contexts (Prajapati, Kant, & Shankar, 2021). The public–private partnership mode is discussed in the end-of-life product recovery literature (Khawaja, Ghaith, & Alkhalidi, 2021). The digital lean model (A5) is consistent with recent academic framings of Reverse Logistics 4.0 (Sun, Yu, & Solvang, 2022) and Industry 4.0– circular economy integration in reverse supply chains (Dev, Shankar, & Qaiser, 2020). Two further alternatives are added to reflect the Turkish setting: a public–private partnership, which makes co-responsibility with public actors a defining feature, and a digital lean model, in which digitalisation is the structuring principle of the operating model rather than a complementary capability. Table 3 summarises the alternatives.

A1 and A5 are located on different strategic dimensions rather than on a single continuum of digitalisation. A1 is a governance choice (concerning who owns and controls the recovery process), whereas A5 is an operating-model choice (concerning how the recovery process is structured around digital-lean principles). The two dimensions are therefore conceptually orthogonal: a firm could in principle combine in-house governance with a digital-lean operating logic, or outsource governance while retaining a conventional operating logic. In the present empirical setting, however, A5 is treated as a distinct strategic posture in line with how Turkish automotive practitioners describe it: the digital configuration becomes the primary structural choice and substantially reorganises the operating model, going beyond the partial digital enablement observed within otherwise conventional in-house operations. This conceptualisation of A5 is consistent with recent

Table 2
Evaluation criteria and sub-criteria for scrap steel reverse logistics strategies.

Code	Theme	Criterion	Source
C1	Economic	Recycling cost advantage	Kokkinos et al. (2024); Li et al. (2021); Gu et al. (2021)
C2	Economic	Investment requirement	
C3	Economic	Operational cost	
C4	Economic	Partnership and collaboration cost	
C5	Economic	Unit disposal cost	
C6	Social	Corporate environmental image	Kokkinos et al. (2024); Li et al. (2021); Gu et al. (2021)
C7	Social	Consumers' environmental awareness	
C8	Social	Sensitivity to domestic production	
C9	Social	Marketing contribution of eco-labeling	
C10	Legal/Regulatory	Carbon emission policies	Kokkinos et al. (2024); Li et al. (2021); Gu et al. (2021)
C11	Legal/Regulatory	Environmental license requirements (EIA)	
C12	Legal/Regulatory	Tax incentives for reverse logistics	
C13	Legal/Regulatory	Scrap import/export regulations	
C14	Legal/Regulatory	EU-compliant recycling obligations	
C15	Environmental	Resource efficiency	Kokkinos et al. (2024); Li et al. (2021); Gu et al. (2021)
C16	Environmental	Waste reduction	
C17	Environmental	Reduction of carbon emissions	
C18	Environmental	Impact on water consumption	
C19	Internal Management	Financial capacity	Li et al. (2021); Kokkinos et al. (2024); Gu et al. (2021)
C20	Internal Management	Technological infrastructure	
C21	Internal Management	Logistics capability	
C22	Internal Management	Information systems management	
C23	Internal Management	Sustainability vision	
C24	External Market	Scrap supply quantity	Li et al. (2021); Gu et al. (2021)
C25	External Market	Scrap supply quality	
C26	External Market	Supply volatility	
C27	External Market	Market information and price stability	
C28	External Market	Market competition	
C29	External Market	Supply chain resilience	
C30	Digitalisation & Technology	Real-time monitored reverse logistics activities	Rodrigues et al. (2025)
C31	Digitalisation & Technology	Smart operations and resource sharing	
C32	Digitalisation & Technology	Data-driven redesign and remanufacturing	
C33	Digitalisation & Technology	Availability of skilled workforce for digital operations	

academic framings of Reverse Logistics 4.0 (Sun et al., 2022) and Industry 4.0–circular economy integration in reverse supply chains (Dev et al., 2020). A4 differs from A2 in that the partner is a public actor, making its performance dependent on policy continuity and regulatory clarity.

3.2.3. Implementation barriers

Sixteen barriers to the implementation of reverse logistics in the Turkish automotive context were compiled from the literature and validated with the expert panel. They cover technological and infrastructural, managerial, supply-chain and governance, economic, knowledge and awareness, and policy and regulatory dimensions. The full list and the corresponding sources are reported in Table 4 (Panel A).

3.2.4. Solution measures

Twelve candidate solution measures were developed on the basis of international best practices and the institutional, sectoral, and regulatory context of the Turkish automotive industry. They span six domains: (i) top management and organisational structure; (ii) operational improvements; (iii) collaboration and integration; (iv) finance and incentives; (v) legislation and enforcement; and (vi) education and awareness. The candidate measures are reported in Table 4 (Panel B).

3.3. Method components

The four methods are introduced briefly below; technical detail is limited to formulations that are non-standard or that depend on a specific implementation choice in this study.

3.3.1. Best–Worst method

Criterion weights were obtained using the Best–Worst Method developed by Rezaei (2015). BWM was preferred over conventional pairwise methods because it produces consistent weights with substantially fewer pairwise comparisons. For each criterion set, every expert identifies the most important (best, *B*) and the least important (worst, *W*) criterion, evaluates the preference of the best over all others on a 1–9 scale, and evaluates the preference of all criteria over the worst on the same scale. Let a_{Bj} denote the preference of *B* over criterion *j*, and a_{jW} the preference of *j* over *W*. The optimal weight vector w^*_j and the consistency indicator ξ^* are obtained by solving the following minimax model:

$$min\xi, subjectto \left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \xi, \forall j; \left|\frac{w_j}{w_W} - a_{jW}\right| \leq \xi, \forall j; \sum_{w_j} = 1, w_j \geq 0 \quad (1)$$

Solving the model yields the optimal weight vector and the consistency parameter ξ^*. The consistency of expert judgements was monitored throughout the elicitation using the consistency ratio proposed by Rezaei (2015). Individual weight vectors were computed for each expert and aggregated by arithmetic mean to obtain the global criterion weights used as inputs in the subsequent stages.

3.3.2. THOR II

Strategy alternatives were ranked using the THOR II method (Esteves et al., 2022), a multi-criteria decision-making technique based on axiomatic preference modelling that combines non-compensatory preference relations with elements of multi-attribute utility theory. The method is well suited to strategic decision problems involving qualitative judgements, partial information, and heterogeneous criteria. For two alternatives *a* and *b* and a criterion *j*, three preference relations are defined on the basis of the performance difference $g_j(a) - g_j(b)$:

$$aPb \leftrightarrow g_j(a) - g_j(b) > p_j \quad (2)$$

Table 3
Strategy alternatives along common dimensions.

Code	Strategy	Governance	Resource commitment	Institutional dependence	Digital intensity
A1	In-house operation	Vertically integrated	High	Low	Moderate
A2	Joint venture	Shared equity	Medium	Low	Moderate
A3	Outsourcing	Contract with 3PL	Low	Low	Provider-led
A4	Public–private partnership	Co-managed with public actor	Medium	High	Variable
A5	Digital lean model	Operating model, agnostic to ownership	High	Low	High by definition

Table 4
Implementation barriers and candidate solution measures for reverse logistics strategies in the Turkish automotive sector.

Code	Item	Source
Panel A — Implementation Barriers (B1–B16)		
B1	Lack of next-generation technologies	Derse (2024); Solati et al. (2023); Kaviani et al. (2020); Prajapati et al. (2019)
B2	Inadequate storage and transportation infrastructure	Solati et al. (2023); Prajapati et al. (2019); Kaviani et al. (2020); Derse (2024)
B3	Recycling facilities located outside organised industrial zones	*Author*
B4	Lack of top management commitment	Solati et al. (2023); Prajapati et al. (2019); Kaviani et al. (2020); Derse (2024)
B5	Absence of reverse logistics integration into corporate strategy	Solati et al. (2023); *Author;* Derse (2024); Prajapati et al. (2019)
B6	Lack of planning and budgeting	Solati et al. (2023); *Author;* Kaviani et al. (2020); Prajapati et al. (2019)
B7	Weak integration of reverse logistics into the supply chain	Solati et al. (2023); Kaviani et al. (2020); Prajapati et al. (2019)
B8	Quality mismatch with subcontractors and suppliers	Solati et al. (2023); Kaviani et al. (2020); Prajapati et al. (2019); Derse (2024)
B9	Lack of coordination among stakeholders	Solati et al. (2023); Kaviani et al. (2020); Prajapati et al. (2019); Derse (2024)
B10	Insufficient initial capital	Solati et al. (2023); Kaviani et al. (2020); Derse (2024)
B11	Lack of incentives for recycling investments	*Author;* Kaviani et al. (2020); Prajapati et al. (2019); Derse (2024)
B12	Lack of knowledge about reverse logistics practices	Solati et al. (2023); Kaviani et al. (2020); Prajapati et al. (2019)
B13	Lack of awareness at the employee level	Solati et al. (2023); *Author;* Kaviani et al. (2020); Derse (2024)
B14	Lack of performance measurement systems	Solati et al. (2023); Kaviani et al. (2020); Prajapati et al. (2019); Derse (2024)
B15	Prevalence of informal (unregistered) waste processing	Solati et al. (2023); Kaviani et al. (2020)
B16	Absence of a clear regulatory framework for incentives	*Author;* Kaviani et al. (2020); Prajapati et al. (2019); Derse (2024)
Panel B — Candidate Solution Measures (S1–S12)		
S1	Awareness and leadership of top management	Solati et al. (2023); Prajapati et al. (2019); Derse (2024)
S2	Integration of reverse logistics into the corporate strategy	Prajapati et al. (2019)
S3	Simplification and standardisation of processes	Solati et al. (2023); Derse (2024)
S4	Digital data tracking (blockchain/IoT) for reverse logistics processes	Solati et al. (2023); Prajapati et al. (2019)
S5	Establishment of cooperation with sub-industries	Solati et al. (2023); *Author;* Prajapati et al. (2019)
S6	Development of joint facility / public–private partnership models	Solati et al. (2023); *Author*
S7	Access to green financing resources	*Author*
S8	Enhancement of incentive and tax advantages	Prajapati et al. (2019)
S9	Legal grounding of reverse logistics incentives	Solati et al. (2023); *Author;* Prajapati et al. (2019)
S10	Stronger sanctions against unregistered operations	*Author*
S11	Training programmes for employees on reverse logistics	Prajapati et al. (2019)
S12	Environmental awareness campaigns for consumers and the public	Solati et al. (2023); Prajapati et al. (2019); Derse (2024)

$$aIb \leftrightarrow -q_j \leq |g_j(a) - g_j(b)| \leq q_j \tag{3}$$

$$aQb \leftrightarrow q_j < |g_j(a) - g_j(b)| \leq p_j \tag{4}$$

where p_j and q_j denote the preference and indifference thresholds, respectively, and the relations P, I, and Q correspond to strict preference, indifference, and weak preference. Pairwise comparisons between alternatives are then aggregated under three dominance scenarios that progressively widen the set of admissible preference relations. Scenario S1 considers only strict preferences, S2 incorporates both strict and weak preferences, and S3 further admits indifference relations. The aggregation rules are:

$$S_1 : \sum\nolimits_j w_j(aP_jb) > \sum\nolimits_j w_j(aQ_jb + aI_jb + aR_jb + bQ_ja + bP_ja) \tag{5}$$

$$S_2 : \sum\nolimits_j w_j(aP_jb + aQ_jb) > \sum\nolimits_j w_j\left(aI_jb + aR_jb + bQ_ja + bP_ja\right) \tag{6}$$

$$S_3 : \sum\nolimits_j w_j(aP_jb + aQ_jb + aI_jb) > \sum\nolimits_j w_j(aR_jb + bQ_ja + bP_ja) \tag{7}$$

where w_j is the weight of criterion j obtained from the BWM stage. The overall ranking of the alternatives is derived by aggregating pairwise comparisons across all scenarios, and robustness is examined by comparing the outcomes of S1, S2, and S3. A discordance threshold d_j is also applied to exercise a veto effect when the unfavourable performance gap on a single criterion is large enough to override otherwise favourable concordance.

A central implementation choice in this study concerns the threshold values. Setting q_j, p_j, and d_j uniformly across all criteria implicitly assumes that every criterion shares the same scale of variability, an assumption that rarely holds when the criteria differ in nature, units, and dispersion across alternatives. To avoid this distortion, criterion-specific thresholds were derived from the empirical dispersion of each criterion's evaluation vector across the alternatives, in line with the discrimination-threshold logic of the ELECTRE family of methods (Roy, 1991; Figueira and Roy, 2002). The indifference threshold was set at $q_j = 0.25 \cdot R_j$, the preference threshold at $p_j = 0.60 \cdot R_j$, and the veto threshold at $d_j = 1.00 \cdot R_j$, where R_j is the range of criterion j. Computations were performed using the THOR-Web platform without activating the Pertinence or Total Compensatory Aggregation (TCA) options, since the present problem does not assume full inter-criterion compensation.

3.3.3. DEMATEL

Causal relationships among the implementation barriers were analysed using the Decision-Making Trial and Evaluation Laboratory method (Tzeng et al., 2007), which is well suited to systems of interacting elements because it separates causally active barriers from causally passive ones. Each element (i,j) of the direct-relation matrix X captures the direct influence x_{ij} from barrier i to barrier j, as assessed by each expert on a four-point linguistic scale. To represent group decision-making, the individual matrices are averaged into the group direct-relation matrix A:

$$a_{ij} = \frac{1}{H}\sum\nolimits_h x^h{}_{ij}, i, j = 1, 2, \cdots, n \tag{8}$$

where H is the number of experts. The matrix A is then normalised by the largest row or column sum to obtain the normalised direct-relation matrix D:

$$s = max\left(max_i \sum\nolimits_j a_{ij}, max_j \sum\nolimits_i a_{ij}\right), D = A/s \tag{9}$$

Summing the direct and indirect effects yields a series that converges to the total relation matrix T:

$$T = D^1 + D^2 + D^3 + \cdots = D(I - D)^{-1} \tag{10}$$

From T, the row sum R_i captures the total influence exerted by barrier i on the rest of the system, and the column sum C_i captures the total influence it absorbs. Two complementary indicators follow: the centrality $(R_i + C_i)$, which reflects the overall importance of a barrier in the network, and the causality $(R_i - C_i)$, whose sign distinguishes driving barriers (positive) from dependent ones (negative) (Tzeng and Huang, 2011). To visualise the network, a threshold value, set as the mean of the elements of T, following Tzeng et al. (2007), is applied to eliminate insignificant interactions, and a cause–effect diagram is constructed on the basis of the retained relations. The stability of this threshold is examined through a sensitivity check reported in Section 4. Barrier weights wi for the QFD stage are obtained as:

$$w_i = \sqrt{(R_i + C_i)^2 + (R_i - C_i)^2}, w_i = \frac{w_i}{\sum_i w_i} \tag{11}$$

The normalised weights are then used as inputs for the QFD analysis in the next stage.

3.3.4. Quality Function Deployment

The driving barriers identified by DEMATEL are translated into prioritised solution measures through Quality Function Deployment, which enables the systematic mapping of critical barriers onto managerial actions. In the House of Quality (HOQ) matrix, the sixteen barriers are placed on the WHATs axis with the DEMATEL-derived weights w_i as the prioritisation criteria, and the twelve candidate solutions are placed on the HOWs axis. The strength of each barrier–solution relationship R_{ij} is rated by the expert panel on a 9–3–1–0 scale (strong, moderate, weak, none), following established QFD practice (Al Amin & Baldacci, 2024). The absolute importance of each solution is computed as:

$$AI_j = \sum_{i=1}^{m} w_i \times R_{ij}, forj = 1, \cdots, n \tag{12}$$

where w_i is the DEMATEL weight of barrier i and R_{ij} is the relationship intensity between barrier i and solution j. AI_j therefore captures the overall effectiveness of solution j in mitigating the identified barriers. To enable comparative prioritisation, the relative importance is defined as:

$$RI_j = \frac{AI_j}{\sum_{j=1}^{n} AI_j}, forj = 1, \cdots, n \tag{13}$$

The relative importance values constitute the normalised ranking of the solutions and identify those with the greatest cumulative impact across the prioritised barriers. The matrix roof of the HOQ further records the synergies and conflicts between solutions, providing a check on the mutual reinforcement of policy choices. The QFD stage thereby closes the analytical chain initiated by the strategy ranking, translating the diagnosis of barriers into a prioritised implementation roadmap for reverse logistics in the Turkish automotive scrap steel supply chain.

4. Results and discussion

4.1. Criteria weighting results using BWM

The Best–Worst Method was applied to determine the relative importance of the evaluation criteria. Five experts from reverse logistics, sustainability, and the automotive sector identified the best and worst criterion within each group and provided pairwise comparisons on a 1–9 scale. Local sub-criterion weights were obtained by solving the BWM optimisation model for each decision-maker; global weights were derived by multiplying local weights by their main-criterion weights and aggregating the five experts' outputs arithmetically.

The results indicate that economic and regulatory factors play a dominant role in reverse logistics strategy selection in the Turkish automotive sector. The most influential criteria are recycling cost advantage (0.0868), unit disposal cost (0.0847), and operational cost (0.0666), highlighting the centrality of cost efficiency. Regulatory aspects; environmental license requirements (0.0558) and carbon emission policies (0.0550) also receive relatively high weights. Digitalisation-related criteria carry moderate weight, with smart operations (0.0438) and real-time monitoring (0.0433) ranking higher than data-driven remanufacturing (0.0239) and digitally skilled workforce (0.0236). Environmental indicators such as waste reduction (0.0064) and water consumption impact (0.0061) carry the lowest weights. The detailed weighting results are presented in Table 5.

The weight structure offers a coherent reading of how Turkish automotive decision-makers conceptualise reverse logistics. The dominance of cost-related criteria reflects the position of scrap steel as a high-volume, price-sensitive input within a sector exposed to global steel-price volatility; the economic case is therefore the primary gate through which any strategy must pass. The high weighting of regulatory criteria mirrors the increasing exposure of Turkish exporters to EU emission and recycling obligations, which translates compliance into a competitive prerequisite rather than an external constraint. Digitalisation is recognised as important but not dominant — consistent with a sector that values digital tools instrumentally, as enablers of cost control and traceability, rather than as ends in themselves. The relatively low weight of pure environmental indicators reflects industrial pragmatism rather than indifference to sustainability: environmental outcomes enter the framework through the regulatory channel rather than as standalone criteria. Several further factors likely shape this pattern. First, decision-makers in emerging-economy manufacturing tend to prioritise criteria with near-term cost and compliance implications over those whose returns materialise over longer environmental horizons, a pattern documented in adjacent emerging-economy automotive contexts (Bhatia, Jakhar, & Dora, 2020). Second, currency volatility, input-cost inflation, and thin operating margins make cost criteria more salient than environmental ones whose benefits are diffused across stakeholders. Third, the expert panel, drawn mainly from operational and commercial functions rather than dedicated sustainability roles, tends to amplify this orientation rather than counterbalance it. Fourth, scrap steel is already a recyclable and economically valuable input, so the recovery activity itself delivers substantial environmental benefit regardless of how environmental criteria are weighted at the strategy-selection stage, consistent with reverse supply chain analyses in the steel industry (Antuchevičienė et al., 2020). The observed weighting pattern is therefore shaped jointly by institutional, economic, organisational, and sectoral factors rather than by any single cause.

4.2. Ranking of reverse logistics strategies using THOR II

The five strategy alternatives were ranked using THOR II through the THOR-Web platform. The criteria weights derived from the BWM analysis served as direct inputs in the form of global priority weights, and the analysis was conducted without the Pertinence and TCA options, since the problem does not assume full inter-criterion compensation. The alternatives were coded as A1 (In-house operation), A2 (Joint venture), A3 (Outsourcing), A4 (Public–private partnership), and A5 (Digital lean model).

A central design choice in THOR II is the specification of the indifference (q), preference (p), and veto (d) thresholds. Uniform thresholds assume that every criterion shares the same scale of variability, an assumption that rarely holds across heterogeneous criteria. To avoid this distortion, criterion-specific thresholds were derived from the empirical dispersion of each criterion's evaluation vector, in line with the discrimination-threshold logic of the ELECTRE family (Roy, 1991; Figueira & Roy, 2002). The indifference threshold was set at 25 % of the criterion's range, the preference threshold at 60 %, and the veto threshold at 100 %. The full set is reported in Appendix A.

Table 6 summarises the THOR II scores under the three dominance scenarios. Both strict (S1) and weak (S2) dominance place A1 clearly above the other alternatives, with scores of 2.041 and 2.301 respectively. The thorough dominance scenario (S3) produces a fully ordered ranking: A1 (2.616) > A3 (2.129) > A5 (2.076) > A2 (1.626) > A4 (1.500).

The dominance of A1 across all scenarios reflects the structure of the BWM weights, in which economic and regulatory criteria carry the highest priorities. In-house operation performs strongest on precisely these dimensions: greater control over operational costs, closer alignment with internal compliance procedures, and direct ownership of the

Table 5
Global and local weights of evaluation criteria obtained using the BWM method.

Main Criteria	Main Weight	Sub-Criteria	Direction	Local Weight	Global Weight
Economical	**0.331**	Recycling cost advantage	Benefit	0.263	0.087
		Investment requirement	Cost	0.142	0.047
		Operational cost	Cost	0.202	0.067
		Partnership and collaboration cost	Cost	0.142	0.047
		Unit disposal cost	Cost	0.257	0.085
Social	**0.100**	Corporate environmental image	Benefit	0.426	0.043
		Consumers' environmental awareness	Benefit	0.178	0.018
		Sensitivity to domestic production	Benefit	0.149	0.015
		Marketing contribution of eco-labelling	Benefit	0.248	0.025
Legal/Regulatory	**0.202**	Carbon emission policies	Benefit	0.272	0.055
		Environmental license requirements (EIA)	Cost	0.277	0.056
		Tax incentives for reverse logistics	Benefit	0.139	0.028
		Scrap import/export regulations	Cost	0.149	0.030
		EU-compliant recycling obligations	Cost	0.163	0.033
Environmental	**0.028**	Resource efficiency	Benefit	0.321	0.009
		Waste reduction	Benefit	0.214	0.006
		Reduction of carbon emissions	Benefit	0.286	0.008
		Impact on water consumption	Cost	0.214	0.006
Technological	**0.134**	Real-time monitoring of RL activities	Benefit	0.321	0.043
		Smart operations and resource sharing	Benefit	0.328	0.044
		Data-driven redesign and remanufacturing	Benefit	0.179	0.024
		Skilled workforce for digital operations	Benefit	0.179	0.024
Internal Mgmt.	**0.100**	Financial capacity	Benefit	0.208	0.021
		Technological infrastructure	Benefit	0.129	0.013
		Logistics capability	Benefit	0.258	0.026
		Information systems management	Benefit	0.102	0.010
		Sustainability vision	Benefit	0.307	0.031
External Market	**0.100**	Scrap supply quantity	Benefit	0.168	0.017
		Scrap supply quality	Benefit	0.129	0.013
		Supply volatility	Cost	0.129	0.013
		Market information and price stability	Benefit	0.218	0.022
		Market competition	Cost	0.119	0.012
		Supply chain resilience	Benefit	0.238	0.024

Table 6
THOR II results under the three dominance scenarios.

Scenario	A1	A2	A3	A4	A5	Ranking
S1 (Strict dominance)	2.041	2.000	2.000	1.500	2.000	A1 > {A2, A3, A5} > A4
S2 (Weak dominance)	2.301	1.500	2.000	1.500	2.000	A1 > {A3, A5} > {A2, A4}
S3 (Thorough dominance)	2.616	1.626	2.129	1.500	2.076	A1 > A3 > A5 > A2 > A4

recovery process, characteristics that are particularly valuable when scrap steel constitutes a critical input. From a governance standpoint, A1 internalises both the decision rights and the residual risk of recovery operations, which under volatile scrap markets becomes a hedge rather than a cost burden. From a resource-dependence standpoint, it minimises exposure to upstream partners whose performance cannot be contractually guaranteed.

Outsourcing (A3) emerges as the second-best option, offering a balanced profile for firms that lack the scale to justify internalisation but still require reliable recovery capacity. The digital lean model (A5) ranks third, with strong performance on the technological criteria but weaker positioning on cost and supply-side dimensions where it depends on infrastructure not yet fully diffused across the Turkish supplier base. Reading A5′s third-place position in this orthogonal-dimension framing, the ranking reflects not the strength of digitalisation as a complementary capability (A1 also possesses this) but the limited maturity of a fully digital-lean operating model as the primary structural choice in the current Turkish automotive setting. Joint venture (A2) ranks fourth, reflecting the limited appeal of shared-equity arrangements in a market where ownership structures are typically family-controlled. Public–private partnership (A4) ranks last in every scenario, consistent with the Turkish institutional context: PPP arrangements presuppose regulatory clarity, inter-agency coordination, and long-term policy commitment that the existing environment does not yet reliably provide. The lower evaluations of A4 therefore mirror real structural constraints rather than a dismissal of the partnership concept.

The stability of these rankings under the criterion-specific threshold scheme is examined in Section 4.3.

4.3. Sensitivity analysis

4.3.1. Sensitivity to criterion weights

A weight-based sensitivity analysis was conducted to verify that the ranking does not depend disproportionately on the priority assigned to any single criterion. The weight of the most influential criterion (recycling cost advantage) was perturbed upward by 20 %, with the remaining weights rescaled proportionally. The THOR II analysis was then re-executed under the perturbed weight set, with the criterion-specific thresholds held constant.

Across all three dominance scenarios, the overall ordering is preserved. A1 retains the top position, with its S3 score moving marginally from 2.616 to 2.623. A4 remains at the bottom with an unchanged score of 1.500, and the middle of the ordering (A3, A5, A2) is preserved without rank reversals. The dominance of A1 is therefore not the product of a narrow set of high-weight criteria but reflects a broader pattern in the evaluation matrix; even substantial perturbation of the leading criterion does not affect the leading alternative.

4.3.2. Sensitivity to threshold specification

The scaling coefficients applied to the empirical dispersion (0.25 for q, 0.60 for p, 1.00 for d) follow an empirical convention in the outranking literature rather than a closed-form theoretical derivation. The structural ordering $q < p < d$ originates in Roy's (1991) ELECTRE formulation, and the specific proportional values reflect a calibration commonly applied in the PROMETHEE family of outranking methods when thresholds are scaled to each criterion's empirical dispersion

(Brans & Mareschal, 2005). Because these values therefore embody a literature convention rather than a theoretical optimum, their robustness was tested directly. A complementary sensitivity exercise was therefore conducted in which all three coefficients were proportionally tightened by 40 %, yielding q = 0.15·R, p = 0.40·R, and d = 0.80·R. The new thresholds were applied to the same performance matrix and BWM weights.

The results are summarised in Supplementary Table S1. Across all scenarios, A1 retains its position as the highest-ranked alternative, with scores increasing slightly as a natural consequence of tighter indifference zones. A4 remains last in every scenario. The only observable movement is in the middle of the ranking: under stricter thresholds, A3 and A5 converge to a tied second position, whereas the baseline analysis had separated them in favour of A3 under S3.

Two conclusions follow. First, the dominance of A1 and the relegation of A4 are robust features of the data rather than artefacts of a specific threshold choice. Second, the relative position of A3 and A5 is mildly sensitive to threshold specification, with the two alternatives converging as indifference zones narrow. This is methodologically interpretable: outsourcing and the digital lean model perform similarly across most criteria, and their separation in the baseline analysis is driven by small differences. Although the present sensitivity exercise focuses on tightened indifference zones, the broad qualitative ordering, with A1 above A2 and A3 and A4 at the bottom, has held under every parameter configuration explored during model development, suggesting that the substantive conclusions are not artefacts of a single threshold specification.

4.4. Causal analysis of implementation barriers using DEMATEL

While THOR II identifies the most appropriate strategy, it cannot reveal whether that strategy is implementable in practice. To address this, the sixteen implementation barriers were analysed using DEMATEL, which decomposes a system of interacting elements into causally active driving barriers and causally passive dependent ones. The distinction matters: targeting a driving barrier propagates improvements through the network, whereas targeting a dependent barrier addresses only a symptom. The five experts assessed the direct influence of each barrier on every other on a four-point linguistic scale; individual matrices were aggregated by arithmetic mean before the standard DEMATEL transformation was applied.

Two complementary indicators are reported for each barrier. The prominence value $r_i + c_i$ captures how central a barrier is within the network. The relation value ($r_i - c_i$) captures the direction of involvement: a positive value identifies a driving barrier, a negative value a dependent one. The normalised weight Wi combines both and serves as the prioritisation criterion for the QFD stage. Supplementary Table S2 reports all four indicators.

The reading of Supplementary Table S2 changes meaningfully once prominence and relation are considered together. The three barriers with the highest prominence; lack of coordination among stakeholders (B9), absence of RL integration into corporate strategy (B5), and lack of planning and budgeting (B6), are all dependent barriers. They are highly visible not because they generate change but because they accumulate the consequences of upstream problems. Acting on prominence alone would lead to a partial and ultimately disappointing implementation effort.

The driving barriers tell a different story. Five barriers combine a positive $r_i + c_i$ with a high prominence value: the prevalence of an informal scrap economy (B15), the absence of a clear regulatory framework (B16), the lack of next-generation technologies (B1), the lack of incentives for recycling investments (B11), and the lack of knowledge about reverse logistics practices (B12). These barriers form the upstream layer. The informal scrap economy distorts price signals and erodes the competitive position of formal flows; the regulatory framework absence prevents standardised reporting and traceability; the technology gap limits real-time monitoring capacity; the incentive gap discourages the capital investment required for in-house operation; and the knowledge gap delays the diffusion of established RL practices. Together, these five barriers generate the visible problems of coordination, strategic integration, and planning that dominate the prominence ranking.

The implications for the in-house operation strategy are direct. A1 is structurally dependent on the firm's ability to internalise recovery, which requires a stable supply of standardised scrap (constrained by B15, B16), the technological infrastructure to monitor and process it (B1, B11), and the internal organisational capacity to design and operate the system (B12). The driving barriers, in other words, define the implementation conditions for the leading strategy.

The choice of the threshold above which a tij value is treated as a meaningful causal link is an analyst's decision, and the cause–effect classification of borderline barriers can in principle be sensitive to it. A threshold sensitivity check was therefore conducted. The baseline threshold corresponds to the mean of the total relation matrix (0.476); this was scaled by ± 10 % to obtain a stricter cut-off (0.524) and a more permissive one (0.429). Twelve of the sixteen barriers preserved their cause–effect classification under both perturbations. The five most prominent driving barriers (B15, B16, B1, B11, B12) and the three most prominent dependent barriers (B9, B6, B5) remained unchanged at every threshold tested, indicating that the core structural reading is robust. The four barriers that reclassified (B3, B4, B7, B13) were located close to the $r_i - c_i = 0$ line, and their movement reflects proximity to zero rather than substantive shift.

The driving barriers identified above form the input to the QFD stage, where they are matched against candidate solution measures to produce a prioritised implementation roadmap.

4.5. Qfd-based prioritisation of solution measures

The driving barriers identified in DEMATEL indicate where intervention is most effective, but they do not specify the form intervention should take. Quality Function Deployment was used at this final stage to translate the barrier diagnosis into a prioritised set of solution measures, with the DEMATEL-derived barrier weights serving as the prioritisation criteria. Twelve candidate solutions were placed on the WHATs–HOWs grid of a House of Quality matrix. Each barrier–solution relationship was rated on the conventional 9–3–1–0 scale by the expert panel, and the Absolute Importance (AI) of each solution was computed as the weighted sum of its ratings across all sixteen barriers, with the Wi values from Supplementary Table S2 as the weights. The Relative Importance (RI) was obtained by normalising AI to a percentage. Table 7 reports the

Table 7
QFD prioritisation of solution measures.

Rank	Code	Solution	AI	RI (%)
1	**S2**	Integration of reverse logistics into corporate strategy	4.846	14.07
2	**S10**	Stronger sanctions against unregistered scrap operations	3.880	11.27
3	**S11**	Employee training programmes on reverse logistics	3.752	10.90
4	**S4**	Digital data-tracking systems (blockchain/IoT)	3.456	10.04
5	**S9**	Legal grounding of reverse logistics incentives	2.976	8.64
6	**S8**	Enhanced incentive and tax mechanisms	2.840	8.25
7	**S7**	Access to green financing instruments	2.632	7.64
8	**S5**	Cooperation with sub-industries on reverse flows	2.234	6.49
9	**S6**	Joint facility and public–private partnership models	2.218	6.44
10	**S1**	Awareness and leadership of top management	1.980	5.75
11	**S3**	Process simplification and standardisation	1.828	5.31
12	**S12**	Environmental awareness campaigns for consumers	1.790	5.20

resulting prioritisation.

A key feature of the result is the alignment between the QFD ranking and the cause–effect structure from DEMATEL. The four highest-ranked solutions correspond directly to the driving barriers. Stronger sanctions against unregistered scrap operations (S10, second) target the informal scrap economy (B15). Employee training programmes (S11, third) address the knowledge gap (B12). Digital data-tracking systems (S4, fourth) close the technology gap (B1) and provide the monitoring infrastructure that the performance-measurement gap (B14) makes visible. The legal grounding of incentives (S9, fifth) and the enhancement of incentive mechanisms (S8, sixth) address the absence of a clear regulatory framework (B16) and the investment-incentive gap (B11). The QFD therefore does not produce a list of independent recommendations; it produces a coherent intervention map in which each highly ranked solution is anchored in a specific upstream barrier.

The top-ranked solution (embedding reverse logistics into corporate strategy, S2) has a different status. It does not address a single driving barrier directly but acts as the organisational precondition that enables every other solution to take effect. Sanctions on unregistered operations only matter if firms have a strategic stake in formalised recovery; training programmes require an institutional setting in which RL is a recognised function; digital tracking systems demand the capital and managerial attention that strategic integration secures. S2 therefore functions as the architectural layer of the implementation roadmap, while S4, S10, S11, S8, S9 form its operational layer, and the remaining solutions constitute a supporting layer.

The implementation roadmap emerges in three reinforcing tiers. The first tier is strategic embedding: positioning RL within corporate planning systems and assigning executive sponsorship, so that the function ceases to be an isolated compliance activity. The second tier is regulatory and informational infrastructure: tightening enforcement on the informal scrap economy, codifying incentive structures, and deploying digital traceability systems that make material flows visible. The third tier is organisational capability building: training the workforce, formalising performance-measurement systems, and stabilising supplier relationships. Each tier is necessary; working only on the third without the first two produces operational capability that has nowhere to deploy, while working only on the first without the second and third produces strategic intent that lacks the means to act.

This three-tier reading aligns directly with the in-house operation strategy identified in Section 4.2 as the most appropriate for the Turkish automotive context. A1 is feasible precisely under the conditions that the QFD ranking prioritises (strategic embedding, regulatory clarity, digital monitoring, and skilled internal staff) and is most likely to falter where those conditions are absent. The framework therefore connects strategy desirability (THOR II), barrier causality (DEMATEL), and intervention design (QFD) in a single argument: the leading strategy succeeds when the upstream barriers are addressed in the order that the QFD prioritisation implies (Supplementary Table S1).

5. Contributions and implications

5.1. Theoretical contributions

The study advances the reverse logistics literature in three directions. First, it bridges the long-standing gap between strategy selection studies, which prioritise desirability, and barrier identification studies, which describe constraints, by formalising a feedback link between the two: the desirability of a strategy is conditioned on the removability of the barriers it faces. Second, reverse logistics decision-making is positioned as an institutionally embedded problem in the Turkish automotive setting, where regulatory uncertainty, the informal scrap economy, and uneven technological diffusion exert first-order effects on which strategies are viable. Third, by foregrounding causal relationships among barriers rather than treating them as a flat list, the framework offers a structured way to reason about transition pathways.

The scope of these contributions can be delineated as follows. The dominance of A1, the causal structure of the barrier network, and the corresponding QFD action priorities are findings supported directly by the Turkish automotive case examined here. The central proposition that strategy desirability is conditioned on barrier removability is plausibly transferable to other emerging-economy manufacturing settings with comparable institutional characteristics, including regulatory exposure to EU-aligned obligations, the coexistence of formal and informal recovery channels, and uneven technological diffusion across the supplier base. Whether desirability–feasibility coupling is a structural feature of reverse logistics decision-making more broadly is a theoretical implication that requires testing in different institutional and sectoral contexts.

This proposition has identifiable limits. It is most informative in emerging-economy manufacturing, where regulations are still developing, informal channels persist, and digital infrastructure is patchy. In mature institutional environments, regulation is stable, informal channels matter less, and technology is broadly available, so many of these barriers disappear or shrink to minor frictions, and desirability and feasibility can be analysed more independently. The proposition also assumes that barriers are not tied to a single strategy, since a barrier blocking only one option leaves nothing to compare. It assumes that barrier removability is something firms can influence; where barriers reflect structural conditions outside the firm's control, the coupling weakens. The proposition is therefore best read as an empirically supported interpretation calibrated to the Turkish automotive context, not a general theoretical principle (Supplementary Table S2).

5.2. Methodological contributions

The integration of BWM, THOR II, DEMATEL, and QFD is, to the author's knowledge, the first attempt to combine these four methods in a single architecture for reverse logistics decision-making. Each method addresses a distinct epistemic task: BWM provides a parsimonious and consistency-checked weighting procedure, THOR II ranks alternatives under dominance logic without imposing full inter-criterion compensation, DEMATEL distinguishes driving barriers from dependent ones, and QFD operationalises the diagnosis into deployable measures. The sequence is constitutive rather than additive, removing any one stage would leave a recognisable gap in the analytical chain. The criterion-specific thresholds applied in the THOR II stage, derived from the dispersion of each criterion's evaluation vector, further strengthen the methodological reliability of the framework and reduce its dependence on arbitrarily chosen parameter values. The framework here is sequential. BWM weights criteria, THOR II ranks strategies, DEMATEL maps the causal structure of barriers, and QFD translates these into actions. Feedback between stages is a natural extension that future work could explore. Barrier structures could be allowed to influence strategy selection, so that strategies facing dense and hard-to-remove driving barriers are downweighted even when their desirability ranking is high. QFD outcomes could similarly feed back to the strategy stage: if implementation actions for a leading strategy prove intractable, the ranking should be revisited. An iterative version, in which each cycle updates the criteria weights, the barrier weights, or both, could converge on a more stable joint solution than a single linear pass. Closed-loop and iterative configurations of this kind have been explored in adjacent reverse logistics literature, including for circular supplier selection (Govindan et al., 2020) and for sustainable reverse supply chain planning in the steel industry (Antuchevičienė et al., 2020); adapting them to a multi-method architecture like the one developed here is a promising direction for future work. The present study retains the linear architecture to keep each stage's contribution transparent and traceable.

5.3. Managerial implications

For firms in the Turkish automotive sector, the analysis suggests that internalising scrap steel reverse logistics (rather than outsourcing it or pursuing partnership-based arrangements) is the most defensible strategy under current conditions, provided that internal capabilities for operational integration and digital monitoring are developed in parallel. The dominance of A1 should not be read as a verdict against digitalisation; on the contrary, the QFD results indicate that digital traceability and real-time monitoring are among the highest-priority solution measures. The practical conclusion is that in-house reverse logistics needs to be digitally enabled to remain competitive, not that digitalisation can substitute for the strategic decision of where to locate the recovery function within the firm.

A second managerial implication concerns the placement of reverse logistics within corporate strategy. The barrier analysis indicates that weak strategic integration is one of the most influential driving barriers; firms that treat reverse logistics as an isolated environmental compliance function are therefore likely to underperform regardless of the operational model chosen. The lever with the greatest system-wide impact is the elevation of reverse logistics to a strategic planning priority.

5.4. Policy implications

The framework also yields actionable implications for policymakers. The persistence of an informal scrap economy emerges as a structural barrier whose effects propagate through the system, weakening price signals, distorting investment incentives, and depressing the relative attractiveness of formalised arrangements such as public–private partnerships. Regulatory measures that improve traceability, standardise reporting requirements, and channel incentives toward formal recovery flows would therefore not only address the informal economy directly but also reshape the relative ranking of strategy alternatives in the longer run. Access to green financing instruments and clearer rules on scrap import–export would amplify these effects.

5.5. Limitations and future research directions

Several limitations bound the conclusions of this study. The expert panel consists of five senior practitioners from the Turkish automotive industry, supported by two academic consultants during the criteria validation phase. This composition is consistent with the panel sizes commonly reported in BWM, THOR II, DEMATEL, and QFD applications, and the same panel participated in all four quantitative stages to preserve judgement coherence; nevertheless, statistical generalisation beyond the panel is necessarily limited. Future research could broaden the empirical base by enlarging the panel, stratifying it across OEMs, suppliers, recyclers, and policy actors, and triangulating expert judgement with longitudinal operational data from firms operating reverse logistics systems.

Beyond panel size, three specific implications of relying on a five-member panel deserve explicit acknowledgement. Expert dominance is one: in a small panel, a single member's views can carry disproportionate weight, and while BWM consistency checks bound the internal coherence of each individual's judgements, they do not control for cross-member influence during validation. Sensitivity to individual judgement patterns is another. With a small panel, idiosyncratic biases such as risk aversion or sector-specific anchoring are not averaged out as effectively as in larger panels, and the resulting weights and rankings can reflect particular cognitive styles rather than the underlying problem structure. The third concerns the aggregation procedure. The arithmetic mean used to combine expert judgements is convenient but treats panel members as exchangeable contributors and gives outlier judgements disproportionate influence when the panel is small. Alternative aggregation rules, such as the geometric mean or weighted means based on domain experience, would change the outputs in principled ways and constitute a worthwhile robustness check for future work.

The framework itself is general, but its parameters are calibrated to the Turkish automotive context. Replication in other emerging economies and in other resource-intensive sectors would test how far the central proposition (that strategy desirability is conditioned on barrier removability) generalises across institutional environments. Methodologically, future extensions could incorporate fuzzy or interval-based evaluations to capture the imprecision of expert judgement more explicitly, and integrate dynamic modelling approaches such as simulation and digital twin-based representations to capture how reverse logistics systems evolve as barriers are progressively removed.

6. Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used Grammarly for language polishing and grammar checking. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wasman.2026.115729.

Data availability

Data will be made available on request.

The data that support the findings of this study (BWM pairwise comparisons, DEMATEL direct-relation matrices, and QFD relationship ratings) were obtained through expert elicitation under confidentiality agreements with practitioners in the Turkish automotive industry. Anonymised aggregated data are available from the corresponding author on reasonable request.

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