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Towards a Sustainable Future: Identification and Prioritization Drivers and Barriers for Circular Business Models in Iranian Industries

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ABSTRACT

This research seeks to enrich the literature by providing insights into the drivers and barriers of adopting circular business models (CBMs) in diverse contexts. This study examines CBMs in Iranian companies across industries and stages of the business lifecycle, addressing specific industry challenges. To achieve this, a mixed research method is employed, incorporating an extended decision-making approach using a q-rung orthopair fuzzy number (q ROFN), as well as the MULTIMOORA and Delphi approaches. By examining Iranian companies of varying sizes and maturity levels, this study provides a comprehensive understanding of CBMs and their potential for achieving resource efficiency and sustainability. The mixed research method employed combines qualitative and quantitative approaches, with the qualitative Delphi phase identifying 12 drivers and 17 barriers, with the quantitative section utilizing q ROFN to enhance decision-making processes. The analysis reveals that the most significant drivers are Comprehensive Monitoring and Ranking (0.0402), Management Attitudes (0.0391), and Compliance with Production Standards (0.0345). The most critical barriers are Limited Market for Waste (0.0507), Restrictive Regulations 0.0495), and Capability Gaps (c24, 0.0483). The primary implication for practice is that successful CBM adoption in Iran requires policymakers to prioritize creating secondary material markets and reforming restrictive regulations, while managers must focus on securing leadership commitment and building internal circular capabilities. These findings provide a strategic decision-making framework for accelerating the transition to a circular economy in Iran and similar emerging economies.

Keywords

q-rung orthopair fuzzy number, Circular business model, MULTIMOORA method, Iranian companies

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1. Introduction

The global economy remains predominantly linear, operating on a "take-make-dispose" model that consumes over 100 billion tons of materials annually and generates immense waste, with projections indicating this could reach 3.88 billion tons by 2050, placing unsustainable pressure on the planet's ecosystems (Circle Economy, 2020; Siregar et al., 2023). Driven by increased consumption, urbanization, stricter regulations, and growing environmental pressures, the transition to a Circular Economy (CE) has accelerated as a viable strategy to alleviate these global ecological pressures (Kristensen et al., 2021). The Circular Economy (CE) has emerged as a critical alternative, defined as an industrial system of actions and behaviours such as eco-design, reuse, repair, and industrial symbiosis that eliminates waste and pollution by design, keeping products and materials in use (Parliament, 2023; Kirchherr et al., 2017). This paradigm shift is not merely an environmental imperative but an economic one, with the potential to boost GDP, create jobs, and foster resilient, low-carbon growth (Forum, 2024; Hailemariam and Erdiaw-Kwasie, 2023).

However, the adoption of Circular Business Models (CBMs)—the micro-level implementation of CE principles by firms—is highly uneven globally. Although supporting policies are gaining attention, research on the Circular Economy has been mainly focused on developed countries, leaving a significant gap from the perspective of emerging economies (Ghisellini et al., 2016). While developed economies in Europe have pioneered CE investments and policies, the concept remains nascent in most developing countries (Marino and Pariso, 2020; Abdul Hamid, 2020). Recent research highlights that regions like Latin America and the Caribbean face unique barriers, including limited governmental incentives, policy inconsistencies, and a cultural adherence to linear models, underscoring that CE transitions are profoundly context-specific and that no single model can be universally applied (Gallego-Schmid et al., 2025; Betancourt Morales and Zartha Sossa, 2020). This underscores a critical contextual research gap: a deep understanding of the drivers and barriers to CBMs adoption within the specific socio-economic landscapes of developing nations is urgently needed but largely absent from the literature.

This study focuses on Iran as a critical and under-researched case. The global impetus for this transition is strong; research from the World Economic Forum highlights that CBMs can drive economic growth, reduce carbon emissions, and create jobs, potentially increasing a nation's GDP by 0.8–7% and generating 0.2–3% more employment (Forum, 2024; Hailemariam and Erdiaw-Kwasie, 2023). These benefits are particularly salient for Iran, which faces a need for innovative growth strategies. The World Bank (2025) reports that Iran's GDP growth slowed to 3.7% in the first nine months of 2024/25, underscoring the urgency for sustainable economic models like CBMs to stimulate development and enhance organizational resilience.

While the principles of a circular economy are universally aimed at resource efficiency and value maximization, the specific drivers and barriers are context-dependent. Although global studies have identified general factors—such as market conditions and financial constraints—their relative importance and unique configuration within Iran remain unknown. To fill this gap, this research asks: What are the main drivers and barriers for CBMs in Iran's manufacturing sector, and how should they be prioritized for strategic action? This study has three main contributions. First, it offers a contextual contribution by creating an empirically-based framework of CBMs' drivers and barriers specific to Iran. Second, it provides a methodological contribution through the innovative use of an advanced multi-criteria decision-making (MCDM) model—combining q-rung orthopair fuzzy sets (q-ROFSs) with the MULTIMOORA method—to quantitatively rank these factors and manage expert judgment uncertainty. Lastly, it offers a practical contribution by providing Iranian managers and policymakers with a prioritized, actionable plan to leverage key drivers and address major barriers, thereby supporting the country's transition to a circular economy.

The subsequent sections of this paper comprise a review of the literature and the research methodology. Next, the research results, discussions, and conclusions are presented. Finally, the limitations of research are highlighted.

2. Literature review

This section moves beyond a descriptive summary to provide a critical analysis of the literature on the drivers, barriers, and strategic implications of Circular Business Models (CBMs). The existing body of work has effectively mapped the terrain, identifying a complex set of challenges and enablers across different contexts. However, a critical gap remains in the comparative analysis of how these factors manifest and interact across diverse geographical and sectoral landscapes, particularly in developing and newly industrialized economies. This review synthesizes these themes to clarify the distinct contribution of the present study.

A strong consensus exists that CBM adoption is hindered by a complex, interconnected web of barriers. Early foundational work established that these obstacles are not confined to a single domain but span organizational, value chain, market, and institutional levels (Guldmann and

Huulgaard, 2020; Geissdoerfer et al., 2023). This multi-level perspective has been consistently validated. For instance, Oghazi and Mostaghel (2018) and Benz (2022) highlighted internal organizational challenges and high failure rates, while Bocken et al. (2019) pointed to systemic gaps in tools and methods. Recent studies have deepened this understanding by applying robust methodologies to specific regional and sectoral contexts, revealing nuanced variations. In the Western Balkans, economic and market barriers such as added costs and lack of consumer demand are statistically significant impediments for firms, whereas the lack of a regulatory framework was surprisingly not a primary factor (Rexhepi Mahmutaj et al., 2025). This contrasts with findings from developing countries in the construction sector, where "governmental support through policy and enforcement" and inadequate infrastructure are consistently identified as foundational, causal barriers (Durdyev et al., 2025; Nguyen et al., 2025). Similarly, Chile's journey, despite its high-income status, is hampered by cultural resistance, limited professional training, and an economy still reliant on extraction, highlighting that economic development alone does not eliminate deep-seated socio-technical barriers (Gallego-Schmid et al., 2025). In response to these barriers, a significant stream of literature has focused on developing strategic frameworks to guide CBM innovation. De Angelis et al. (2023) proposed an integrated framework linking business models with open strategy and dynamic capabilities, emphasizing the need for new organizational competencies. This aligns with Santa-Maria et al. (2021), who called for a better integration of Circular Business Model Innovation (CBMI) with conventional Business Model Innovation (BMI) processes. The quest for clarity and structure is also evident in works aiming to define CBM fundamentals (Nußholz, 2017) and to synthesize innovation approaches (Pieroni et al., 2019; Chen et al., 2020).

The strategic imperative is further underscored by studies that move beyond barrier identification to formulate actionable strategies. Firdaus et al. (2025), for example, used a combination of SLR, Pareto, and SWOT analyses to develop validated strategic models for Indonesia's batik industry. Their findings emphasize that the most effective strategy (S-O) leverages internal knowledge of CE principles and external government support, demonstrating the importance of aligning internal capabilities with external enablers.

The literature increasingly recognizes that the CBM journey is not one-size-fits-all. Geissdoerfer et al. (2023) found that drivers for start-ups differ from those for established firms undergoing transformation. Levänen et al. (2023) and von Kolpinski et al. (2023) focused on small companies, revealing how they navigate sustainability tensions and internal dynamics, respectively. This highlights a gap in understanding of CBM adoption within large, incumbent corporations, a key focus of this study. Furthermore, the new content underscores a significant geographical bias in the literature. While much research has focused on European contexts, the challenges in Latin America (Gallego-Schmid et al., 2025), Southeast Asia (Firdaus et al., 2025; Nguyen et al., 2025), Eastern Europe (Rexhepi Mahmutaj et al., 2025), and Central Asia (Durdyev et al., 2025) are distinct and often more severe, particularly concerning institutional voids, infrastructure, and financial access. Table 1 shows a summary of the literature on Circular Business Models.

Table 1. Summary of literature on circular business models

Author(s) (Year)	Sectoral / Geographical scope	Method used	Key contribution(s)
Guldmann and Huulgaard (2020)	12 Danish companies / Cross-sectoral	Multiple-Case Study	Empirically identified and analyzed multi-level barriers (organizational, value chain, market, institutional).
Chen et al. (2020)	Firm-level / Theoretical	Integrated Framework Proposal	Linked CBM typologies, transition processes, and tools to address fragmented literature.
Santa-Maria et al. (2021)	Incumbent Firms / Multiple Cases	Literature Review, Multiple-Case Study	Proposed a framework for the Circular Business Model Innovation (CBMI) process and its key elements.
Benz (2022)	Expert Perspective / Various	Expert Interviews	Developed a framework of Critical Success Factors (9 top-codes, 37 sub-codes) for CBMI and linked them to the UN's Sustainable Development Goals (SDGs).
Geissdoerfer et al. (2023)	21 Organisations / Various	Structured Literature Review, Multi-Case Study	Categorized 25 barriers and 10 drivers, showing they differ by type of CBM innovation.
De Angelis et al. (2023)	Theoretical / Strategic	Conceptual Framework	Proposed a strategic framework integrating business models, open strategy, and dynamic capabilities.
Levänen et al. (2023)	SMEs / Developing Countries	Multiple Case Study Analysis	Showed how business models adapt to sustainability tensions in contexts of resource scarcity.
von Kolpinski et al. (2023)	Young Companies and SMEs / Germany	Case Study Investigation	Explored internal dynamics, barriers, and enablers within small, sustainable companies.
Durdyev et al. (2025)	Construction / Kazakhstan, Malaysia, Turkey	Fuzzy DEMATEL	Identified "governmental support" and "infrastructure" as universal causal barriers in developing countries' construction sectors.
Firdaus et al. (2025)	Textile/Batik Industry / Indonesia and Global	SLR (PRISMA), Pareto, SWOT, Interviews	Developed and validated four strategic models for a cultural industry's transition to sustainability.

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Author(s) (Year)	Sectoral / Geographical scope	Method used	Key contribution(s)
Gallego-Schmid et al. (2025)	National / Chile (Latin America)	22 Semi-structured Interviews, Qualitative Analysis	Analyzed isomorphic pressures and persistent cultural/economic barriers in a high-income Latin American country despite a national roadmap.
Nguyen et al. (2025)	Construction / Vietnam	Mixed-Methods (RII, DEMATEL, Survey, Interviews)	Ranked barriers and identified policy, knowledge, and financial barriers as causal groups; highlighted coordination and sociocultural barriers.
Rexhepi Mahmutaj et al. (2025)	Firms / Western Balkans	Quantitative (Logistic Regression on Survey Data)	Statistically validated that cost, skills, and demand—but not regulation—are significant barriers.
present study	Multiple Industries / Iran	Mixed-Method (Delphi, q-ROFN, MULTIMOORA)	Provides a prioritized, context-specific framework of drivers and barriers for Iran, using an advanced fuzzy MCDM method to guide strategic decision-making in emerging economies.

As Table 1 illustrates, the existing literature provides a robust catalog of CBM drivers and barriers across diverse contexts. However, a critical analysis reveals two pivotal gaps that this study is designed to address, positioning it as a significant step forward in both methodological application and contextual understanding.

First, while prior research has successfully identified a wide array of factors influencing CBMs adoption, the vast majority stop at identification or qualitative discussion. There is a pronounced scarcity of studies that move beyond listing factors to provide a definitive, mathematically-grounded prioritization. This is a critical shortcoming for decision-makers in resource-constrained environments like Iran, who need to know not just what the challenges are, but which ones are most critical to resolve. Our study directly addresses this by employing a novel mixed-method approach that integrates the Delphi technique with the q-rung orthopair fuzzy number (q-ROFN) and MULTIMOORA method. This advanced framework allows us to systematically capture expert judgment under uncertainty and transform it into a clear, actionable hierarchy of drivers and barriers. This methodological innovation provides a level of decision-making clarity absent from the current literature.

Second, the contextual landscape of CBMs research, while expanding, has entirely overlooked the Iranian context. Iran represents a crucial case study as an emerging economy facing unique regulatory pressures, a specific industrial structure, and distinct market dynamics.

Our research fills this geographical void by providing the first comprehensive empirical investigation of CBMs across diverse Iranian industries.

Therefore, this study's contribution is threefold:

1. It delivers a prioritized decision-making framework for Iran.
2. It methodologically advances the field by demonstrating the power of q-ROFN and MULTIMOORA for complex sustainability decision-making in high-uncertainty contexts.
3. It provides empirical insights from a previously unstudied region, offering a valuable comparative benchmark for other emerging economies and enriching the global understanding of the context-dependent nature of the circular transition.

By doing so, this study provides Iranian policymakers and managers with a targeted, evidence-based blueprint for action.

3. Research method

The present research adopts a mixed-method approach, combining qualitative and quantitative methods.

3.1. Case study description

The present study was conducted in the city of Mashhad, Iran. This research examines five companies in different industries and at different stages of the life cycle: a saffron product manufacturer in the entrepreneurial and introduction stage (OP.1), an organic cosmetics manufacturer in the growth stage (OP.2), a manufacturer of Arcopal products in the development stage (OP.3), a toy manufacturer in the maturity stage (OP.4), and finally a packaging carton manufacturer in the decline stage (OP.5).

3.2. Research design and expert panel selection

In this approach, the factors extracted from the study of the literature review, the drivers and barriers of the circular business model, were administered to a selected sample of experts in the form of the Delphi technique. After going through the necessary steps and reaching the final components through the design of a researcher-made questionnaire, steps were taken to mathematically prioritize these components using the MULTIMORA approach. In the Delphi section, and in order to achieve the necessary theoretical saturation, 10 experts were selected from among the experts. The selection of experts for collecting data followed a purposive sampling strategy to ensure the inclusion of individuals with deep and relevant knowledge.

The selection criteria required experts to possess:

1. A minimum of 5 years of professional experience in fields directly related to the research topic, such as sustainable manufacturing, supply chain management, environmental policy, business strategy, or circular economy initiatives.
2. Current involvement in strategic decision-making, operational management, or academic research pertinent to business model innovation or sustainability in the Iranian industrial sector.
3. A willingness and ability to participate actively in multiple rounds of the study.

The composition of the expert panel included two distinct groups: five academics, all of whom were PhD-holding university faculty with at least a decade of experience, and five industry professionals with five or more years of practical experience, among whom two possessed a master's degree and three a bachelor's degree.

The first Delphi round presented experts with the 8 drivers and 17 barriers derived from the literature review. Following this round, experts were asked to suggest any additional critical factors in an open-ended question. Multiple experts consistently suggested four new drivers. Consequently, these two factors were integrated into the questionnaire, and Round 2 commenced with a total of 12 drivers and 17 barriers. All subsequent rounds were conducted using this final set of 12 drivers and 17 barriers.

The drivers for Circular Business Model (CBM) adoption are multifaceted, encompassing regulatory, market, and internal organizational factors; a questionnaire was developed based on a comprehensive literature review. Key regulatory and competitive drivers include change in laws towards sustainability (C1; Geissdoerfer et al., 2023), compliance with production standards (C2; Geissdoerfer et al., 2023), and increased competition intensity (C5; Comberg and Velamuri, 2017). From a strategic and internal perspective, drivers are bolstered by management attitudes (C8; Snihur and Zott, 2020), the adoption of a sustainable strategy (C9; Bouwman et al., 2018), and the cultivation of an innovation culture (C11; experts). Furthermore, enablers such as comprehensive monitoring and ranking (C3; experts), transparency technologies (C4; Tiscini et al., 2020), and adequate resources and infrastructure (C12; experts) provide the necessary foundation, while goals like business expansion (C6; Geissdoerfer et al., 2023), customer satisfaction (C7; Müller et al., 2018), and a sense of environmental responsibility (C10; experts) create a compelling business case for adoption.

Conversely, significant barriers impede widespread CBM implementation. According to Geissdoerfer et al. (2023) financial constraints are a primary hurdle, manifesting as high initial investment (C13), a short-term financial focus (C14), and the perceived Financial Viability Risk

(C15). The external environment presents further challenges, including Restrictive Regulations (C17), customer preference for cost-efficiency (C18), and a limited market for waste (C21). Internally, organizations face substantial operational and knowledge-based barriers, such as capability gaps (C24), a lack of relevant experience (C27), and a lack of coordination (C28). Additional critical obstacles include infrastructure and investment risk (C16), lack of awareness (C19), competition challenges (C22), recyclability issues (C23), and difficulties in managing organizational change (C26), all of which collectively slow down the transition to circular economies. Upon achieving theoretical saturation, a finalized questionnaire was developed and distributed to the experts. In order to determine the content validity, the content validity ratio (CVR) index designed by Lawshe was used. This coefficient was calculated for each of the questions. The obtained coefficients were compared with the Lawshe content validity table and the content validity of the tool was evaluated. In this regard, for 10 expert individuals, the Lawshe coefficient was 0.99, which is an acceptable value. Cronbach's alpha coefficient was also used to examine the reliability of the designed questionnaire, which was higher than 0.7 for all components. Then, the collected questionnaire data were analyzed using the MULTIMOORA method under a q-ROFSs (quantitative-Rough Set and fuzzy sets) environment. The method used in the analysis is named the q-ROF-entropy-RSWM-MULTIMOORA method. The steps of the present research are presented in the form of two phases in Figure 1. The proposed framework, visualized in Figure 1, integrates the q-ROF weighting system with the MULTIMOORA whose three subordinate models (RS, RP, FMF) are central to the ranking process.

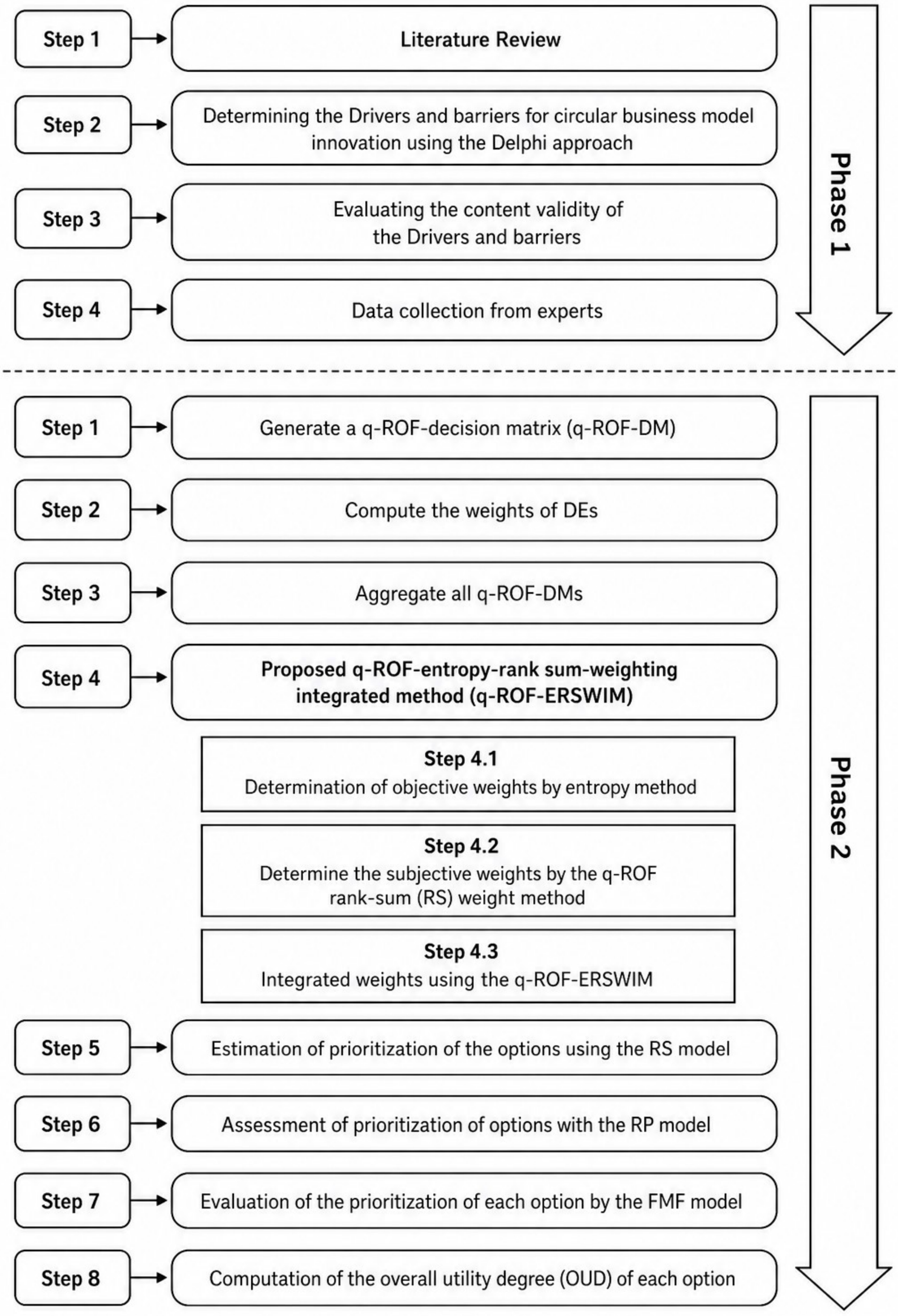

Figure 1. Steps of the present research

Following two rounds of the Delphi technique, the final items, comprising 12 drivers (shown in Table 3) and 17 barriers (shown in Table 4), were identified.

To assess theoretical consensus among experts on the model's final items, the Kendall coefficient test was used. The Kendall correlation coefficient (represented by "w") is a non-parametric test used to assess the level of agreement among expert opinions. It ranges between 0 and 1, with a value above 0.7 indicating a strong agreement or consensus. This test is deemed reliable in the context of the Delphi technique. The results of the Kendall correlation coefficient test, obtained after two rounds of the Delphi technique, can be observed in Table 2.

Table 2. Results of the kendall correlation coefficient test

N	Kendall's W	Asymp. Sig.
10	0.780	0.000

In this study, the calculated Kendall statistic was 0.780, indicating a consensus and agreement among 78% of the experts, surpassing the threshold of 0.7. Additionally, the significance level (sig) was lower than 0.05, demonstrating the test's significance with 99% confidence.

3.3. Fundamental concepts of q-rung orthopair fuzzy number

Here, we present the elementary definitions associated with the q-rung orthopair fuzzy number (q ROFN).

Definition 1. A q-ROFN B on a Universe of Discourse $\aleph = \{f_1, f_2, \ldots, f_n\}$ is defined as follows: $N = \{(f_i,\ \mu_N(f_i),\ v_N(f_i)\ ))|f_i \in \aleph\}$, where μ_N shows the BD of an element $f_i \in \aleph$ and v_N expresses the NBD of an element $f_i \in \aleph$, with the following condition: $\mu_N(f_i) \in [0,1]$, $v_N(f_i) \in [0,1], 0 \leq (\mu_N(f_i))^q + (v_N(f_i))^q \leq 1\ with\ q \geq 1$. $\pi_N(f_i)$ is degree of hesitancy and calculated as $\pi_N(f_i) = \sqrt[q]{1 - (\mu_N(f_i))^q - (v_N(f_i))^q}$. $\mu_N(f_i), v_N(f_i)$ is referred as q-ROFN numbers and denoted as $\tau = (\mu_\tau, v_\tau)$ (Yager, 2016).

Definition 2. According to Liu and Wang (2018), let three q-ROFNs $\tau = (\mu_\tau, v_\tau)$, $\tau 1 = (\mu_{\tau 1}, v_{\tau 1})$ and $\tau 2 = (\mu_{\tau 2}, v_{\tau 2})$, then the basic operations are:

$$\tau^c = (\mu_\tau, v_\tau);$$

$$\tau 1 \oplus \tau 2 = (\sqrt[q]{\mu_{\tau 1}^q + \mu_{\tau 2}^q - \mu_{\tau 1}^q \mu_{\tau 2}^q}, v_{\tau 1} v_{\tau 2}); \tag{1}$$

$$\tau 1 \otimes \tau 2 = (\mu_{\tau 1}\mu_{\tau 2}, \sqrt[q]{v_{\tau 1}^q + v_{\tau 2}^q - v_{\tau 1}^q v_{\tau 2}^q});$$

$$\varphi\tau = \left(\sqrt[q]{1-(1-\mu_\tau^q)^\varphi}, v_\tau^\varphi\right), \varphi > 0;$$

$$\tau^\varphi = \left(\mu_\tau^\varphi, \sqrt[q]{1-(1-v_\tau^q)^\varphi}\right), \varphi > 0;$$

Definition 3. According to Liu and Wang (Liu and Wang, 2018) consider $\tau = (\mu_\tau, v_\tau)$ be a q-ROFN. Then, the score of τ is defined as $\mathbb{S}(\tau) = \mu_\tau^q - v_\tau^q$ wherein $\mathbb{S}(\tau) \in [-1,1]$ and the accuracy value of τ is $\hbar(\tau) = \mu_\tau^q + v_\tau^q$ wherein$\hbar(\tau) \in [0,1]$.

Definition 4. The normalized score value of $\tau = (\mu_\tau, v_\tau)$ is defined as $\mathbb{S}^*(\tau) = \frac{1}{2}(\mathbb{S}(\tau)+1)$ such that $\mathbb{S}^*(\tau) \in [0,1]$ and normalized uncertainty value is calculated by $\hbar^*(\tau) = 1 - \hbar(\tau)$ such that $\hbar^*(\tau) \in [0,1]$. For any two q-ROFNs $\tau 1 = (\mu_{\tau 1}, v_{\tau 1})$ and $\tau 2 = (\mu_{\tau 2}, v_{\tau 2})$,

If $\mathbb{S}^*(\tau 1) > \mathbb{S}^*(\tau 2)$, then $\tau 1 > \tau 2$;

If $\mathbb{S}^*(\tau 1) = \mathbb{S}^*(\tau 2)$, then we have two cases:

(i): If $\hbar^*(\tau 1) > \hbar^*(\tau 2)$, then $\tau 1 > \tau 2$;

(ii): If $\hbar^*(\tau 1) = \hbar^*(\tau 2)$, then $\tau 1 = \tau 2$.

Definition 5. Liu et al., (2019) stated a discrimination measure between two q-ROFNs $\tau 1$ and $\tau 2$ is calculated by Equation 2 :

$$d(\tau 1, \tau 2) = \frac{1}{2}\left(\left|\mu_{\tau 1}^q - \mu_{\tau 2}^q\right| + \left|v_{\tau 1}^q - v_{\tau 2}^q\right| + \left|\pi_{\tau 1}^q - \pi_{\tau 2}^q\right|\right) \quad (2)$$

The use of q-rung orthopair fuzzy numbers (q-ROFNs) is justified by the need to model the inherent uncertainty and imprecision in expert judgments. When evaluating complex factors like drivers and barriers, experts naturally think in linguistic terms (e.g., "very significant") rather than precise numbers. q-ROFNs provide a robust mathematical framework to convert these qualitative assessments into quantitative data while preserving the experts' degrees of confidence and hesitation. This approach yields more realistic and reliable results than using crisp values, which cannot capture the nuance of human judgment.

3.4. Q-ROF-entropy-RSWM-MULTIMOORA approach

This section develops a MULTIMOORA method under a q-ROFSs environment for solving decision-making applications and is named the q-ROF-entropy-RSWM-MULTIMOORA method. The calculation procedure of the proposed method is given by:

Step 1: Content validity assessment of identified components

In the present study, after phase 1, the Drivers and barriers of the circular business model were extracted. In the second phase, the identified indicators were subjected to initial assessment. In this stage, the Content Validity Ratio (CVR) index designed by Lawshe was employed to measure the content validity of the identified indicators. To calculate this index, the opinions of experts in the field of the targeted identified indicators were used. To explain the study's objectives and provide operational definitions for the identified indicators, experts were asked to classify each question into one of three Likert categories: "Essential Indicator," "Useful Indicator but not Essential," and "Not Essential Indicator." Then, based on the following formula, the Content Validity Ratio was calculated by Equation 3:

$$CVR = (N_e - N/2)/(N/2) \tag{3}$$

In this formula, N represents the total number of experts, and $N_e$represents the number of experts who considered the indicator as essential. In the current study, the number of experts who assessed the indicators was 5. Therefore, the acceptable minimum value for CVR for this number of experts should be considered as 0.99. If the calculated CVR for an indicator is less than this value, that indicator is not considered to have acceptable content validity and should be removed.

Step 2: Generate a q-ROF-decision matrix (q-ROF-DM)

A collection of n "Decision Experts (DEs)" denoted by A = {A1,A2,…,An} defines the sets of m options F = {F1,F2,…,Fm} and n criteria C = {C1,C2,…,Cn}, respectively. Due to the imprecision of human thinking, lack of data, and imprecise knowledge about the options, the DEs assign q-ROFNs to assess their decision about option Fi with respect to criterion Cj. Let $\mathbb{Z}(k) = (\propto_{ij}(k))_{m\times n}$, where i = 1, 2, …, m and j = 1, 2, …, n, be the decision matrix recommended by the DEs, and $\propto_{ij}$ (k) be the evaluation of an option Fi over a criterion Cj in the form of q-ROFN specified by the kth expert.

Step 3: Calculate the weights of decision experts (DEs)

In order to calculate the weights of the DEs, we first assign linguistic values (LVs) to represent the degrees of importance of each DE. These LVs are then expressed using q-ROFNs. To calculate the weight of the kth DE, we use$A_k = (\mu_k, v_k, \pi_k)$ as the q-ROFN. The weight of the expert is then determined by Equation 4:

$$w_k = \frac{(\mu_k^q + \pi_k^q * (\frac{\mu_k^q}{\mu_k^q + v_k^q}))}{\sum_{k=1}^{n}(\mu_k^q + \pi_k^q * (\frac{\mu_k^q}{\mu_k^q + v_k^q}))}, with\ w_k \geq 0\ and \sum_{k=1}^{n} w_k = 1, k = 1,2, \dots, n. \quad (4)$$

Step 4: Combine all q-ROF-DMs

Form the "aggregated q-ROF-decision-matrix (A-q-ROF-DM)", we employ the "q-ROF weighted averaging (q-ROFWA)" operator. This yields $\mathbb{Z}(k) = (\propto_{ij}(k))_{m\times n}$, where:

$$\propto_{ij} = (\sqrt[q]{1 - \prod_{k=1}^{n}(1-\mu_k^q)^{w_k}}, \prod_{k=1}^{n}(v_k^q)^{w_k}) \quad (5)$$

Step 4: Proposed q-ROF-entropy-rank sum-weighting integrated method (q-ROF-ERSWIM)

Step 4.1. Objective weights determination using the entropy method

It is not assumed that all criteria are of equal importance. Let $w = (w_1, w_2, \dots, w_n)^T$be the weight of the criterion set, with $\sum_{j=1}^{n} w_j = 1$ and$w_j \in [0,1]$. To determine the weights of the criteria, the entropy model is extended in the q-ROFS environment.

$$w_j^o = \frac{\sum_{i=1}^{m}(1 - E(\propto_{ij}))}{\sum_{j=1}^{n}(\sum_{i=1}^{m}(1 - E(\propto_{ij})))} \quad (6)$$

Mishra and Rani (2023) denote the entropy measure of $\tilde{\propto}_{ij}$ as Equation 7:

$$E(\propto_{ij}) = \frac{1}{n(1-\exp(-1/2))}\sum_{i=1}^{n}\left[\left\{1 - \exp(-(\frac{v_{ij}^q + (1-\mu_{ij}^q)}{2}))\right\} I_{[\mu_{ij}^q \geq v_{ij}^q]} + \left\{1 - \exp(-(\frac{\mu_{ij}^q + (1-v_{ij}^q)}{2}))\right\} I_{[\mu_{ij}^q < v_{ij}^q]}\right] \quad (7)$$

Step 4.2. Subjective weights determination

The subjective weights are determined using the q-ROF rank-sum (RS) weighting method. This subjective weighting system allows decision-makers to reflect on their thoughts and values. These procedures aim not only to consider the alternatives but also to highlight the importance of the prevailing criteria. In the decision-making process, the decision-makers' opinions on each alternative with dependent criteria are crucial in selecting the best choice for a given problem. In this critical situation, the decision-maker assigns their subjective weight

(Stillwell et al., 1981) and (Narayanamoorthy et al., 2020). The procedure of the rank-sum weight method helps the decision-maker to assign ranking values to selected criteria. The formula for this method is given as Equation 8:

$$w_j^s = \frac{n - r_j + 1}{\sum_{j=1}^{n}(n - r_j + 1)} = \frac{2(n + 1 - r_j)}{n(n + 1)} \tag{8}$$

In this equation, w_j^s refers to the weight assigned to each criterion j, and n represents the total number of criteria. The value rj indicates the rank of each criterion, with j taking on values from 1 to n.

Step 4.3. Combining subjective and objective weights using q-ROF-ERSWIM.

To incorporate both subjective and objective weights, the decision-maker uses the following integrated weighted equation based on the A-q-ROF-decision matrix:

$$w_j = \tau w_j^o + (1 - \tau) w_j^s \tag{9}$$

Where τ is an objective factor of the A-q-ROF-DM weights, with $\tau \in [0,1]$. In the Equation 9, the weight w_j^o represents the objective weight, while w_j^s represents the subjective weight.

Step 5: involves estimating the prioritization of options with the RS model.

The process of the RS model can be outlined as follows:

Step 5.1: Calculate $\boldsymbol{Y_i^+}$ and $\boldsymbol{Y_i^-}$

Using the q-ROFWAO approach, where Y_i^+ and Y_i^- represent the importance of option Fi based on benefit-type and cost-type attributes, respectively.

$$Y_i^+ = (\sqrt[q]{1 - \prod_{j \in C_b} \left(1 - \mu_{ij}^q\right)^{w_j}}, \prod_{j \in C_b} (v_{ij}^q)^{w_j}) \tag{10}$$

$$Y_i^- = (\sqrt[q]{1 - \prod_{j \in C_n} \left(1 - \mu_{ij}^q\right)^{w_j}}, \prod_{j \in C_n} (v_{ij}^q)^{w_j}) \tag{11}$$

Step 5.2: Evaluate the normalized score values of $\boldsymbol{Y_i^+}$ and $\boldsymbol{Y_i^-}$.

$$y_i^+ = \mathbb{S}^*(Y_i^+) \tag{12}$$

$$y_i^- = \mathbb{S}^*(Y_i^-) \tag{13}$$

Step 5.3: Determine the overall degree of significance by estimating the overall significance degree.

$$y_i = y_i^+ - y_i^- \tag{14}$$

Step 6. Evaluating the prioritization of options using the RP model.

The procedure of the RP model can be outlined as follows:

Step 6.1: estimating of the reference values

Firstly, in step 6.1, the reference values are estimated, where each coordinate of the reference point $p^* = \{p_1^*, p_2^*, \dots, p_n^*\}$ is computed using q-ROFN.

$$p_j^* = \begin{cases} (max_i\mu_{ij}, min_i v_{ij}), for\ C_b \\ (min_i\mu_{ij}, max_i v_{ij}), for\ C_n \end{cases} \tag{15}$$

Step 6.2: computing of the weighted discrimination

In step 6.2, the weighted discrimination to all coordinates of the reference values is computed using D_h, which represents the discrimination between $\propto_{ij}$ and p_j^* by Eqs. (1), (3), and (11). This formula is as Equation 16:

$$D_{ij} = w_j(D_h(\propto_{ij}, p_j^*)) \tag{16}$$

Step 6.3: the highest discrimination of each option

In step 6.3, the highest discrimination of each option is obtained using Equation 17:

$$d_i = max_j D_{ij}, i = 1,2, \dots, m. \tag{17}$$

Step 7: Assessing the prioritization of each option using the FMF model

The procedure of the FMF model can be described as follows:

Step 7.1: Calculate the U_i^+ and U_i^- using the q-ROFWGO method as:

$$U_i^+ = (\prod_{j\in C_b} (\mu_{ij})^{w_j}, \sqrt[q]{1 - \prod_{j\in C_b} \left(1 - v_{ij}^q\right)^{w_j}}) \tag{18}$$

$$U_i^- = (\prod_{j\in C_n} (\mu_{ij})^{w_j}, \sqrt[q]{1 - \prod_{j\in C_n} \left(1 - v_{ij}^q\right)^{w_j}}) \tag{19}$$

Step 7.2: Determine the α_i and β_i values using the normalized score value as:

$$\alpha_i = \mathbb{S}^*(U_i^+) \tag{20}$$

$$\beta_i = \mathbb{S}^*(U_i^-) \tag{21}$$

Step 7.3: Calculate the utility degree (UD) for each option as:

$$u_i = \frac{\alpha_i}{\beta_i} \tag{22}$$

Step 8: Calculating the overall utility degree (OUD) for each option.

To determine the overall utility degree, the normalized values of the RS, RP, and FMF models (y_i^*, d_i^*, and u_i^*) are estimated using the vector normalization process. The computation of the overall utility degree for each option is as follows:

$$U(F_i) = y_i^*.\frac{m-\rho(y_i^*)+1}{(\frac{m(m+1)}{2})} + u_i^*.\frac{m-\rho(u_i^*)+1}{(\frac{m(m+1)}{2})} - d_i^*.\frac{\rho(d_i^*)}{\left(\frac{m(m+1)}{2}\right)}, i = 1,2,\dots,m. \tag{23}$$

Wherey_i^*, u_i^* and d_i^* calculated as follow:

$$y_i^* = \frac{y_i}{\sqrt{\sum_{i=1}^{m}(y_i)^2}} \tag{24}$$

$$d_i^* = \frac{d_i}{\sqrt{\sum_{i=1}^{m}(d_i)^2}} \tag{25}$$

$$u_i^* = \frac{u_i}{\sqrt{\sum_{i=1}^{m}(u_i)^2}} \tag{26}$$

$\rho(y_i^*)$, $\rho(d_i^*)$ and $\rho(u_i^*)$ represent the priority orders of the RS, RP, and FMF models, respectively. The option with the highest overall utility degree (OUD) of U(Fi) is considered the best choice.

4. Results

To ensure reliability and expert consensus, a Delphi method was employed to identify the key drivers and barriers. Following a comprehensive literature review that established an initial set of factors, two rounds of the Delphi process were conducted to refine and finalize the list. This finalized list, presented in Tables 3 (drivers) and 4 (barriers), forms the basis for the subsequent analysis.

Table 3. Identified drivers for the adoption of circular business models

Code	Drivers	Description
C1	Change in Laws towards Sustainability	Change in laws towards sustainability and support for the production of environmentally friendly products. Governments implementing new regulations and policies that promote sustainability and environmentally friendly practices can drive companies to adopt such practices.
C2	Compliance with Production Standards	Companies' obligation to comply with up-to-date production standards. Companies are increasingly required to adhere to strict production standards that prioritize sustainability and environmental considerations.
C3	Comprehensive Monitoring and Ranking	Comprehensive monitoring of companies and their ranking based on their attention to environmental issues.
C4	Transparency Technologies	Technological advancements enable companies to track and measure their environmental impact accurately. These technologies can help identify areas for improvement and facilitate the adoption of sustainable practices.
C5	Increased competition intensity	Companies face growing competition in the market, and offering environmentally friendly products can be a strategic advantage. It also aligns with consumer preferences for sustainable options.
C6	Business Expansion	Embracing sustainability can open up new market opportunities for companies. Consumers and businesses increasingly prioritize environmentally friendly products and services, creating a demand for sustainable businesses
C7	Customer Satisfaction	Customer satisfaction by providing environmentally friendly products.
C8	Management Attitudes	The mental and behavioral patterns of company managers and owners and their level of attention to sustainability in production.
C9	Sustainable Strategy	The company's strategy design for sustainable innovation by introducing environmentally friendly products.
C10	Environmental Responsibility	The company's responsibility for environmental issues.
C11	Innovation Culture	Existence of a culture of innovation acceptance within the company.
C12	Resources and Infrastructure	Availability of resources and infrastructure needed for sustainable innovation.

Table 4. Identified Barriers for the Adoption of Circular Business Models

Code	Barriers	Description
C13	High Initial Investment	There is a need for a high initial investment to offer environmentally friendly products.
C14	Short-Term Financial Focus	The company's inclination towards achieving short-term financial results.
C15	Financial Viability Risk	Existence of the financial viability risk on investment in providing environmentally friendly products.
C16	Infrastructure and Investment Risk	Previous infrastructure and investments are at risk with the implementation of innovation.
C17	Restrictive Regulations	Existence of restrictive regulations in the field of sustainable innovation.
C18	Customer Preference for Cost-Efficiency	Greater customer preference for cost-effective products over environmentally friendly ones.
C19	Lack of Awareness	Lack of societal awareness of the effects of sustainable businesses.
C20	Lack of demand for environmentally friendly products	Lack of demand for environmentally friendly products.
C21	Limited Market for Waste	Lack of a market for company waste for use in other products.
C22	Competition Challenges	Challenges of competition between innovative companies and established ones in the market.
C23	Recyclability Issues	Challenges related to incorporating recyclability into products, which can either reduce the product's lifespan or increase it to meet customer needs.
C24	Capability Gaps	The company's lack of capability in creating sustainable innovation in products.
C25	Management Attention	Lack of attention from company managers to sustainable innovation and environmentally friendly products.
C26	Organizational Change	Challenges related to organizational change towards sustainable innovation.
C27	Lack of relevant experience	Lack of relevant experience with sustainable innovation and environmentally friendly products.

Code	Barriers	Description
C28	Lack of coordination	Lack of coordination in the existing procurement system when offering sustainable products.
C29	Lack of transparency	Lack of transparency and trust in information regarding the natural materials used in products.

In step 1 of phase 1, we consider Table 5, which illustrates the importance of Decision Experts (DEs) and their characteristics represented as Latent Variables (LVs). These LVs are subsequently transformed into Quantitative Ratings of Functional Necessities (q-ROFNs).

Table 5. Linguistic Term to q-ROFNs

LVs	q-ROFNs
Extremely important (EI)	(0.95,0.20)
Very important (VI)	(0.90,0.30)
Important (I)	(0.80,0.40)
Moderately important (MI)	(0.75,0.45)
Medium (M)	(0.60,0.55)
Moderately unimportant (MU)	(0.45,0.70)
Unimportant (U)	(0.30,0.80)
Very unimportant (VU)	(0.20,0.85)
Extremely unimportant (EU)	(0.10,0.98)

Based on the scales in Table 5, experts provided their assessments for each factor, resulting in the linguistic decision matrix shown in Table 6. This matrix is the raw input from the experts before any aggregation.

Table 6. Linguistic decision matrix

		c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24	c25	c26	c27	c28	c29
DE1	option1	VI	MU	MU	VU	EI	MU	VI	VI	MI	M	I	VI	MI	EI	MI	I	VU	EI	EI	EI	VI	EI	VI	VU	U	U	M	EU	M
	option2	I	M	U	EU	I	U	MI	EI	I	I	M	M	M	MI	MU	I	U	MI	VI	I	VI	I	MI	U	MU	MU	MI	M	M
	option3	M	MI	M	VU	MI	MU	MI	VI	VI	MI	MI	MI	VI	U	MU	VI	EU	M	EI	M	M	M	MU	MU	U	I	I	MI	I
	option4	EI	VU	MU	U	MI	VU	M	I	EI	M	M	EI	I	U	MU	M	VU	EI	EI	M	MU	U	M	I	U	VI	VI	I	VI
	option5	M	EU	EU	MU	I	U	M	I	I	U	I	M	EI	VI	EI	EI	MU	I	M	I	U	M	EU	EI	I	MU	EI	VI	U
DE2	option1	I	MU	M	MI	MI	MI	VI	VI	I	MU	MI	MI	I	I	M	MI	U	I	VI	VI	M	I	I	U	MU	MU	MI	U	MI
	option2	MI	M	U	M	MU	M	EI	I	MI	M	M	I	MU	M	M	MI	VU	M	MI	MI	MI	MI	MI	MU	M	M	M	MU	MU
	option3	M	MI	MU	MU	M	MU	I	MI	I	U	MI	M	MI	MU	MU	I	M	I	I	I	MU	MU	M	M	VU	MI	M	MI	M
	option4	U	U	MI	U	VI	U	MI	I	M	VU	M	MU	M	MU	I	MI	MI	I	I	U	U	MU	MU	MI	MU	I	EI	M	MI
	option5	VI	I	U	VU	I	MI	I	VI	VI	M	MI	M	I	I	VI	I	I	MI	MU	VI	EU	MI	VU	I	MI	M	EI	MI	M
DE3	option1	U	MI	MU	MU	MI	I	MI	I	I	M	EI	MU	M	MI	I	M	M	MI	I	I	I	VI	VI	MU	VU	VU	MU	MU	MU
	option2	MU	M	M	U	M	MI	M	MI	MI	MU	VI	M	U	MU	MI	MU	MU	M	I	M	I	I	M	M	MU	MU	MU	MI	M
	option3	MI	I	MI	M	I	M	MI	EI	M	M	I	EI	M	M	VU	M	M	VI	MI	MU	M	U	U	U	M	M	MI	I	MI
	option4	VI	M	U	MI	M	M	I	I	MI	MI	MI	I	VI	EU	M	U	VU	MI	MI	MU	VU	VU	U	M	M	MI	MI	I	MU
	option5	EI	MU	MU	MU	MI	MI	M	MI	VI	I	MI	M	MI	EI	I	MI	MI	M	U	EI	VU	I	U	VI	VI	MI	I	I	MU
DE4	option1	MI	MU	I	EI	EI	M	MI	I	VI	VI	I	MI	MU	I	MU	U	MU	I	EI	VI	EI	MI	EI	VU	MU	MU	M	M	U
	option2	I	M	M	I	I	M	M	VI	EI	M	MU	M	MU	M	I	M	U	MI	M	I	VI	M	MU	MU	U	VU	MI	M	M
	option3	M	MI	MU	MI	VI	U	I	MI	I	MI	M	I	I	VU	EU	U	VU	I	VI	U	MU	M	MI	MU	MU	MI	I	MI	MI
	option4	MU	U	VU	M	M	MU	MI	I	MI	MU	MI	MI	I	VU	U	VU	EU	VI	EI	M	MU	MU	VU	MI	MI	I	I	I	I
	option5	EI	VU	MU	U	I	MI	M	VI	I	M	M	M	VI	I	MI	MU	MI	VI	VU	I	EU	MI	EU	MI	I	U	EI	EI	VU

Using Equation (3), calculate the importance of DEs when evaluating manufacturing firms and conducting assessments for different criteria in each option. The calculated weights are as follows: DE1 = 0.254384, DE2 = 0.2529393, DE3 = 0.24752219, and DE4 = 0.245153497. based on four DEs, has been integrated using Equation (3) to create an A-q-ROF-DM ℤ denoted as (ξij)m×n, and this matrix is provided in Table 7 for Drivers and Barriers for circular business models (CBMs) in Iran.

Table 7. Aggregated q-ROF-DM

c1			c2			c3			c4			c5			c6		
μ	v	Π	μ	v	Π	μ	V	Π	μ	v	Π	μ	v	Π	μ	v	Π
0.783	0.454	0.752	0.572	0.627	0.827	0.628	0.574	0.825	0.779	0.483	0.744	0.893	0.300	0.638	0.690	0.513	0.811
0.740	0.473	0.787	0.600	0.550	0.851	0.500	0.665	0.834	0.600	0.646	0.800	0.709	0.498	0.803	0.614	0.575	0.832
0.648	0.523	0.835	0.763	0.437	0.778	0.601	0.590	0.832	0.583	0.621	0.825	0.795	0.416	0.751	0.477	0.681	0.831
0.830	0.426	0.704	0.418	0.740	0.804	0.540	0.678	0.809	0.573	0.632	0.823	0.763	0.448	0.774	0.445	0.716	0.816
0.905	0.286	0.617	0.572	0.694	0.782	0.375	0.788	0.770	0.380	0.759	0.797	0.789	0.411	0.760	0.698	0.520	0.803
c7			c8			c9			c10			c11			c12		
μ	v	Π	μ	v	Π	μ	v	Π	μ	v	Π	μ	v	Π	μ	v	Π
0.846	0.366	0.701	0.860	0.345	0.684	0.823	0.384	0.727	0.719	0.512	0.789	0.854	0.347	0.693	0.775	0.452	0.760
0.808	0.404	0.740	0.878	0.321	0.661	0.846	0.358	0.702	0.653	0.538	0.826	0.721	0.502	0.792	0.672	0.507	0.826
0.776	0.424	0.769	0.871	0.332	0.669	0.808	0.402	0.741	0.661	0.547	0.818	0.738	0.459	0.794	0.832	0.376	0.718
0.737	0.460	0.794	0.800	0.400	0.751	0.825	0.427	0.711	0.584	0.619	0.825	0.687	0.498	0.819	0.826	0.397	0.719
0.672	0.507	0.826	0.852	0.356	0.694	0.860	0.346	0.685	0.641	0.559	0.825	0.738	0.458	0.793	0.600	0.550	0.851
c13			c14			c15			c16			c17			c18		
μ	v	Π	μ	v	Π	μ	v	Π	μ	v	Π	μ	v	Π	μ	v	Π
0.692	0.511	0.811	0.856	0.345	0.691	0.691	0.512	0.811	0.685	0.528	0.809	0.445	0.716	0.816	0.856	0.345	0.691
0.478	0.680	0.831	0.627	0.554	0.834	0.689	0.514	0.812	0.692	0.511	0.811	0.337	0.786	0.780	0.688	0.497	0.819
0.797	0.414	0.750	0.446	0.715	0.816	0.367	0.797	0.762	0.760	0.476	0.767	0.488	0.708	0.807	0.806	0.403	0.742
0.806	0.403	0.742	0.320	0.825	0.739	0.620	0.591	0.821	0.573	0.638	0.820	0.510	0.749	0.764	0.878	0.321	0.661
0.878	0.321	0.661	0.883	0.313	0.653	0.879	0.320	0.660	0.827	0.396	0.718	0.723	0.488	0.796	0.795	0.415	0.751

c19			c20			c21			c22			c23			c24		
μ	v	Π	μ	v	Π	μ	v	Π	μ	v	Π	μ	v	Π	μ	v	Π
0.9176	0.2631	0.5937	0.9020	0.2906	0.6229	0.8661	0.3400	0.6776	0.8787	0.3214	0.6607	0.9010	0.2921	0.6247	0.3239	0.7978	0.7710
0.7976	0.4141	0.7499	0.7531	0.4459	0.7852	0.8528	0.3569	0.6940	0.7535	0.4456	0.7850	0.6720	0.5270	0.8194	0.4769	0.6822	0.8311
0.8784	0.3217	0.6611	0.6210	0.6006	0.8163	0.5384	0.6202	0.8459	0.5210	0.6414	0.8409	0.5878	0.6108	0.8287	0.4785	0.6807	0.8316
0.8982	0.2913	0.6304	0.5206	0.6419	0.8408	0.3804	0.7597	0.7971	0.3802	0.7598	0.7970	0.4489	0.7136	0.8174	0.7386	0.4590	0.7939
0.4489	0.7136	0.8174	0.8836	0.3133	0.6537	0.2111	0.8985	0.6426	0.7374	0.4600	0.7946	0.2100	0.8990	0.6416	0.8787	0.3214	0.6607
c25			c26			c27			c28			c29					
μ	v	Π	μ	v	Π	μ	v	Π	μ	v	Π	μ	v	Π			
0.3802	0.7598	0.7970	0.3802	0.7598	0.7970	0.6275	0.5549	0.8349	0.4423	0.7435	0.7950	0.5907	0.6083	0.8285			
0.4787	0.6805	0.8316	0.4725	0.6907	0.8267	0.6706	0.5281	0.8199	0.6259	0.5661	0.8308	0.5710	0.5949	0.8450			
0.4456	0.7166	0.8161	0.7386	0.4590	0.7939	0.7526	0.4464	0.7856	0.7638	0.4371	0.7780	0.7380	0.4595	0.7943			
0.5868	0.6122	0.8284	0.8251	0.3828	0.7256	0.8789	0.3212	0.6603	0.7662	0.4336	0.7768	0.7875	0.4399	0.7527			
0.8241	0.3838	0.7267	0.5887	0.6100	0.8286	0.9309	0.2374	0.5646	0.8775	0.3232	0.6624	0.4479	0.7145	0.8170			

The objective weights for each driver and barrier of Circular Business Models (CBMs) in Iranian industries were determined via the q-ROF entropy-based method based on Equation (5). The resulting weights are detailed in Table 8.

The subjective weights for the CBM drivers and barriers were calculated via the q-ROF rank-sum weighting procedure, as defined in Equation (7). The resulting subjective weight values are presented in in Table 8.

Following the proposed q-ROF-entropy-RSWM algorithm, the objective weights (derived from q-ROF entropy) and subjective weights (derived from q-ROF rank-sum) for the CBM drivers and barriers were integrated using Equation (8). For an integration parameter of τ=0.5\tau = 0.5τ=0.5, the resulting combined weights are summarized in in Table 8.

Table 8. Objective, subjective, and integrated weights for CBM drivers and barriers

Criterion	q-ROF Entropy (Objective Weight)	q-ROF Rank-Sum (Subjective Weight)	Integrated Weight	Criterion	q-ROF Entropy (Objective Weight)	q-ROF Rank-Sum (Subjective Weight)	Integrated Weight
C1	0.0344	0.0138	0.0241	C16	0.0344	0.0046	0.0195
C2	0.0345	0.0345	0.0345	C17	0.0346	0.0644	0.0495
C3	0.0345	0.046	0.0402	C18	0.0344	0.0207	0.0276
C4	0.0345	0.0253	0.0299	C19	0.0346	0.0529	0.0437
C5	0.0344	0.0161	0.0253	C20	0.0345	0.0368	0.0356
C6	0.0345	0.0276	0.031	C21	0.0346	0.0667	0.0507
C7	0.0344	0.0115	0.023	C22	0.0345	0.0506	0.0425
C8	0.0345	0.0437	0.0391	C23	0.0346	0.0598	0.0472
C9	0.0345	0.023	0.0287	C24	0.0346	0.0621	0.0483
C10	0.0344	0.0023	0.0183	C25	0.0346	0.0552	0.0449
C11	0.0344	0.0069	0.0206	C26	0.0345	0.0483	0.0414
C12	0.0344	0.0092	0.0218	C27	0.0345	0.0299	0.0322
C13	0.0345	0.0322	0.0333	C28	0.0345	0.0391	0.0368
C14	0.0346	0.0575	0.046	C29	0.0344	0.0184	0.0264
C15	0.0345	0.0414	0.0379				

Figure 2 displays the outcomes of objective weights, subjective weights, and the integrated weight.

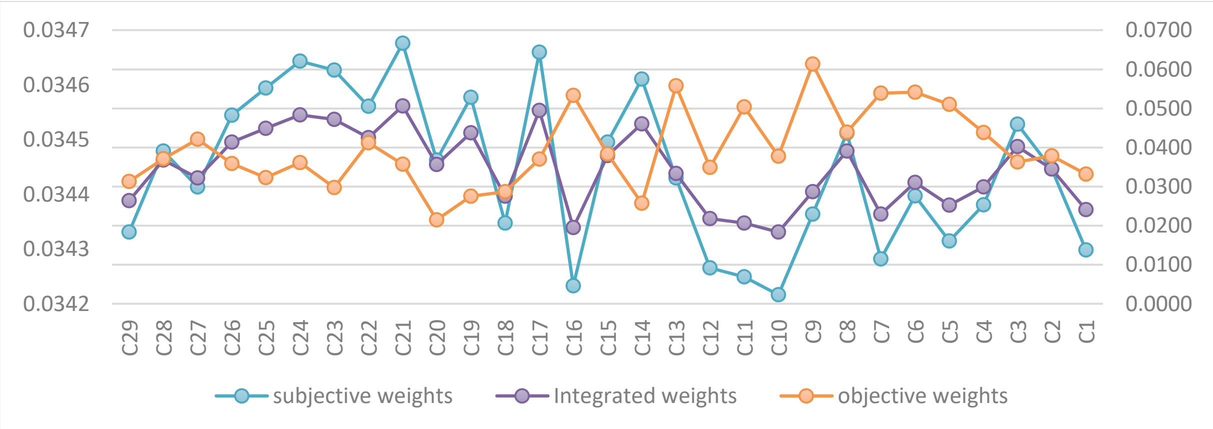

Figure 2. Weights of drivers and barriers for circular business models (CBMs)

The outcomes of weight analysis indicate that within the context of drivers for circular business models, "Comprehensive Monitoring and Ranking (c3)" has emerged as the most significant driver, carrying a weight value of 0.0402. Following closely, "Management Attitudes (c8)" holds the second-highest importance, with a weight value of 0.0391. "Compliance with Production Standards (c2)" ranks third, having a weight value of 0.0345.

The weight analysis results reveal that among the barriers associated with circular business models, "Limited Market for Waste (c21)" stands out as the most significant barrier, carrying a weight value of 0.0507. Following closely, "Restrictive Regulations (c17)" ranks as the second most important barrier, with a weight value of 0.0495. "Capability Gaps (c24)" takes the third position, with a weight value of 0.0483. Table 9 shows the ranking results from the Ratio System (RS) model (Equations 9-13). This model ranks the firms based on the maximization of beneficial criteria (drivers) and the minimization of non-beneficial criteria (barriers). A higher rank indicates better overall performance concerning CBMs adoption factors.

Table 9. Ranking of RS model

Firms	$\mathbb{S}^*(Y_i^+)$	$\mathbb{S}^*(Y_i^-)$	y_i	Rank of RS model
OP.1	0.412641	0.544106	-0.13146	3
OP.2	0.372689	0.462101	-0.08941	2
OP.3	0.384995	0.457991	-0.073	1
OP.4	0.353609	0.486698	-0.13309	4
OP.5	0.37195	0.563297	-0.19135	5

Table 10 displays the reference values p_j^* calculated for the RP (Ranking and Prioritization) model (Equations 14-16). These points represent the ideal performance for each driver and barrier. The RP model then ranks firms based on minimizing their deviation from this ideal reference point.

Table 10. Results for reference values p_j^*

c1			c2			c3			c4			c5			c6		
0.9050	0.2866	0.6173	0.7638	0.4371	0.7780	0.6285	0.5741	0.8255	0.7795	0.4838	0.7448	0.8932	0.3001	0.6385	0.6980	0.5137	0.8064
c7			**c8**			**c9**			**c10**			**c11**			**c12**		
0.8464	0.3663	0.7010	0.8784	0.3217	0.6611	0.8602	0.3464	0.6854	0.7197	0.5127	0.7897	0.8547	0.3471	0.6937	0.8322	0.3763	0.7181
c13			**c14**			**c15**			**c16**			**c17**			**c18**		
0.4788	0.6805	0.8316	0.3201	0.8255	0.7397	0.3670	0.7976	0.7624	0.5737	0.6382	0.8200	0.3379	0.7860	0.7807	0.6887	0.4975	0.8194
c19			**c20**			**c21**			**c22**			**c23**			**c24**		
0.4489	0.7136	0.8174	0.5206	0.6419	0.8408	0.2111	0.8985	0.6426	0.3802	0.7598	0.7970	0.2100	0.8990	0.6416	0.3239	0.7978	0.7710
c25			**c26**			**c27**			**c28**			**c29**					
0.3802	0.7598	0.7970	0.3802	0.7598	0.7970	0.6275	0.5549	0.8349	0.4423	0.7435	0.7950	0.4479	0.7145	0.8170			

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The outcome of this ranking process is presented in Table 11, which presumably displays the ranked options based on the RP model's calculations. This table should provide information on how the different options or alternatives have been ranked or prioritized according to the specific criteria and factors used in the RP model, where a lower maximum deviation from the ideal $\boldsymbol{max_j D_{ij}}$ leads to a better rank (Rank 1).

Table 11. Ranking of RP model

Firms	$\boldsymbol{max_j D_{ij}}$	Rank
OP.1	0.039774	5
OP.2	0.039014	4
OP.3	0.024391	2
OP.4	0.023741	1
OP.5	0.03073	3

The results of prioritizing each option using the FMF model are obtained by applying Equations (17-21). This model ranks firms based on a utility function. A higher utility score indicates a more favourable position. The outcome of this prioritization process is presented in Table 12.

Table 12. Rank of the FMF model

Firms	Drivers		Barriers		$\boldsymbol{\alpha_i}$	$\boldsymbol{\beta_i}$	$\boldsymbol{u_i}$	Rank
	U_i^+		U_i^-					
	$\prod_{j\in C_b}(\mu_{ij})^{w_j}$	$\sqrt[q]{1-\prod_{j\in C_b}\left(1-v_{ij}^q\right)^{w_j}}$	$\prod_{j\in C_n}(\mu_{ij})^{w_j}$	$\sqrt[q]{1-\prod_{j\in C_n}\left(1-v_{ij}^q\right)^{w_j}}$				
OP.1	0.908784	0.33845242	0.735707	0.530638	0.78516	0.60253	1.303	2
OP.2	0.87843	0.378000887	0.715491	0.525834	0.75021	0.59482	1.261	3
OP.3	0.886785	0.36459722	0.706323	0.545792	0.76109	0.58026	1.311	1
OP.4	0.860063	0.419567284	0.706121	0.56219	0.72024	0.57196	1.259	4
OP.5	0.858743	0.427574802	0.73279	0.560528	0.71558	0.58613	1.220	5

Finally, to derive a single, robust ranking from the three MULTIMOORA models (RS, RP, FMF), an overall utility degree (OUD) was calculated for each firm (Equations 22-25). Table 13 presents these final results. The firm with the highest $\boldsymbol{U(F_i)}$ value is considered the top-performing firm in terms of CBMs adoption potential, providing a conclusive ranking that synthesizes all previous analyses.

Table 13. Results of the overall utility degree

Firms	y_i^*	d_i^*	u_i^*	$U(F_i)$	Rank
OP.1	-0.4511	0.551195	0.458279	-0.15174	5
OP.2	-0.3068	0.540665	0.443551	-0.13728	4
OP.3	-0.25047	0.338019	0.461277	0.025199	1
OP.4	-0.45668	0.32901	0.442856	-0.02378	2
OP.5	-0.65658	0.425866	0.429355	-0.10032	3

5. Conclusion

The circular economy model offers significant benefits, yet its implementation in developing countries like Iran remains nascent and fraught with challenges. This study addressed a critical research gap by systematically identifying and evaluating the drivers and barriers to the adoption of Circular Business Models (CBMs) in the Iranian context. The present study has used a mixed qualitative-quantitative method. In the qualitative phase, the Delphi technique was employed to identify 12 drivers and 17 barriers; in the second phase, a new MCDM method employing q-ROFSs was employed to confirm the validity of the identified drivers and barriers. This analytical method ranks, prioritizes, and evaluates the drivers and barriers to implementing the circular economy model.

The outcomes of the weight analysis indicate that, among the drivers of circular business models, "Comprehensive Monitoring and Ranking (c3)" is the most significant, with a weight of 0.0402. Following closely, "Management Attitudes (c8)" holds the second-highest importance, with a weight value of 0.0391. "Compliance with Production Standards (c2)" ranks third, having a weight value of 0.0345. The weight analysis results reveal that among the barriers associated with circular business models, "Limited Market for Waste (c21)" stands out as the most significant barrier, carrying a weight value of 0.0507. Following closely, "Restrictive Regulations (c17)" ranks as the second most important barrier, with a weight value of 0.0495. "Capability Gaps (c24)" takes the third position, with a weight value of 0.0483. The findings of the present study indicate that, according to the RS and FMF models, the top rank was given to the company producing Arcopal products, which was in the development stage. According to the RP model, the top rank was given to the toy manufacturing company, which was in the maturity stage. Finally, the results of the present study showed that the overall utility degree (OUD) ranking also placed the Arcopal product manufacturing company first.

5.1. Practical and managerial implications

The findings of this study offer several actionable recommendations for managers, entrepreneurs, and policymakers in Iran seeking to accelerate the transition to a circular economy. For policymakers and regulatory bodies, the primary recommendation is to develop secondary material markets to address the most significant barrier, the limited market for waste. This can be achieved by establishing industrial symbiosis networks and by providing tax incentives for the use of recycled materials. Furthermore, a thorough review of existing regulations is urgently needed to reform restrictive regulations, replacing them with policies that support circular innovation. Implementing transparent environmental monitoring and public ranking systems for companies would also leverage the top driver, comprehensive monitoring, by creating a powerful incentive for improved sustainability performance.

For company managers and entrepreneurs, the findings underscore that CBM adoption is a strategic decision requiring top management commitment. Senior leadership must champion sustainability, integrate circular principles into the core company strategy, and allocate necessary resources. To overcome the critical barrier of capability gaps, companies should invest in training programs to build internal expertise in circular design and collaborate with universities. The strong performance of a development-stage company suggests that firms in growth phases may be more agile; therefore, mature companies could benefit from piloting circular initiatives in specific divisions to build experience before a full-scale transformation.

5.2. Limitations and avenues for future research

While this study provides valuable insights, certain limitations should be acknowledged. The focus on a select set of Iranian companies may limit the generalizability of the findings; therefore, future studies should expand the scope to include a larger, more diverse sample across various sectors. The reliance on the Delphi technique is subject to the biases of the selected expert panel; future research could therefore employ complementary qualitative methods, such as in-depth case studies, to triangulate the identified factors. Finally, although the q-ROFS method is powerful, its application is complex, indicating that future studies could replicate this research using alternative multi-criteria decision-making techniques to validate the rankings and enhance comparability.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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