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An integrated framework for evaluating the barriers to successful implementation of reverse logistics in the automotive industry

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ABSTRACT

Reverse logistics (RL) strategy can have a positive impact on productivity, and the diminishing resources, along with the strict environmental regulations, have strengthened the need for this strategy. The purpose of this study is to develop an integrated framework for identifying: (1) the critical barriers to the successful implementation of RL in the automotive industry; (2) the importance and implementation priorities of these barriers; and (3) the causal relations among them. The proposed framework is composed of the Delphi method to identify the most relevant barriers, the best-worst method (BWM) to determine their importance, and the weighted influence non-linear gauge system (WINGS) to analyze their causal relationships. The proposed framework is applied to a case study in the automotive industry. The results indicate the economic barriers are the most important, and the knowledge barriers are the least important barriers to the successful implementation of RL in the automotive industry.

1. Introduction

An increasing number of environmental issues such as climate change, air pollution, contaminated land, and overusing natural resources has forced companies to be more environmentally conscious (Abdulrahman et al., 2014; Bowen et al., 2018; Panda et al., 2020). Can a company be environmentally conscious and, at the same time, profitable? The answer is, yes! Environmental consciousness and business profit are not mutually exclusive. Most large corporations have shown trade-offs between environmentalism and profitability are not necessary, and the quest for sustainability is often a path to increase in profitability (Tavana et al., 2016a). The increasing environmental and competitive pressure has forced companies to seek out new methods to decrease production costs and survive in competitive markets. Reverse logistics (RL) refers to reusing and remanufacturing defective products to protect the environment and decrease operational expenses. In recent years, several companies have deployed RL to efficiently and effectively manage their resources (Baenas et al., 2011; Kumar and Dixit, 2018; Prajapati et al., 2019a). The underlying research questions in this study are:

(1) What are the critical barriers that need to be considered in the successful implementation of RL in the automotive industry?

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(2) What are the importance and implementation priorities of these barriers?
(3) What are the causal relations among these critical barriers?

An integrated framework is proposed to address these research questions. The Delphi method is used to identify the most relevant and critical barriers. The best-worst method (BWM) is used to determine the importance and priorities of these barriers to the successful implementation of RL in the automotive industry. The weighted influence non-linear gauge system (WINGS) is used to analyze the causal relationships among the barriers. The answers to these questions should lead to a better understanding of the RL implementation barriers, which is still in its infancy stage of implementation in the automotive industry.

Waqas et al. (2018) and Abdulrahman et al. (2014) have discussed the need for studies to determine, verify, and evaluate barriers to the successful implementation of RL using quantitative tools and techniques. The integrated Delphi, BWM, and WINGS proposed here is quantitative, structured, and comprehensive. Some of the benefits of Delphi methods are the anonymity of responses, controlled feedback, and statistical analysis of responses. The BWM is a quantitative method used here because its structured approach to pairwise comparisons reduces the number of comparisons and improves the consistency of judgments. The WINGS method is also a quantitative method used here because it is a structural model for analyzing intertwined factors with causal relations. This study addresses additional research gaps in the literature. Mi et al. (2019) show there is still a gap in the literature to combine the BWM with other techniques to solve complex decision-making problems. When facing a multitude of barriers, a logistics manager gains insight by knowing not only the internal importance of a barrier but also their external influence on other barriers.

Several studies have used the Decision making trial and evaluation laboratory (DEMATEL) approach to evaluate the barriers to RL implementation but failed to assess the internal strength (importance) of the barriers (e.g., Xia et al., 2015; Kumar and Dixit, 2018; Chauhan et al., 2018). The reasons for using the WINGS method in this study are fivefold: (1) The WINGS method and its unique structure allow for the internal evaluation of the barriers by considering their strengths in relation to the other barriers in multi-criteria decision making (MCDM) problems. (2) The WINGS method, on the one hand, enriches the DEMATEL approach by evaluating the internal strength (importance); and, on the other hand, allows the researchers to go beyond the limiting assumption of criteria independence by introducing the influence among the concepts involved in the problem. (3) The WINGS method, in comparison to the analytic network process (ANP), has a more intuitive network structure (without clusters) and is much simpler to implement. In addition, there is no need to make complete and cumbersome pairwise comparisons. (4) The WINGS method also has an advantage over the fuzzy cognitive map, as the latter is based on an arbitrary choice of the threshold function, which can distort the results (Penn at al. 2013). (5) Finally, since the WINGS method provides a weighted directed graph of system components for analyzing the dependencies among barriers, enriching this method with a robust tool like the BWM produces a powerful integrated framework.

This study identifies and prioritizes the barriers to the successful implementation of RL in the automotive industry. An initial set of barriers is selected using a literature review and the Delphi method. These barriers are then analyzed with respect to their relevance to the automotive industry using an integrated framework that combines the BWM and the WINGS method. The remainder of this paper is organized as follows. Section 2 presents a review of the RL and its barriers. Section 3 presents the integrated framework proposed in this study. A case study is presented in Section 4 to demonstrate the applicability and efficacy of the proposed method. Section 5 presents conclusions and future research directions.

2. Literature review

This section presents an overview of the literature in RL, MCDM methods in RL, and the critical barriers to RL implementation.

2.1. Reverse logistics

The top-performing companies have recognized that efficient logistics and supply chain operations are the source of competitive advantage. Wu and Dunn (1995) show an efficient supply chain is the result of an information system that pre-determines consumer satisfaction without bottlenecks during the initial process until delivery. The cost-benefit consideration is part of the goals and an integral part of the corporate strategy. In the sustainable business models, RL is considered as a process that leads to plenty of benefits such as cost reduction, revenue growth, and further profitability for organizations and their supply chains as a whole. On the other hand, having an effective RL empowers enterprises to sustain their competitive advantages with their rivals (Srivastava, 2013). Reviewing the literature on RL implementation procedures reveals that there are a plethora of successful experiences in diverse industries that are promising for end-of-life and end-of-use products. Table 1 presents a summary of these studies.

Despite the fact that RL systems have been implemented in different manufacturing companies successfully, reviewing the literature demonstrates that there is still a lack of deep understanding of the benefits of RL implementation in emerging economics (Abdulrahman et al., 2014). Consequently, management awareness plays a crucial role in supporting RL implementation as a strategic decision in developing countries. Although the commitment of the firm's policymakers is essential in the process of RL implementation, they may have some concerns on how to initiate and implement an RL system (Ho et al., 2012; Govindan and Bouzon, 2018; Ho et al., 2012).

Reviewing the literature shows several studies have justified the need for identifying and exploring the barriers and drivers to the successful implementation of the RL systems. Govindan and Bouzon (2018) conducted a comprehensive study of 36 barriers to the implementation of RL systems and identified the intrinsic barriers which lack management awareness and support. They highlighted the economic, technological, and management structure constraints, which hinders the successful implementation of sustainable processes. Rameezdeen et al. (2016) studied the barriers to RL implementation in the construction industry and identified four critical barriers, including regulations, extra costs, lack of recognition, and additional efforts. Shaharudin et al. (2015) classified the barriers to RL implementation into external and internal factors. Their study revealed financial and resource constraints as internal barriers and customers' perception and operational performance as external barriers. Xia et al. (2015) investigated the internal barriers in the automotive industry and proposed some solutions to eradicate these barriers. Kapetanopoulou and Tagaras (2011) focused on the adoption of product recovery processes in the Greek manufacturing industry. They found the Greek manufacturing companies engage in product recovery and RL primarily to service to their customers because they are hesitant to complicate their manufacturing processes. The next section presents an overview of the MCDM methods in RL implementation.

Table 1
RL implementation in major industries.

Sector	Study
Automotive industry	Ravi and Shankar (2005); Schultmann et al. (2006); González-Torre et al. (2010); Dhouib (2014); Mathivathanan et al. (2018); Simic (2015); Chakraborty et al. (2019); Schneider (2010); Kuşakcı et al. (2019); Karagoz et al. (2020); Yang et al. (2019); Wang et al. (2020); D'Adamo et al. (2020); and Rosa and Terzi (2018).
Construction industry	Nunes et al. (2009); Chileshe et al. (2016); Chileshe et al. (2018); Pushpamali et al. (2019).
Pharmaceutical industry	Kumar et al. (2009); Narayana et al. (2014); Kongar et al. (2015); and Campos et al. (2017).
Electrical and electronics industry	Prakash and Barua (2015); Bouzon et al. (2016); Agrawal et al. (2016); Guarnieri et al. (2016); Caiado et al. (2017); Kumar and Dixit (2018); and Prajapati et al. (2019b).
Fashion industry	Abraham (2011) and Bouzon and Govindan (2015)
Plastic industry	Pohlen and Theodore Farris (1992) and Halabi et al. (2013).

2.2. Multiple criteria methods in reverse logistics

A large number of RL studies have focused on the investigation of the RL components (Rezaei, 2015). Most of these studies have focused on barriers and critical success factors for facilitating the implementation of RL systems in terms of classification and prioritization in different industries. For example, Barker and Zabinsky (2011) used the analytic hierarchy process (AHP) method to derive critical decisions about the RL network, based on two criteria (business relationship and cost) and several sub-criteria (production, test cost, scarp shipped, the original facility, proprietary knowledge, and customer interaction). In addition, their model considers eight alternatives. In another study, Bouzon et al. (2018) displayed a method to evaluate RL barriers by grey decision-making. In this research, after extracting barriers, the grey-DEMATEL (decision-making trial and evaluation laboratory) was used to illustrate the relationships among these barriers. The novelty of this research was in discovering which barriers were dominant or dominated. Kumar and Dixit (2018) applied a framework to identify and assess the obstacles in the implementation of RL systems and used the DEMATEL approach to analyze the interactions among them. The review of the literature shows diverse applications of decision-making tools, in particular, MCDM methods, in the RL systems. MCDM has been successfully used to solve RL problems such as third-party RL selection (Tavana et al., 2016b; Bai and Sarkis, 2019), outsourcing RL activities (Tavana et al., 2016a; Zarbakhshnia et al., 2019), performance assessment of RL systems (Han and Trimi, 2018), and critical analysis of the RL barriers (Lamba et al., 2019; Gardas et al., 2019).

The review of the literature also shows several hybrid MCDM approaches such as AHP and TOPSIS (the technique for order of preference by similarity to ideal solution) under a fuzzy environment (Prakash and Barua, 2015; Sirisawat and Kiatcharoenpol, 2018), fuzzy analytic network process (ANP) and VIKOR (the acronym is in Serbian: VlseKriterijumska Optimizacija I Kompromisno Resenje, meaning multi-criteria optimization and compromise solution) (Phochanikorn et al., 2019), ISM (interpretive structural modeling) and MICMAC (matrix-based multiplication applied to a classification) (Gardas et al., 2018), fuzzy Delphi and AHP (Bouzon et al., 2016), and ANP and balanced scorecard (Ravi et al., 2005) are successfully used in RL. Table 2 presents a summary of the recent MCDM techniques applied to RL implementation.

2.3. Critical barriers in RL implementation

The logistics managers face significant difficulties in implementing end-of-life product collection processes in RL (Ravi and Shankar, 2005; Phochanikorn et al., 2019). According to Da Silva and Gouveia (2020), these difficulties are due to (but are not limited to) drawbacks such as lack of commitment and willingness of top management, lack of technology infrastructure, absence of supportive government regulations, weak coordination among supply chain entities, and lack of trust in the remanufactured products by customers. The end-of-life products refer to those products that have already ended their useful life, and the end-of-use products refer to those products that have the opportunity to return to a particular stage of life (Kongar et al., 2015; Paula et al., 2019).

Above all, the implementation of RL systems runs into numerous barriers that different studies have identified as a management problem (Kumar and Dixit, 2018; Bouzon et al., 2016; Govindan and Bouzon, 2018). Motivated by the research question, "how can we implement RL systems in the Indian electronics industry?" Prakash and Barua (2015) investigated and defined some impediments, including strategic, economic, policy, infrastructural, and market-related barriers to RL implementation. Caiado et al. (2017) considered the lack of governmental support as the main barrier to the implementation of RL. Chileshe et al. (2016) classified the obstacles in the implementation of RL systems into four groups of organizational, operational, social, and environmental barriers.

Govindan and Bouzon (2018) provide a comprehensive study of 36 barriers to the implementation of RL systems and identifies the obstacles that are intrinsic to the organization in terms of lack of awareness or management support. They highlighted the economic, technological, and management structure constraints, which hinders the successful implementation of sustainable processes (Govindan and Bouzon, 2018). On the other hand, the authors point out that there are external barriers, which are related to governmental pressures, whether in the absence of policies, and incentive legislation, that often makes the process expensive for organizations. Table 3 presents the most significant and prevalent barriers to RL implementation. The extracted RL implementation barriers are categorized into seven barriers and sub-barriers as follows:

- Economic-related barriers (X_1)
- Governance and supply chain process barriers (X2)
- Knowledge-related barriers (X_3)
- Competitors- and market-related barriers (X_4)
- Management-related barriers (X_5)
- Policy-related barriers (X_6)

3. The proposed framework

A three-phase framework is intended to evaluate the barriers to the successful implementation of RL in the automotive industry. In Phase I, the Delphia method is used to identify the RL barriers and sub-barriers utilizing the literature review and field experts. In Phase II, the BWM is used to determine the priority weight of the RL barriers and their sub-barriers. In Phase III, the WINGS method is used to determine the cause-and-effect relationship between RL

Table 2
Summary of recent MCDM techniques applied to RL implementation.

Author(s)	Analysis	Method
Ravi and Shankar (2005)	RL barriers	Interpretive Structural Modelling (ISM)
González-Torre et al. (2010)	RL barriers	Structural Equation Model
Dhouib (2014)	Reverse manufacturing alternatives	Fuzzy MACBETH
Prakash and Barua (2015)	RL barriers	Fuzzy AHP and Fuzzy TOPSIS
Bouzon and Govindan (2015)	RL drivers	AHP
Agrawal et al. (2016)	RL critical success factors	Fuzzy TOPSIS
Luthra et al. (2017)	RL critical success factors	AHP
Prakash and Barua (2017)	RL barriers	fuzzy AHP and interpretative ranking process
Bouzon et al. (2018)	RL barriers	Grey-based DEMATEL
Sirisawat and Kiatcharoenpol (2018)	RL barriers	Fuzzy AHP and Fuzzy TOPSIS
Abbas (2018)	RL barriers	ISM
Waqas et al. (2018)	RL barriers	Structural equation modelling
Gardas et al. (2018)	RL barriers	ISM and MICMAC
Gardas et al. (2019)	RL critical success factors	TISM and MICMAC
Nakiboglu, (2019)	RL barriers	AHP
Prajapati et al. (2019b)	RL barriers	SWARA and WASPAS

Table 3
Internal and external RL barriers adopted from the literature.

RL barriers	RL sub-barriers (Internal/External)		Reference
Economic-related barriers (X_1)	Lack of funding for training human resources (X_{11})	Internal	Ravi and Shankar (2005); González-Torre et al. (2010); Ho et al. (2012); Subramoniam et al. (2013); Kannan et al. (2014); Abdulrahman et al. (2014); Prakash and Barua (2015); Bouzon et al. (2015); Govindan and Bouzon (2018); Nakiboglu (2019); Lamba et al. (2019); and Schneider (2010); Xiao et al. (2019); Wang et al. (2020).
	Lack of initial capital (X_{12})	Internal	
	Lack of economy of scale (X_{13})	Internal	
	Uncertainty related to economic barriers (X_{14})	Internal	
	Lack of economic justification in product recovery activities (X_{15})	Internal	
	The pressure of the economic sanctions (X_{16})	Internal	
Governance and supply chain process barriers (X2)	Problems with supply chain members (X_{21})	Internal	Ravi and Shankar (2005); Govindan et al. (2013); Abdulrahman et al. (2014); Shaharudin et al. (2015); Bouzon et al. (2015); Govindan and Bouzon (2018); and Lamba et al. (2019).
	Limited forecasting and planning (X_{22})	External	
	Inconsistent product quality compared to the forward logistics (X_{23})	External	
	Complexity to find third-party RL provider (X_{24})	Internal	
	Lack of proper performance management system (X_{25})	Internal	
Knowledge-related barriers (X_3)	Lack of information on RL practice (X_{31})	Internal	Rahimifard et al. (2009); González-Torre et al. (2010); Ho et al. (2012); Wiel et al. (2012); Subramoniam et al. (2013); Bouzon et al. (2015); Govindan and Bouzon (2018); García-Sánchez et al. (2019); Chileshe et al. (2018); Kuşakcı et al. (2019); Simic (2015); Chakraborty et al. (2019); and Prajapati et al. (2019a).
	Lack of knowledge on RL channels (X_{32})	External	
	Lack of knowledge of RL advantages (X_{33})	Internal	
	Difficulties with undeveloped recovery markets (X_{41})	Internal	
Competitors- and market-related barriers (X_4)	Lack of customer's trust in the recovered product due to lower quality (X_{42})	External	Rahimifard et al. (2009); González-Torre et al. (2010); Bouzon et al. (2015); Abraham (2011); Shaharudin et al. (2015); Govindan and Bouzon (2018); Paula et al. (2019); De Oliveira et al. (2019); and Orji (2019).
	Slight perception of competitive advantage (X_{43})	External	
	Monopoly competition (X_{44})	Internal	
Management-related barriers (X_5)	Low emphasis on RL comparing to other barriers (X_{51})	Internal	Ravi and Shankar (2005); Sarkis et al. (2010); González-Torre et al. (2010); Abdulrahman et al. (2014); Chan et al. (2010); Govindan and Bouzon (2018); Lara et al. (2019); Prajapati et al. (2019b); and Orji (2019).
	Low involvement of top management and paying not enough attention to RL in strategic planning (X_{52})	Internal	
	Limited approval of disposal licenses (X_{53})	Internal	
Policy-related barriers (X_6)	Lack of supportive laws (X_{61})	External	González-Torre et al. (2010); Govindan et al. (2013); Krikke et al. (2013); Abdulrahman et al. (2014); Bouzon et al. (2015); Govindan and Bouzon (2018); Lara et al. (2019); Singh and Swati Sharma (2019); Kuşakcı et al. (2019); Chakraborty et al. (2019); and Wang et al. (2020).
	Lack of clear return and waste management policies (X_{62})	External	
	Lack of motivation regulations (X_{63})	External	
	Firm policies against RL (X_{64})	External	
	Lack of skilled human resources (X_{71})	Internal	
	Lack of IT systems standards (X_{72})	External	
Technology and infrastructure barriers (X_7)	Lack of newest technologies (X_{73})	Internal	Ravi and Shankar (2005); González-Torre et al. (2010); Kapetanopoulou and Tagaras (2011); Govindan et al. (2013); Bouzon et al. (2015); Shaharudin et al. (2015); Govindan and Bouzon (2018); Nakiboglu (2019); Lamba et al. (2019); Schneider (2010); and Wang et al. (2020).
	Lack of industrial infrastructure (X_{74})	Internal	
	Limitation of technology and research and development barriers related to RL practices (X_{75})	External	
	Complexity of RL implementation in operation (X_{76})	Internal	
	Lack of initial capital (X_{12})	Internal/ External	

barriers and sub-barriers. Phase I is devoted to reviewing the literature and extracting the relevant barriers to RL implementation. The Delphi method is used to aid experts in assessing the extracted barriers and arriving at a consensus on the barriers and sub-barriers to be considered in Phases II and III. In Phase II, experts are asked to assess the importance of the barriers quantitatively using the BWM. In this phase, the best and the worst barriers are determined, and pairwise comparisons are used to compare the

other barriers to the best and the worst barriers in each category. In Phase III, the hidden interactions among the barriers are discovered by using the outputs of the BWM as inputs in the WINGS method. In this phase, comprehensive comparisons among the barriers and sub-barriers are conducted to assess the internal strength of each barrier quantitatively using the WINGS method (see Fig. 1).

Next, a brief overview of the methods utilized in the proposed framework, including the Delphi method, the BWM, and the WINGS method, are presented in Sections 3.1, 3.2, and 3.3, respectively.

3.1. The Delphi method

The Delphi method is a prevalent systematic method for reaching a consensus among a group of experts (Giannarou and Zervas, 2014). This method is applicable to multilateral and complex studies where a convergence of ideas among the experts is preferred (Giannarou and Zervas, 2014; Grisham, 2009). The experts participating in a Delphi study express their opinions through questionnaires in multiple rounds. Delphi method anonymously circulates the experts' responses using a facilitator aiming at reaching consensus in several rounds (Okoli and Pawlowski, 2004).

Since its inception, the Delphi technique has been employed in a wide range of applications. In particular, there are many logistics supply chain and management studies in which the Delphi tool has been applied in the empirical part of the research (Govindan et al., 2014, 2019; Kaviani et al., 2019). More interestingly, there are several studies in the literature that have used the Delphi technique along with diverse MCDM methods for assessing barriers related to RL implementation (Bouzon et al., 2016; Waqas et al., 2018). Delphi method is often incorporated in multi-criteria RL problems because it provides a more flexible and comprehensive environment for solving sophisticated RL problems requiring expert judgments and opinions.

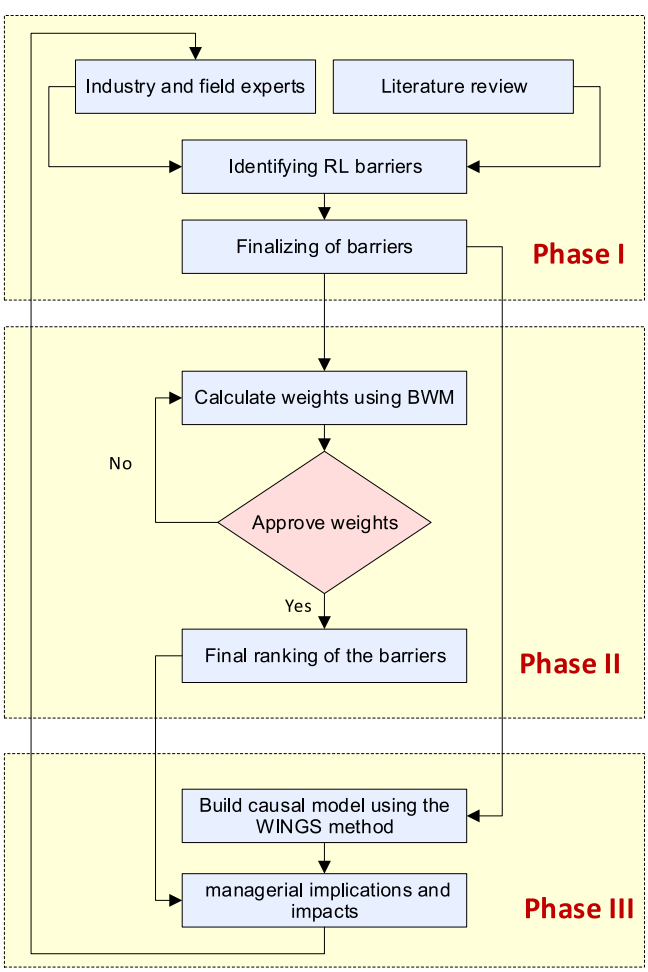

Fig. 1. Proposed framework.

3.2. The best-worst method

It is often difficult for a decision-maker to select the best alternative when a large number of factors require pairwise comparisons. The BWM helps decision-makers opt for the best and the worst criteria instead of a large number of pairwise comparisons (Rezaei, 2015; Rezaei, 2016). In contrast with other MCDM methods like SAW, SMART, and AHP, this method provides more reliable and consistent results. The following are the advantages of using the BWM over other MCDM methods (Rezaei, 2015; Rezaei, 2016):

- It provides a flexible decision-making environment.
- It considers the consistency of the decision-makers.
- It uses a limited number of pairwise comparisons in comparison with other methods (e.g., AHP).

The BWM has been used in a wide range of applications including supply chain and sustainability (Ahmad et al., 2017; Ahmadi et al., 2017; Govindan et al., 2019); logistics (Rezaei et al., 2018), and technological innovation (Gupta and Barua, 2016). The mathematical steps required for the BWM are described as follows:

Step 1: Identify a set of barriers through literature review and expert opinions.
Step 2: Identify the best and the worst barrier.
Step 3: Determine the preference of the best barrier over all other barriers using a number between 1 and 9 and construct the best-to-others (A_B) vector:

$$A_B = (a_{B1},\ a_{B2}, \ldots.., a_{Bn)} \tag{1}$$

where, a_{Bj} denotes the preference of the best barrier B over barrier j.

Step 4: Determine the preference of all barriers over the worst barrier using a number between 1 and 9 and construct the others-to-worst (A_w) vector:

$$A_w = (a_{1w},\ a_{2w}, \ldots.., a_{nw)}T \tag{2}$$

where, a_{jw} indicates the preference of barrier j over the worst barrier W.

Step 5: Determine the optimal weight of the barriers $(w_1^*, w_2^*, \ldots, w_n^*)$:

$$\begin{aligned} &\min\max_j \{|w_B - a_{Bj}w_j|,\ |w_j - a_{jw}w_w|\} \\ &\text{s.t.} \\ &\sum_j w_j = 1, \\ &w_j \geq 0 \quad \text{for all } j \end{aligned} \tag{3}$$

Formulation (3) can be transformed into the following linear programming formulation (4) (Rezaei, 2016):

$$\begin{aligned} &\text{Min } \xi^* \\ &\text{s.t.} \\ &|w_B - a_{Bj}w_j| \leq \quad \text{for all } j \\ &|w_j - a_{jw}w_w| \leq \quad \text{for all } j \\ &\sum_j w_j = 1 \\ &w_j \geq 0 \quad \text{for all } j \end{aligned} \tag{4}$$

The optimal weights $(w_1^*, w_2^*, ..., w_n^*)$ and ξ* are obtained after solving the linear programming formulation (4). Using the consistency index (*CI*) suggested by Rezaei (2015) (see Appendix A), the consistency ratio (*CR*) can be obtained by utilizing ξ* and the corresponding *CI* as given below:

$$CR = \frac{\xi^*}{CI} \tag{5}$$

A value of *CR*, which is closer to zero, indicates higher consistency. Although there is no threshold value for *CR* in the BWM, the *CR* values closer to zero are preferred and recommended as they confirm higher consistency of judgments (Rezaei, 2015; Rezaei, 2016; Kumar et al., 2019; Rahimi et al., 2020).

3.3. The WINGS method

The WINGS method proposed by Michnik (2013) is an ideographic causal map-based method for the analysis of intertwined factors and their causal relations. This technique has been employed in various contexts like the analysis of key competencies for a position in a medium-size automotive company (Kashi and Franek, 2014), industry risk assessment (Rego Mello and Gomes, 2015), selection of a public relations strategy during a reputation crisis (Michnik and Adamus-Matuszyńska, 2015), supporting decision making in civil engineering (Radziszewska-Zielina and Śladowski, 2017), innovation project selection (Michnik, 2018), classification of multimarket investment funds (Sallum et al., 2018), and prioritization of stock investment funds (Sallum et al., 2019). Recently, a new extended form of WINGS has been introduced and used to evaluate the impact of strategic offers on the financial and strategic health of a company (Banaś and Michnik, 2019) and improve city image building (Adamus-Matuszyńska et al., 2019).

The first stage of the WINGS procedure is devoted to structuring the problem. Initially, the experts identify the primary factors and then examine the causal relations among them that lead to a systemic model of the problem. Such a qualitative picture is usually presented as a digraph, which is a cognitive map of the problem. In the cognitive map, nodes represent factors (also called concepts or system components), and arcs represent existing causal relations (influences or impacts among concepts).

In the WINGS method, the concepts are characterized by internal strength (importance, power). This feature differentiates the role played in the system by different concepts. During the procedure, the experts are asked to verbally assess both: the internal strength and influence. It is advised to use the same scale to represent the internal strength and keep the influences balanced. In the first step of the WINGS procedure, the system, components, and important interdependencies among them are determined. Thereafter, a diagram is obtained where the nodes illustrate components, and the arrows display their joint influences. Continuing the qualitative part of the procedure, a user assesses the strength of all the influences with a verbal scale. Usually, a few positions are used, such as very weak, weak, medium, strong, and very strong. The number of points can be enlarged to express a more precise description. For example, adding four intermediary points between those defined above will result in a 9-point scale.

In the next stage, the analysis of the system under study progresses to the quantitative level. The user is asked to represent the verbal scale developed in the previous stage with a numerical scale. The most convenient way is to use integers, e.g., 1, 2, 3, 4, and 5, that represent the verbal descriptions from very weak to very strong, accordingly. As the method requires the ratio scale, it is essential that this mapping represents the user knowledge about the system and defines the ratios between scale levels as precisely as possible. The first non-zero level serves as a unit, and higher levels are compared to it.

All values – influences and strengths – estimated by the user are inserted into a direct strength-influence matrix D in such a way that:

- values expressing strengths of components are inserted into the basic diagonal, i.e., d_{ii} = the strength of the component *i*,
- values demonstrating influences are inserted so that for $i \neq j$, d_{ij} = the influence of component *i* on the component *j*.

The scale of the Matrix D is computed using the following formula:

$$S = \frac{1}{s} D \tag{6}$$

where the scaling factor is given by

$$s = \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} \tag{7}$$

where *n* is the number of components in the system.

Next, the consecutive powers of the Matrix *S* are calculated and added together to find the cumulative effect of all direct and indirect impacts. With the scaling defined by Eqs. (6) and (7), the following series converges, and Matrix T is obtained:

$$T = S + S^2 + S^3 + \ldots = S(I - S)^{-1} \tag{8}$$

The measure for the *total impact* exerted by component *i* on all the other system components (I_i) is derived by summing up the elements from row *i*.

$$I_i = \sum_{i=1}^{n} t_{ij} \tag{9}$$

The sum of the elements from column $i - R_i$ represents the total impact received by component *i* from all the other system components and is called *total receptivity.*

$$R_i = \sum_{j=1}^{n} t_{ij} \tag{10}$$

The *total involvement* (the sum of total involvement and total receptivity, $I_i + R_i$), and the *total role* (the difference between total involvement and total receptivity, $I_i - R_i$), are calculated for a more in-depth insight into the relative importance of the system components and their roles.

4. Application in the automotive industry

This automotive industry is the second largest industry in Iran, after the gas and oil industry, and the most important reason for the fluctuations in the gross domestic product (Govindan et al., 2016).

Table 4
Information about the Delphi phase of the study.

Delphi round	Automotive industry experts	Academic researchers	Government experts	Response rate
First round (35)	21	8	6	18 (52%)
Second Round (33)	20	8	5	15 (46%)

Table 5
The first round of the Delphi study for identifying the barriers.

Barrier	Sub-barrier	Average score	Accept/ Reject
Economic-related barriers (X_1)	Lack of funding for training human resources (X_{11})	3.82	Accept
	Lack of initial capital (X_{12})	3.75	Accept
	Lack of economy of scale (X_{13})	2.10	Reject
	Uncertainty related to economic barriers (X_{14})	4.08	Accept
	Lack of economic justification in product recovery activities (X_{15})	4.46	Accept
	The pressure of the economic sanctions (X_{16})	3.76	Accept
Governance and supply chain process barriers (X2)	Problems with supply chain members (X_{21})	3.68	Accept
	Limited forecasting and planning (X_{22})	3.83	Accept
	Inconsistent product quality compared to the forward logistics (X_{23})	3.66	Accept
	Complexity to find third-party RL provider (X_{24})	3.78	Accept
	Lack of proper performance management system (X_{25})	4.07	Accept
	Unsuitable organizational cooperation (X_{26})	3.65	Accept
Knowledge-related barriers (X_3)	Lack of information on RL practice (X_{31})	3.79	Accept
	Lack of knowledge on RL channels (X_{32})	3.88	Accept
	Lack of knowledge of RL advantages (X_{33})	3.83	Accept
	Difficulties with undeveloped recovery markets (X_{41})	3.46	Reject
Competitors- and market-related barriers (X_4)	Lack of customer's trust in the recovered product due to lower quality (X_{42})	4.21	Accept
	Slight perception of competitive advantage (X_{43})	3.65	Accept
	Monopoly competition (X_{44})	3.71	Accept
Management-related barriers (X_5)	Low emphasis on RL comparing to other barriers (X_{51})	4.07	Accept
	Low involvement of top management and paying not enough attention to RL in strategic planning (X_{52})	4.05	Accept
	Limited approval of disposal licenses (X_{53})	3.59	Accept
Policy-related barriers (X_6)	Lack of supportive laws (X_{61})	4.15	Accept
	Lack of clear return and waste management policies (X_{62})	4.22	Accept
	Lack of motivation regulations (X_{63})	2.71	Reject
	Firm policies against RL (X_{64})	3.64	Accept
	Lack of skilled human resources (X_{71})	3.66	Accept
	Lack of IT systems standards (X_{72})	3.78	Reject
Technology and infrastructure barriers (X_7)	Lack of newest technologies (X_{73})	3.62	Accept
	Lack of industrial infrastructure (X_{74})	3.93	Accept
	Limitation of technology and research and development barriers related to RL practices (X_{75})	4.32	Accept
	Complexity of RL implementation in operation (X_{76})	3.56	Accept
	Lack of funding for training human resources (X_{11})	3.64	Accept
	Lack of initial capital (X_{12})	3.77	Accept

This industry is also responsible for the creation of various automotive-related industries with strong and steady job growth. Domestic automobile companies in Iran have to compete within themselves and with the automotive manufacturing companies worldwide to survive. RL is a manufacturing strategy that can potentially help the automotive industry in Iran gain competitive advantage internally and globally. There are thirteen companies in the Iranian automotive industry, of which two have captured over 75% of the market share. A couple of these companies have tried RL implementation with no success. The main reason for their failure is copying the RL models developed by multinational automotive companies. The Iranian automotive manufacturers have learned RL strategies developed in Europe and North American are not applicable to the automotive industry in Iran.

The barriers to a successful implementation of RL in the automotive industry in developed countries do not apply to the Iranian automotive industry because the industry faces unique difficulties. The Iranian automotive industry has been under growing pressure because of economic, demographic, environmental, and technological challenges. Economic sanctions re-imposed by the U.S. against Iran have been devastating. These sanctions forced foreign automotive companies such as Peugeot and Renault to leave Iran, causing car production to drop by 30 percent. The public's decreasing access to cars had intersected with the baby boom during the first decade of the revolution when the population almost doubled. Price controls also played a critical role in deepening losses in the automotive industry. Nearly 75 percent of the population lives in urban neighborhoods, increasing the need for cars when public transportation is limited or unavailable. Iran's demand for cars created unique problems that ranged from dangerous levels of pollution to outdated technology, which continues to complicate the industry. Almost 40 percent of the municipal buses in Iran are between 10 and 20 years old, and nearly 25 percent of trucks in urban areas are more than 20 years old.

The purpose of this study is to provide a clear blueprint for RL implementation in the Iranian automotive industry. The proposed integrated framework is intended to produce a roadmap for RL implementation by identifying the most important barriers to implementation and the dependencies among them.

4.1. Phase I — Identifying critical barriers to RL implementation

The Delphi method is utilized to identify the critical barriers in three steps: (i) forming an expert panel, (ii) identifying the relevant

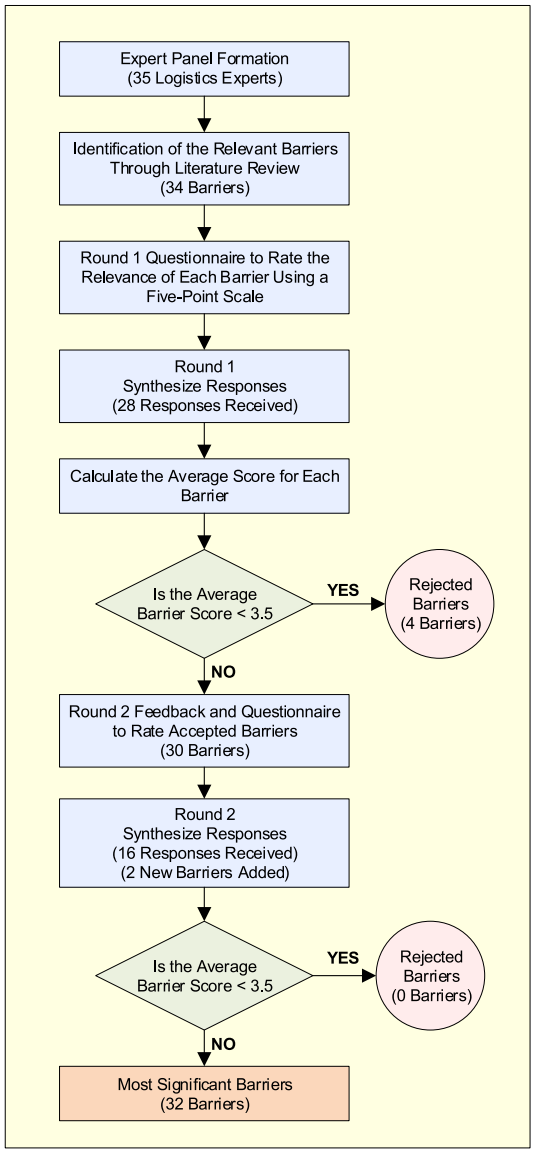

Fig. 2. Delphi flowchart.

and feasible barriers through literature review, (iii) shortlisting the most significant barriers to RL implementation in the automotive industry through a series of negotiation rounds. The process begins by selecting 35 automotive industry, academic researchers, and government experts with experience in logistics. The selected experts had at least ten years of RL experience in the automotive industry, academic, or government. Table 4 presents some relevant information about the participants in this study.

Next, the 34 barriers presented in Table 3 are used in a questionnaire and sent the questionnaire to 35 logistics experts. In the first round, each expert was asked to rate the relevance of each barrier on a 5-point scale. 28 responses (80% response rate) were received during the first round. The experts' responses were compiled next using a threshold of 3.5 for rejecting the barriers (Okoli and Pawlowski, 2004; Kaviani et al., 2019). If the average score of a barrier was less than 3.5, that barrier was eliminated. After finishing the first round, four barriers of the *financial burden of tax*, *lack of taxation knowledge on returned products*, *conflicting laws owing to inter-ministerial communication*, and *abusing environmental laws* were removed as the experts found them not important to the automotive industry. The results of the first round of the Delphi study are presented in Table 5.

In the second round of Delphi, anonymous responses from round 1 were circulated among the experts, and they were asked to add any missing barrier to the list. During the second round, 16 responses (46% response rate) were received. During the second round, two new barriers of *competitors- and market-related barriers* and *economic-related barriers* groups were added to the list. After two rounds of Delphi, no barriers are rejected, and a consensus is reached. Fig. 2 presents a flowchart for the Delphi method used in this study. All selected 32 barriers with an average score of more than 3.5 are presented in Table 6:

4.2. Phase II - Determining the importance of the RL barrier

In Phase II, a questionnaire was prepared with a 1–9 scale asking the experts to evaluate the barriers. This data was used to select the best and the worst barriers, and each expert compared the selected best and worst barriers with other barriers. Using Eqs. (1)–(4), the final weights of the barriers were calculated, and the mean weights of the barriers were computed. The relative importance of the barriers and sub-barriers are shown in Table 7.

Next, Eq. (5) was used to check the consistency ratio (CR) of the experts' judgments (Rezaei, 2015; Gupta and Barua, 2016; Rezaei, 2016).

4.3. Phase III - Determining the cause and effect relationship among RL barriers

The experts' evaluations are used next to analyze the effect of the interactions among the barriers with the WINGS method. The five-point verbal scale of very weak (1), weak (3), medium (5), strong (7), and very strong (9) is used in this study. These weights are then rescaled by setting the maximal value to 9 to maintain the balance between the weights and the impacts. Table 6 presents the average experts' evaluations of the impacts and weights (on the main diagonal) for the main barriers. The impacts and weights for the sub-barriers are presented in Tables B1 to B8 in Appendix B. Data from Tables B1 to B8 are then used to calculate the WINGS outputs presented in Tables C1 to C7 in Appendix C. The information contained in Tables B1 to B8 is depicted graphically in Figs. 3–10.

Fig. 3 presents a map of the relationship between the main barriers. The *Economic-related barriers* (X_1) and the *competitors- and market-related barriers* (X_4) were assessed by the experts as the strongest barriers to RL implementation. The *knowledge-related barriers* (X_3) and the *management-related barriers* (X_5) are characterized by the largest number of relations with other barriers on the map. The impacts of *economic-related barriers* (X_1) – the strongest factor – on *technology and infrastructure barriers* (X_7) and on *knowledge-related barriers* (X_3) are also perceived as the strongest. These preliminary observations are confirmed by the result of the WINGS method, which includes all the direct and indirect relations between the barriers as well as their internal strengths (e.g., *economic-related barriers* (X_1) absolutely dominate others in the involvement-role graph presented in Fig. 11).

A similar analysis is carried out for the maps of all the categories of sub-barriers. *The pressure of the economic sanctions* (X_{16}) is given the highest internal strength among the barriers in *the economic cluster* (X_1) (Fig. 4). This concept also has the highest number of relations. However, most of them are incoming arrows (which means it is influenced by other barriers), and they are not very strong in comparison to the other impacts (influences). The *lack of economic justification in product recovery activities* (X_{15}) is the second strongest barrier, and together with *the pressure of the*

Table 6
Finalized barriers and sub-barriers to RL implementation after the second round of Delphi.

Barrier	Sub-barrier	Reference
Economic-related barriers (X_1)	Lack of funding for training human resources (X_{11})	Literature
	Lack of initial capital (X_{12})	Literature
	Lack of economy of scale (X_{13})	Literature
	Uncertainty related to economic barriers (X_{14})	Literature
	Lack of economic justification in product recovery activities (X_{15})	Literature
	The pressure of the economic sanctions (X_{16})	Expert opinion
Governance and supply chain process barriers (X2)	Problems with supply chain members (X_{21})	Literature
	Limited forecasting and planning (X_{22})	Literature
	Inconsistent product quality compared to the forward logistics (X_{23})	Literature
	Complexity to find third-party RL provider (X_{24})	Literature
	Lack of proper performance management system (X_{25})	Literature
	Unsuitable organizational cooperation (X_{26})	Literature
Knowledge-related barriers (X_3)	Lack of information on RL practice (X_{31})	Literature
	Lack of knowledge on RL channels (X_{32})	Literature
	Lack of knowledge of RL advantages (X_{33})	Literature
Competitors- and market-related barriers (X_4)	Difficulties with undeveloped recovery markets (X_{41})	Literature
	Lack of customer's trust in the recovered product due to lower quality (X_{42})	Literature
	Slight perception of competitive advantage (X_{43})	Literature
	Monopoly competition (X_{44})	Expert opinion
Management-related barriers (X_5)	Low emphasis on RL comparing to other barriers (X_{51})	Literature
	Low involvement of top management and paying not enough attention to RL in strategic planning (X_{52})	Literature
	Limited approval of disposal licenses (X_{53})	Literature
Policy-related barriers (X_6)	Lack of supportive laws (X_{61})	Literature
	Lack of clear return and waste management policies (X_{62})	Literature
	Lack of motivation regulations (X_{63})	Literature
	Firm policies against RL (X_{64})	Literature
Technology and infrastructure barriers (X_7)	Lack of skilled human resources (X_{71})	Literature
	Lack of IT systems standards (X_{72})	Literature
	Lack of newest technologies (X_{73})	Literature
	Lack of industrial infrastructure (X_{74})	Literature
	Limitation of technology and research and development barriers related to RL practices (X_{75})	Literature
	The complexity of RL implementation in operation (X_{76})	Literature

economic sanctions (X_{16}), they have a quite strong impact on the *lack of economy of scale* (X_{13}). The *economy of scale* (X_{13}), in turn, strongly influences the *lack of funding for training human resources* (X_{11}) and the *lack of initial capital* (X_{12}) and feeds back into *the pressure of the economic sanctions* (X_{16}). The *economic-related barriers* (X_1) cluster is a good example of complicated and balanced interrelations.

Among the sub-barriers in the *governance cluster* (X_2), the *complexity to find third party RL provider* (X_{24}) is the strongest, while *inconsistent product quality compared to the forward logistics* (X_{23}) has the highest number of relations. As shown in Fig. 5, the moderately strong feedback loops can be observed between the *inconsistent product quality compared to the forward logistics* (X_{23}) and three other concepts: *limited forecasting and planning* (X_{22}), *complexity to find third party RL provider* (X_{24}) and the *lack of proper performance management system* (X_{25}).

The maps of the next four clusters, including *knowledge* (X_3), *competitors* (X_4), and *management and policy* (X_6) are all relatively simple with a small number of relationships. The *lack of knowledge* is much stronger than the other two barriers in the *knowledge* cluster. Each barrier has a feedback loop with other barriers, as shown in Fig. 6.

In the *competitors* (X_4) cluster, the main role is played by monopoly *competition* (X_{44}), as shown in Fig. 7. There is also a single additional link from *lack of customers' trust to the recovered product due to lower quality* (X_{42}) to a *slight perception of competitive advantage* (X_{43}).

The strongest barrier in the *management* (X_5) cluster, *low involvement of top management, and paying not enough attention to RL in the strategic planning* (X_{52}) influences two other barriers, which also form a feedback loop, as shown in Fig. 8.

A close examination of the map of the *policy* cluster (X_6), presented in Fig. 9, shows a *lack of supportive laws* (X_{61}) is the strongest barrier. Still, the *lack of motivation regulations* (X_{63}) has the highest number of strong and moderate relations (with half incoming and half outgoing arrows).

The *technology* cluster presented in Fig. 10 is also a complicated map with a high number of relations. The *lack of newest technologies* (X_{73}) is the strongest barrier; however, the *limitation of technology and research and development barriers related to RL practices* (X_{75}) is also strong. Both (X_{73}) and (X_{75}) barriers and the *lack of IT systems standards* (X_{72}) share the first place in terms of the number of relations.

The position of the concepts on the *Involvement-Role* plane is the result of implementing the WINGS procedure. The corresponding charts, shown in Figs. 11–18, facilitate an analysis of the importance and roles of all barriers recognized in the studied problem.

The output presented in Table C1 and Fig. 11 shows the *Economic-related* barriers are considered the most important barriers in the Iranian automotive industry. Both their involvement and influencing roles have the highest scores. It can be concluded that although the barriers related to the implementation of RL have an economic advantage in the moderate and long term, they can still be perceived as barriers consistent with the Ravi and Shankar (2005) and Prakash and Barua (2015) studies. In addition, *policy- and management-related barriers* belong to the influencing group. The other four main barriers (*knowledge-related* (X_3), *competitors- and market-related* (X_4), *governance and supply chain process* (X_2), and *technology and infrastructure* (X_7)) pertain to the influenced group. The *knowledge-related barriers* and *competitors- and market-related* sub-criteria occupy the second and third place on the involvement scale.

Table 7
Final weights of the barriers and their respective sub-barriers.

Barrier	Weight	Sub-barrier	Local weights	Local rank	Final weights	Final rank
Economic-related barriers (X_1)	0.365	Lack of funding for training human resources (X_{11})	0.051	6	0.019	17
		Lack of initial capital (X_{12})	0.105	4	0.038	8
		Lack of economy of scale (X_{13})	0.123	3	0.045	6
		Uncertainty related to economic barriers (X_{14})	0.067	5	0.025	14
		Lack of economic justification in product recovery activities (X_{15})	0.269	2	0.098	3
		The pressure of the economic sanctions (X_{16})	0.385	1	0.141	1
Governance and supply chain process barriers (X_2)	0.128	Problems with supply chain members (X_{21})	0.057	6	0.007	24
		Limited forecasting and planning (X_{22})	0.082	5	0.010	22
		Inconsistent product quality compared to the forward logistics (X_{23})	0.089	4	0.011	21
		Complexity to find third party RL provider (X_{24})	0.417	1	0.053	5
		Lack of proper performance management system (X_{25})	0.226	2	0.029	12
		Unsuitable organizational cooperation (X_{26})	0.130	3	0.017	20
Knowledge-related barriers (X_3)	0.039	Lack of information on RL practice (X_{31})	0.125	3	0.005	31
		Lack of knowledge on RL channels (X_{32})	0.745	1	0.029	11
		Lack of knowledge of RL advantages (X_{33})	0.130	2	0.005	29
Competitors- and market-related barriers (X_4)	0.250	Difficulties with undeveloped recovery markets (X_{41})	0.134	3	0.033	10
		Lack of customer's trust in the recovered product due to lower quality (X_{42})	0.259	2	0.065	4
		Slight perception of competitive advantage (X_{43})	0.068	4	0.017	19
		Monopoly competition (X_{44})	0.539	1	0.135	2
Management-related barriers (X_5)	0.074	Low emphasis on RL comparing to other barriers (X_{51})	0.329	2	0.024	15
		Low involvement of top management and paying not enough attention to RL in strategic planning (X_{52})	0.591	1	0.044	7
		Limited approval of disposal licenses (X_{53})	0.079	3	0.006	27
Policy-related barriers (X_6)	0.068	Lack of supportive laws (X_{61})	0.549	1	0.037	9
		Lack of clear return and waste management policies (X_{62})	0.097	3	0.007	26
		Lack of motivation regulations (X_{63})	0.269	2	0.018	18
		Firm policies against RL (X_{64})	0.084	4	0.006	28
Technology and infrastructure barriers (X_7)	0.076	Lack of skilled human resources (X_{71})	0.094	4	0.007	25
		Lack of IT systems standards (X_{72})	0.067	5	0.005	30
		Lack of newest technologies (X_{73})	0.376	1	0.028	13
		Lack of industrial infrastructure (X_{74})	0.049	6	0.004	32
		Limitation of technology and research and development barriers related to RL practices (X_{75})	0.289	2	0.022	16
		Complexity of RL implementation in operation (X_{76})	0.125	3	0.009	23

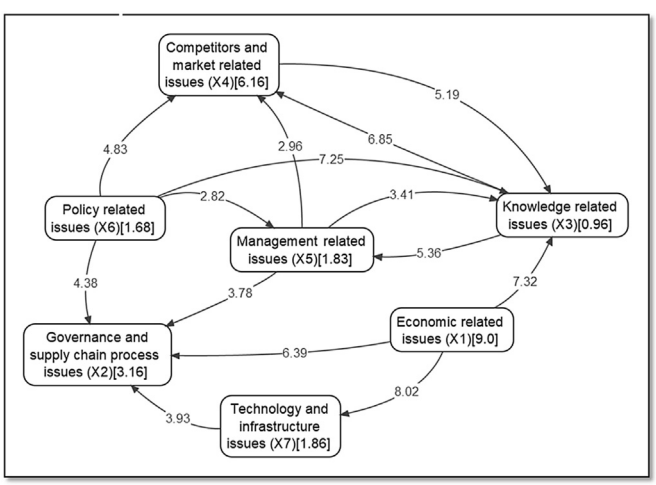

Fig. 3. Map of the relations for the main barriers.

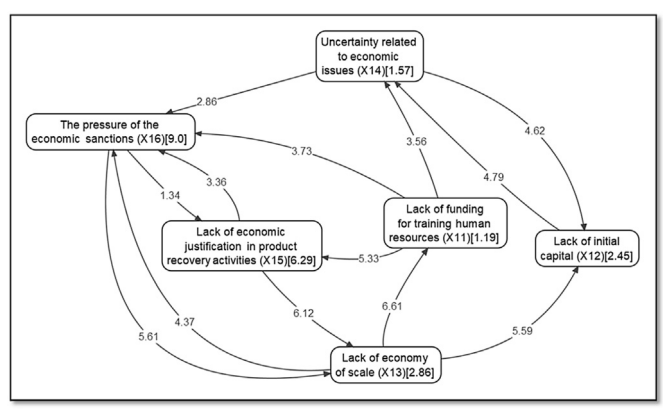

Fig. 4. Map of the relations for the sub-barriers in the *economic* cluster.

Half of the barriers in the *economic* cluster (X_1) including the *lack of economy of scale* (X_{13}), the *lack of economic justification in product recovery activities* (X_{15}) and the *lack of funding for training human resources* (X_{11}) belong to the influencing barriers group, while the other half including the *pressure of the economic sanctions* (X_{16}), the *lack of initial capital* (X_{12}) and the *uncertainty related to economic barriers* (X_{14}) belong to the influenced barriers group as shown in Table C2 and Fig. 12. However, the last one lies close to zero on the Role scale (its position is almost neutral). The *pressure of the economic sanctions* (X_{16}) and the *lack of economy of scale* (X_{13}) is the most involved barriers in the *economic* cluster.

Similarly, half of the barriers associated with the *governance and supply chain process barriers* (X_2) including the *lack of proper performance management system* (X_{25}), the *unsuitable organizational cooperation* (X_{26}), and the *problems with supply chain members* (X_{21}) belong to the influencing barriers group as shown in Table C3 and Fig. 13. The *complexity to find third-party RL provider* (X_{24}), the *inconsistent product quality compared to the forward logistics* (X_{23}) are influenced, but at the same time, they are the two most involved barriers. The *limited forecasting and planning* (X_{22}) is the remaining influenced barrier.

The *knowledge-related cluster* (X_3) contains only three barriers

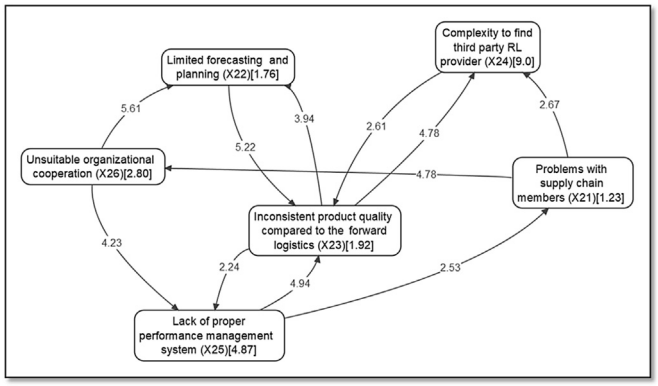

Fig. 5. Map of the relations for the sub-barriers in the *governance* cluster.

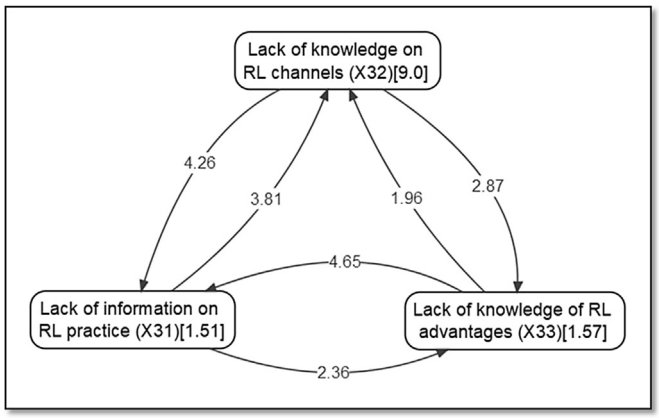

Fig. 6. Map of the relations for the sub-barriers in the *knowledge* cluster.

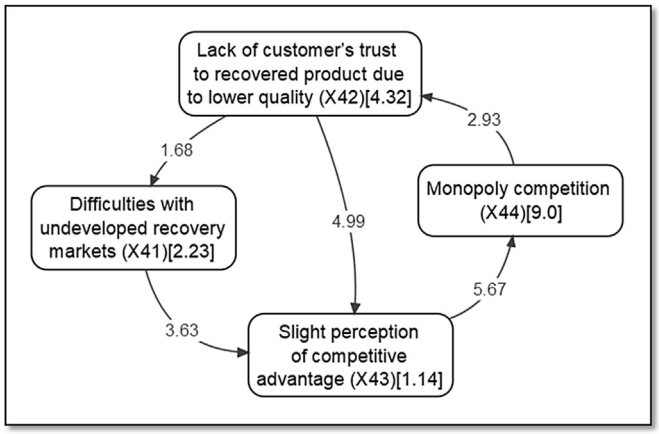

Fig. 7. Map of the relations for the sub-barriers in the *competitors* cluster.

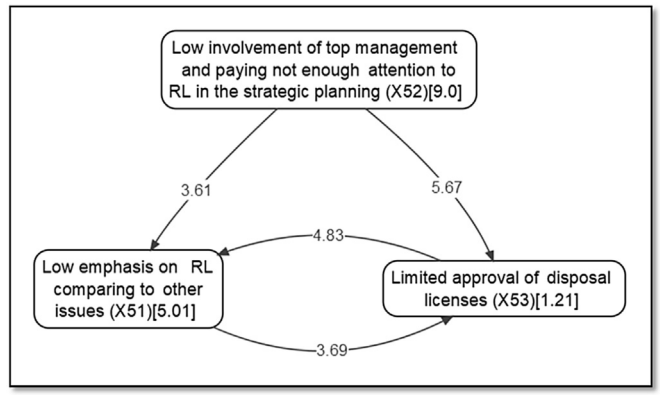

Fig. 8. Map of the relations for the sub-barriers in the *management* cluster.

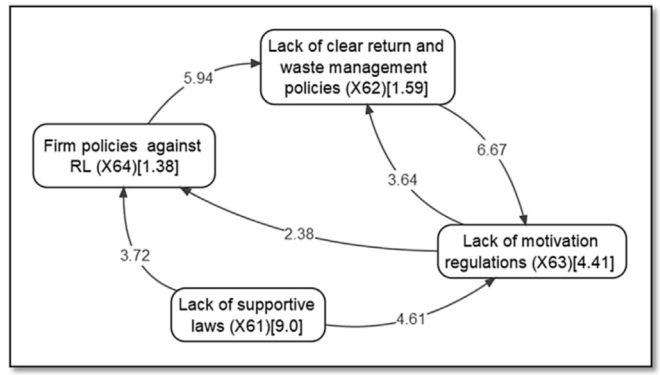

Fig. 9. Map of the relations for the sub-barriers in the *policy* cluster.

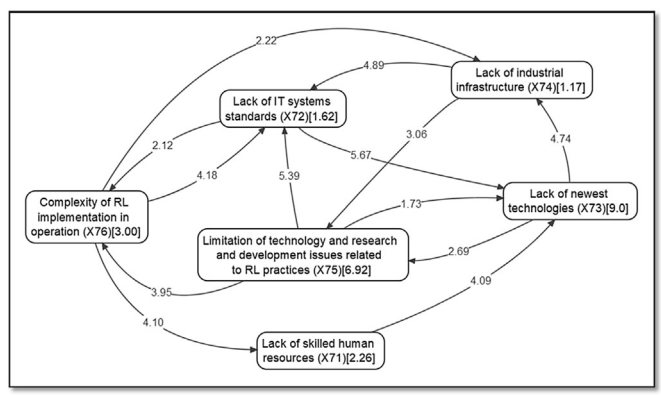

Fig. 10. Map of the relations for the sub-barriers in the *technology* cluster.

(see Table C4 and Fig. 14). The *lack of knowledge on RL channels* (X_{32}) and the *lack of knowledge of RL advantages* (X_{33}) are influencing barriers, and the *lack of information on RL practice* (X_{31}) is an influenced barrier. In this cluster, the *lack of knowledge on RL channels* (X_{32}) has a dominating position being the first in the Involvement and Role.

In the *competitors- and market-related* (X_4) cluster presented in Table C5 and Fig. 15, again half of the barriers: *lack of customer's trust to the recovered product due to lower quality* (X_{42}) and *difficulties with undeveloped recovery markets* (X_{41}) belong to influencing group, while the other half: *monopoly competition* (X_{44}) and *slight perception of competitive advantage* are in the influenced group. The *monopoly competition* (X_{44}) is the first in Involvement and is followed by the *lack of customer's trust in the recovered product due to lower quality* (X_{42}).

The *management-related barriers* (X_5) cluster is dominated by the *low involvement of top management and paying not enough attention to RL in the strategic planning* (X_{52}) that influences two other barriers of the *limited approval of disposal licenses* (X_{53}) and the *low emphasis on RL comparing to other barriers* (X_{51}) as shown in Table C6 and Fig. 16.

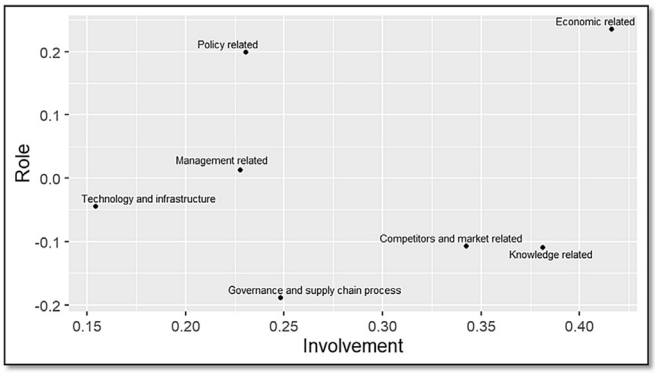

Fig. 11. Relationship between *role* and *involvement* for the main barriers.

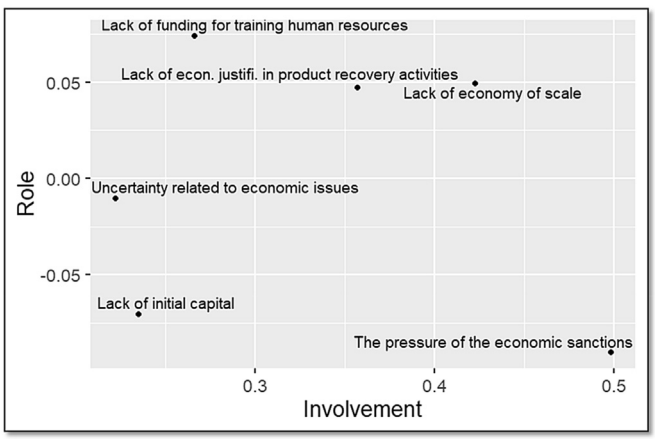

Fig. 12. Relationship between *role* and *involvement* for the sub-barriers in the *economic* cluster.

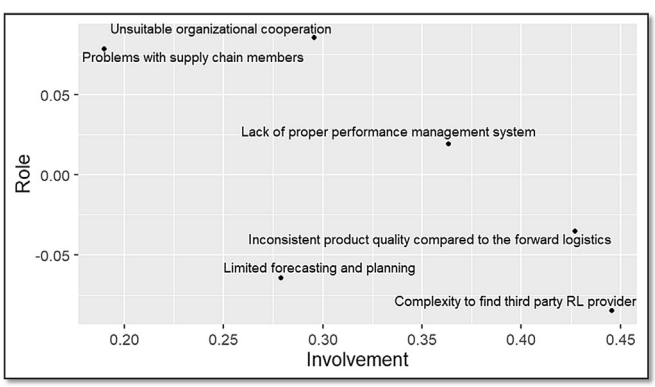

Fig. 13. Relationship between *role* and *involvement* for the sub-barriers in the *governance* cluster.

In the *policy-related barriers* (X_6) cluster shown in Table C7 and Fig. 17, the top position is occupied by the *lack of supportive laws* (X_{61}), which influence all the others barriers including the *lack of motivation regulations* (X_{63}), the *lack of clear return and waste management policies* (X_{62}), and the *firm policies against RL* (X_{64}).

When considering *technology and infrastructure barriers* (X_7), the majority of these barriers: the *limitation of technology and research and development barriers related to RL practices* (X_{75}), the *complexity of RL implementation in operation* (X_{76}), the lack of industrial infrastructure (X_{74}), and *the lack of skilled human resources* (X_{71}) in

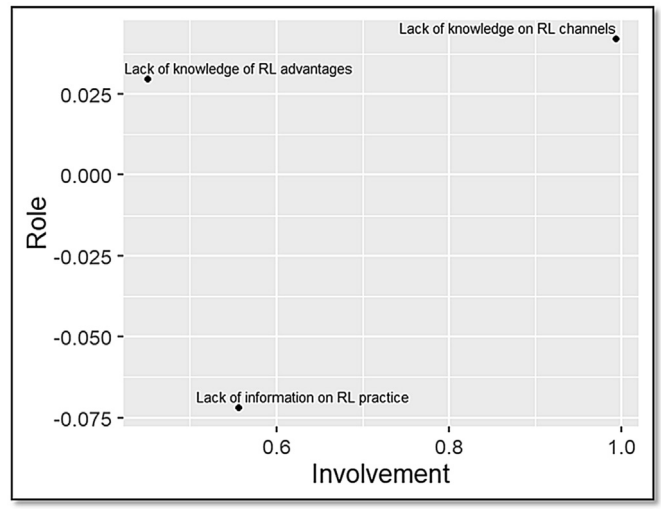

Fig. 14. Relationship between *role* and *involvement* for the sub-barriers in the *knowledge* cluster.

Fig. 15. Relationship between *role* and *involvement* for the sub-barriers in the *competitors* cluster.

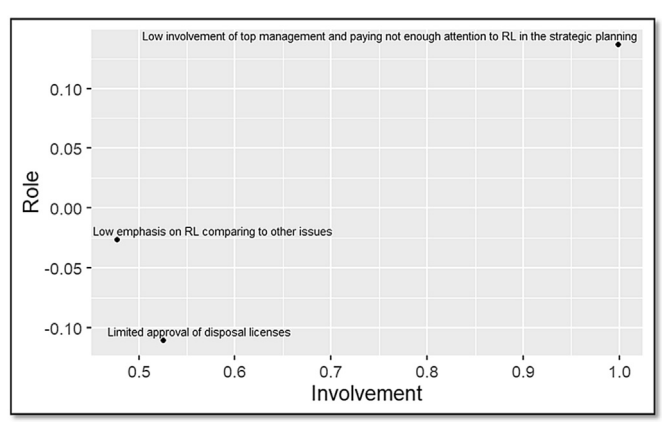

Fig. 16. Relationship between *role* and *involvement* for the sub-barriers in the *management* cluster.

Table C8 and Fig. 18 belong to the influencing group, while only the *lack of newest technologies* (X_{73}), and the *lack of IT systems standards*

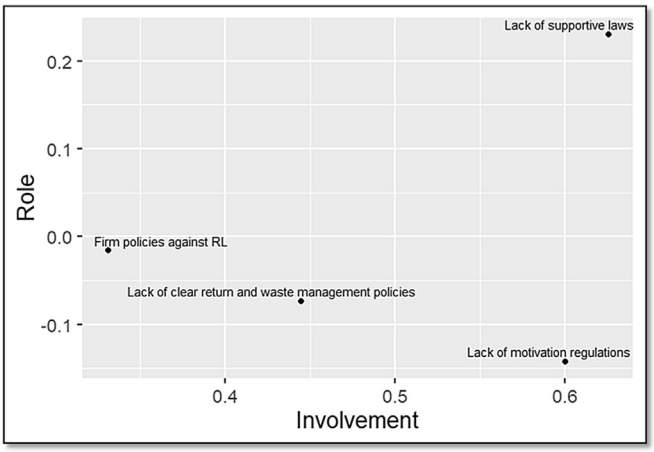

Fig. 17. Relationship between *role* and *involvement* for the sub-barriers in the *policy* cluster.

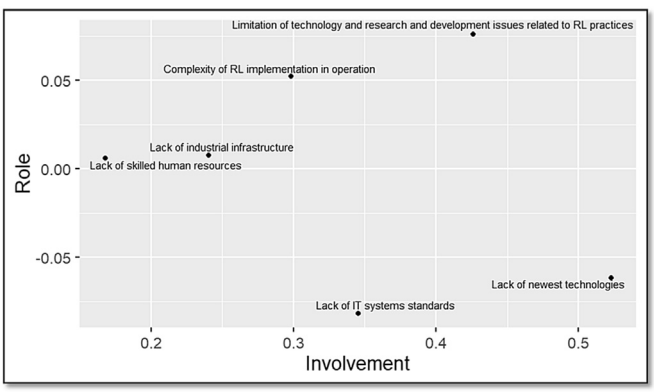

Fig. 18. Relationship between *role* and *involvement* for the sub-barriers in the *technology* cluster.

(X_{72}) are the influenced ones.

4.3.1. Managerial implications and recommendations

The results of the proposed integrated BWM-WINGS framework allow us to draw a number of conclusions. The analysis of the barriers' positions on the plane involvement-role facilitates the prioritization and selection of those barriers that play a crucial role in RL implementation.

As discussed in Section 5, *economic barriers* have a dominant role among the main barriers. Diminishing the economic pressures can have a direct impact on other barriers, such as *knowledge-related* and *competitors- and market-related*. Similar inferences can be made concerning barriers in each cluster. Here are some examples of such implications and recommendations that can be deduced from the results.

With regard to the *economic barriers,* it can be concluded *improving the economy of scale,* and *economic justification in product recovery activities* (with high involvement and role) could diminish *the pressure of the economic sanctions* and *the influence of lack of initial capital*.

Thanks to the moderate position in involvement and role in *governance and supply chain process barriers*, improving the *performance of the management system* would support the *consistency of product quality,* and finding third-party RL providers.

Increasing knowledge of RL channels would be beneficial in getting more information about RL practices. The lack of knowledge about RL advantages is also a robust influencing factor, but it is very weakly involved in *the knowledge cluster*, so too much influence cannot be expected from it. This aspect of management is also reflected in González-Torre et al. (2010), together with the lack of commitment of the senior management, as well as the lack of skilled workforce (Diabat et al., 2013).

Raising up the customer's trust in the quality of recovered products seems to be the most important activity in the *competitors- and market-related* barriers. It can also be concluded that *monopoly competition* with its high involvement is an influenced barrier hindering the improvement in this cluster. An analysis of the barrier positions in Fig. 15 leads to the conclusion that increasing the *involvement of top management* in developing RL plays an important role in the *management cluster*. This is similar to the *lack of supportive laws* in the *policy cluster*.

The *technology cluster* also reveals interesting relations among its components. *The limitations of technology and research and development* are the most important barrier that can reinforce the knowledge of the newest technologies and help in setting information technology standards. The related literature revealed important information about the lack of adequate technology in relation to RL implementation (Chauhan et al., 2018; Xia et al., 2015).

4.3.2. Sensitivity analysis

A sensitivity analysis was conducted to confirm the managerial implications and demonstrate the robustness of the results. The majority of experts assigned the highest weight to the *economic barriers* in the Iranian automotive industry. However, some exceptions can be observed in this norm. Some experts valued the *economic barriers* (X_1) lower, and at the same time, they assigned a higher weight to the *competitors- and market-related* barriers (X_4). To further study the sensitivity of this phenomenon, a sensitivity analysis was performed by decreasing the importance weight of X_1 to 7 and increasing the importance weight of X_4 to 8 (see Table B1). This change did not have any impact on *economic barriers*, but both *knowledge-related* (X_3) and *competitors- and market-related* barriers received somewhat higher involvement than *economic barriers*. However, this slight change did not have any impact on the overall conclusion.

Similarly, in the *competitors- and market-related barriers* cluster monopoly competition (X_{44}) has the highest average weight, and the average weight of the *lack of customer's trust in the recovered product due to lower quality* (X_{42}) is about half of the highest importance weight. Despite that, some experts identified X_{42} as the most substantial barrier. The WINGS' output was recalculated with the weight of X_{44} decreased from 9 to 7, and the weight of X_{42} increased to 6, to check the influence of this view on final results (see Table B5). As can be expected, X_{42} increased its involvement, but even with such substantial change, the general scheme of the relations in Fig. 14 remained unchanged with no impact in the managerial implications.

5. Conclusions and future research directions

RL systems are integral parts of sustainable operations and cleaner production. There are different barriers to the implementation of RL systems, particularly in developing countries, which inhibit companies from fulfilling their environmental responsibilities. Identifying and eliminating obstacles to RL play a crucial role in clean production. The RL system implementation is of high significance in the context of developing countries in general and high-pollution industries like the automotive industry in particular. This study focused on the automotive industry and evaluated the critical barriers to RL implementation in the

automotive sector by proposing and using an integrated BWM-WINGS framework. The literature reports on several published works studying industry- and region-specific barriers to RL implementation. However, there are no one-size-fits-all solutions for RL implementation. This study investigated the barriers to RL implementation in the Iranian automotive industry. The results showed economic-related barriers are the most critical obstacles to RL implementation, while knowledge-related barriers are the least significant among the other considered barriers. Moreover, within the sub-barriers, the *pressure of the economic sanctions* was the most critical barrier to the implementation of RL systems in the Iranian automotive industry. Aside from the financial sanctions imposed on the Iranian industries that arise from the current political environment, the Iranian government must create and propose comprehensive environmental legislation to mitigate the RL implementation barriers in the automotive industry.

Further studies could attempt to investigate the role of different parameters like moderating influence of the firm size, performance, and efficiency on RL system implementation using diverse hypotheses. Furthermore, the uncertainty of the experts in their assessment of the barriers to the RL implementation can be modeled with tools and techniques such as fuzzy, grey, and intuitionistic fuzzy. Finally, the framework proposed in this study can be applied to explore barriers to RL implementation in other countries and industries.

CRediT authorship contribution statement

Mohamad Amin Kaviani: Conceptualization, Formal analysis, Methodology. **Madjid Tavana:** Methodology, Project administration, Supervision, Visualization, Writing - review & editing. **Anil Kumar:** Methodology, Resources, Software. **Raziyeh Niknam:** Methodology, Resources, Validation, Investigation, Resources, Software. **Elaine Aparecida Regiani de Campos:** Investigation, Resources, Software.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2020.122714.

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