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Assessing the development barriers for f-commerce circular supply chain by using best-worst method

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A B S T R A C T

Based on the Best-Worst Method (BWM) of the multi-criteria decision-making (MCDM) theory, this research aims at solving the obstacles of the development of circular supply chains in the F-commerce (Facebook commerce) industry. The findings indicate that the most relevant barrier is the high entry costs, for small and medium-sized enterprises (SMEs), followed by cultural stereotypes against product's returns. These results reflect the double barrier, economic and socio-cultural that act as impediments to the take-up of circular practices such as reverse logistics, environmentally friendly packaging, and reuse of product. Although operational and infrastructural barriers such as feeble reverse logistics and lack of technology support exist, they are the secondary challenges compared with that of financial and cultural issues. The research highlights the importance of supportive policies, such as subsidies and soft loans, and culturally sensitive consumer education to support circular actions.

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1. Introduction

The world economy has reached such a paradigm shift because a linear, take-make-waste-based system of production cannot be regenerative and used as an alternative to the circular economy (CE). The idea is to make the environment bear less pressure, retain resources and improve the lifecycle of products by using such tasks as recycling, remanufacturing, reuse, and reverse logistics (Geissdoerfer et al., 2017; Kirchherr et al., 2018). The operational embodiment of the CE principles in supply chain, Circular Supply Chain Management (CSCM), involves forward and reverse flows via synthesizing closed-loop systems, and, as such, augments sustainability and the economy (Batista et al., 2018). Although CSCM is progressive because it has been evaluated in several industries, the understanding of its use in digitally enabled micro and small enterprises, especially those that are running on social commerce sites like Facebook (popularly known as F-commerce), is grievously unstudied.

F-commerce is a distinct and emerging smaller part of e-commerce, especially in the developing world like Bangladesh, Indonesia, and India. In contrast to traditional e-commerce systems, f-commerce uses social networking sites, particularly Facebook, to endorse products, communicate with customers, and receive a payment (Sultana & Akter, 2022). The reason why it is rapidly gaining popularity among micro-entrepreneurs is the low cost of setting up, low technological demands and reaching customers directly. Nonetheless, the informality and decentrality of business models of f-commerce also create particular obstacles to circular practices implementation, namely the lack of standardization of logistics, their non-environmental compliance, and low integration with reverse supply networks.

Even though more literature has emerged concerning the adoption of circular supply chains in general e-commerce environments (Govindan & Hasanagic, 2018; Mangla et al., 2018), research can be characterized by an emphasis on big organizations with established systems and ability to access green technologies. These articles outline various hampering factors toward CSCM, such as a shortage of funds, poor technology infrastructure, poor stakeholder cooperation, regulatory confusion, and consumer ignorance (Rizos et al., 2016; Jabbour et al., 2020). Nonetheless, such obstacles do not always imply the situation in f-commerce, in which there are informality of supply chains, unstructured returns, and strongly intuitive approaches to decision-making. Consequently, there is an urgent necessity to gain a systematic evaluation and prioritization of the particular issues that micro- and small-sized f-commerce businesses encounter when implementing CSCM.

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In that respect, it is the decision-support models that can emerge as the means of comprehending and resolving these obstacles. The Analytic Hierarchy Process (AHP) or the Fuzzy TOPSIS are examples of traditional Multi-Criteria Decision-Making (MCDM) methods that have been widely employed in the assessment of a supply chain but tend to have a high pairwise comparison burden and be subject to inconsistency (Saaty, 2008; Shankar et al., 2013). To overcome these constraints, the Best-Worst Method (BWM) formulated by Rezaei (2015) will provide a more effective and repeated method of calculating the weights of the criteria to be used by the experts in terms of their assessment with fewer parallels. BWM has reportedly demonstrated much promise in sustainability analysis, green supplier identification, and risk assessment (Choudhary & Shankar, 2022; Kazancoglu et al., 2021), whereas its use in the scenario of circular supply chains in f-commerce SMEs remains untouched.

Consequently, the need of this study encompasses bridging this gap by working on a decision support model based on BWM in order to name the most crucial impediments to CSCM implementation within f-commerce companies and prioritize them. The proposed study will interview professionals and practitioners who know the dynamics of social commerce to provide a ranked system structure of obstacles that policymakers, businesspeople, and digital services may use in the development of effective interventions. The study not only builds on the existing literature based on circular economies and digital commerce, but it also satisfies the contextually specific requirements of the digital business owners on the grass root level working in the fast-changing resourcing limited environment.
The objective of this research is to identify and evaluate the key development barriers for implementing circular supply chain practices in F-commerce with the aim to prioritize these barriers based on their impact. This will support better decision-making and encourage sustainable growth in the digital retail ecosystem.

2. Literature Review

The shift to Circular Supply Chain Management (CSCM) has become the strategic need of e-commerce companies, mainly regarding the increased attention to sustainability issues, growing waste volumes, and regulation demands. Edwards et al. (2000) covered it with a description of CSCM as coordinating forward and reverse flows to improve economic, social, and ecological sustainability. Their study was also focusing on the significance of product design and closed (flow) logistics, supplier partnerships along the supply chain, stressing that structural frameworks were necessary to facilitate circularity within fast-moving and high-returning e-commerce operations.

Reverse logistics (RL) is one of the most significant frontiers CSC can bring to e-commerce, as compared to bricks-and-mortar retailing a high number of goods are returned. Researchers like GarcÃa et al. (2021) found out that as many as 30 percent of e-commerce-based products are returned, which poses significant operational and environmental costs. Other recent study findings by Agarwal et al. (2021) involved the application of decision tools such as fuzzy TOPSIS to assess third-party logistics (3PL) providers in terms of RL services.

Digital technologies have also become one of the key enablers of CSCM in e-commerce. According to Hossen et al. (2022), technologies, including IoT, RFID, and real-time data systems, allow product monitoring, status measurement, and effective coordination of the logistics network. Bibliometric reviews on Hettiarachchi et al. (2022) revealed the increase in research interest on using the tools of Industry 4.0, including big data and blockchain, in order to enhance transparency, traceability, and data-driven decision-making in circular supply chains. As these technologies have become more widely available, their implementation among small and medium e-commerce companies is not even.

An interesting approach to the problem of trust and accountability in circular systems is traceability, especially on blockchain. Dasaklis et al. (2020) proposed a blockchain model of monitoring mobile phone returns and refurbishment pointing at its effectiveness in achieving authenticity and compliance in high-value e-commerce returns. Such frameworks are most likely to be applicable in electronics or manufacturing industries, however, can be manipulated into consumer e-commerce based on product reuse, repair, and resale being important.

There are several frameworks suggested on how to implement CSC. As an example, Amir (2023) proposes a multi-level model that considers such areas as modular product design, ICT-enabled recovery, and regulatory issues that have particular importance in the context of e-commerce. Mayantia and Helob (2024) combined such concepts as green packaging, product-service system and waste reduction in the framework of the lifecycle based CSCM framework, which can be applied to any logistic, inventory and fulfilment procedures. Even though these frameworks have provided some contributions, most of the frameworks are generic and do not design to work with unique pressures of e-commerce (e.g., customer returns, real time delivery expectations).

Bibliometric and empirical studies have also revealed the growth of scholarly interest towards sustainable e-commerce logistics. According to Seuring et al. (2022), there are prominent clusters of digital logistics, reverse logistics, and circular design that have dominated the post-2020 studies. Such works emphasize the need to have integrated solutions that do not only seek to solve the efficiency aspect of logistics but also seek mechanisms to be environmentally responsible. But, the

majority of empirical models are based on qualitative surveys or descriptive statistics and there is no sound prioritization mechanism that can give guidance to decision-making under uncertainty.
Nevertheless, there is still a visceral research gap to deliver systematic decision-support to circular e-commerce SMEs planning to implement circular supply chain movements. On the one hand, numerous studies point to barriers, although, on the other hand, fewer studies provide a systematic framework to rank or prioritize such barriers depending on their relative importance. In addition, despite the intense coverage of general e-commerce platforms in existing literature, there is scant coverage on f-commerce (Facebook-based commerce) a sector that has increased massively in developing economies. This will be able to perform practically, fact-driven, and scalable implementation of CSCM considering the fast-changing digital fcommerce world.

In a bid to understand the barriers to implementing a circular supply chain in the scenario of f-commerce in a systematic way, review of literature was done exhaustively. The difficulties encountered by e-commerce and the small-to-medium enterprises (SMEs) with respect to embracing the circular economy are discussed in several studies. On the basis of this review, several categories of critical barriers have been deducted, which are anchored by pertinent scholarly sources.
The major barriers identified in the literature are summarized in table 1 below with all the barriers being categorized into thematic categories like financial, technological, organizational and regulatory constraints. The existence of such barriers has been repeatedly mentioned in various works and is the core of the prioritization model suggested in the current research. The mentioned studies empirically and conceptually justify the inclusion of each factor in the framework of decision making.

Table 1
Factors related to Development Barriers for F-commerce

Factors	Notation	Reference
High cost of initial investment	A	Batista et al. (2018); Mangla et al. (2018); Rizos et al. (2016)
Insufficient IT infrastructure and challenges with data security	B	Hettiarachchi et al. (2022); Mangla et al. (2018); Govindan et al. (2015)
Lack of understanding regarding the principles of the circular economy	C	Rizos et al. (2016); Garcia et al. (2021); Khan et al. (2021)
Insufficient law enforcement	D	Govindan & Hasanagic (2018); Rizos et al. (2016)
Limited cooperation between partners	E	Batista et al. (2018); Mangla et al. (2018); Kazancoglu et al. (2021)
Stereotypes against product returns due to culture.	F	Rizos et al. (2016); Khan et al. (2021); Bressanelli et al. (2018)
Data-driven monitoring tools are deployed less frequently.	G	Hettiarachchi et al. (2022); Choudhary & Shankar (2022)

Experts frequently must make tough decisions in today's environment because there are so many possibilities, each having advantages and downsides. Conventional methods of decision-making are not always effective in these complex circumstances. This is where MCDM modelling is useful. It is a method for intelligently and methodically arranging data and coming to judgments. Engineering, business, finance, the environment, healthcare, and the social sciences are just a few of the fields that benefit from MCDM modelling. To assist in decision-making, professionals have developed a wide range of methods within MCDM. Some of these methods and their applications in various sectors are examined in this paper.

Piegat (2015) used the TOPSIS, AHP, and COMET methods to solve chronic liver disease. In this regard, these models allowed a coherent way to choose the most appropriate treatment plan by means of assisting in evaluating and ordering treatment procedures according to different one's health-based criterions. TOPSIS, DEMATEL and MACBETH were the Enterprise Resource Planning (ERP) software packages of Ghosh & Biswas (2016). Assessing different organizational objectives and a complex interrelationship among the criteria, these models supported the selection of ERP systems, i.e. in choosing the most suitable ERP system. AHP and SAW models were employed by Ruby Annette et al. (2016). Using these MCDM models, the users were able to choose the best service for their service requirements by evaluating service providers on the basis of performance, price, and other relevant considerations. In another study, Ceballos et al. (2016) reviewed multi-MOORA, TOPSIS, and VIKOR approaches for various problems. Through analysis of performance under different settings, they manifested how well these models can adapt to the different forms of decision making. To assist with prioritizing the selection of equipment in terms of cost, efficiency and durability, methods such as CODAS, EDAS, WASPAS and MOORA were applied to the feature analysis of the material handling equipment. It was thus easier to pick the best option of the industrially applicable equipment (Mathew & Sahu, 2018).

Valipour et al. employed in their study the same method in their article. (2018) used several techniques, including SWARA, COPRAS, fuzzy ANP, fuzzy AHP, fuzzy TOPSIS, SAW, and EDAS specifically to analyse the risks in investments in PPP projects. Special stress was put on the value of fuzzy logic in minimizing the subjectiveness and vagueness in evaluation of risk in PPP projects. Antoniou and Aretoulis (2018) apply MAUT, TOPSIS, PROMETHEE, and PROMETHEE GDSS to select contracts in the field of highway construction. It also helps to ensure that the most suitable contractors are selected for the project as well as employing a series of criteria to assist in evaluating and rating a contractor. Ing et al. Only Jeiranikhameneh et al. Considering sustainability, affordability and environmental costs of alternative sources of energy, the models were able to identify a sustainable renewable energy source. Nesticò & Somma (2019) used AHP, ELECTRE, TOPSIS, and VIKOR to rank rehabilitation projects on the basis of the technical feasibility, cost, and historical importance, since it involved restoring old structures. By considering sustainability, cost, and strength, Moradian et al. (2019) applied

MOORA, TOPSIS, VIKOR to help select the optimal materials for different purposes. AHP, TOPSIS, ELECTRE III and PROMETHEE II were also the techniques provided to the method for developing the building performance simulation, by Kokaraki et al., (2019). The models allowed the selection of the most attractive designs, considering construction plans scrutinised for cost, impact on the environment and energy efficiency. Harirchian et al, (2020) employed WSM, WPM, AHP, and TOPSIS to investigate RC buildings to facilitate an easy way of assessing how a structure performs with respect to durability, cost, and safety. Ghaleb et al., (2020) employed AHP, TOPSIS, and VIKOR to evaluate manufacturing operations including manufacturing processes that enable the enhancement of ease in the processes, as part of improving manufacturing operations while considering elements like the excellence, cost, and effectiveness.

Kaya (2020) studied the consequences of COVID-19 based on MABAC and WASPAS. The models contributed to formulating successful response strategies by assessing the impact of the pandemic on different businesses. T. Li et al utilized WSM, TOPSIS, PROMETHEE, ELECTRE, and VIKOR methods. (2020) in reviewing renewable energy choices. This research shares a similar focus with the work of Ing et al. (2019), which analysed energy sources considering multiple criteria, seeking the most ecologically friendly options. Sun et al. (2020) estimated disaster risk that applied the WSM, TOPSIS and ELECTRE. By taking other risk factors into account, these models were able to assess what disaster scenarios might befall and develop ways to mitigate them. In another study, Vakilipour, et al. (2021) employed TOPSIS, SAW, VIKOR, and ELECTRE to evaluate quality of urban life. The models provided guidelines for evaluating metropolitan areas according to environmental needs, utility infrastructure, and quality of life. Also, Islam & Arakawa (2022, 2023) applied different models in the supplier's selection such as IFS and fuzzy AHP and fuzzy TOPSIS and Vague set and HFS and WGHFPG and AHP and TOPSIS and Rolling Planning. These researches showed that MCDM models could be applied for evaluating and selecting the suppliers based on criteria such as cost, reliability, and quality.

Indeed, many MCDM models such as AHP, TOPSIS, VIKOR, PROMETHEE and those using fuzzy logic application in their methodology are widely applied in articles, particularly in AHP, TOPSIS, VIKOR, PROMETHEE or others MCDM using fuzzy logic application in their methodology, but yet there is no specific study can be found that used a MCDM model for ranking the obstacles preventing the implementation of a circular supply chain ranking for emerging, informal sector in general and for f-commerce in particular. While existing models are shown to be powerful, many rely on relatively large sample pairwise comparisons and may be inconsistent or expert-fatigued, especially in data-sparse regimes. The BWM – Best-Worst Method (BWM), one of the less familiar MCDM methods, designed by Rezaei (2015) is applied in this paper to fill this hole. It enhances consistency in decisions and reduces the number of comparisons. Of note, BWM is particularly suitable for the condition of expert opinions, small size of samples, and a desire to get reasonable priorities. This paper applies the BWM methodology, and a simple but powerful model is developed to systematically evaluate the major barriers towards successful deployment of circular supply chains in the f-commerce industry and rank those that are most important in order to provide clearer direction for policy makers, businesses and platform players.

3. Methodology

3.1 Research Design: A MCDM approach was adopted in this study to identify and prioritize the key barriers for developing a circular supply chain in F-commerce in Bangladesh. At first some key barriers were identified based on literature review and discussion with experts. Then a pairwise comparison-based MCDM technique, Best-Worst Method (BWM), was used to rank the identified barriers based on expert judgments. The selection of BWM was motivated by its As BWM offers a strong consistency, requires fewer comparisons, and produces reliable results even with a limited number of comparisons.
3.2 Expert Selection and Sampling: Approximately 80 experts had been approached using judgmental and snowball sampling techniques to obtain reliable and relevant insights. However, about 53 experts actually engaged in the discussion and survey process. Experts included both academic scholars and industry practitioners, ensuring a fair mix of theoretical and practical perspectives. The inclusion criteria for experts were as following:

- Minimum of 1 year of professional or academic experience in supply chain, e-commerce, sustainability, or entrepreneurship;
- Engagement with the F-commerce ecosystem, or in circular economy-related research;
- Ability and willingness to provide structured responses for BWM analysis.

3.3 Data Collection: Data were collected in two phases: (1) Identification of Barriers: A preliminary literature review and consultation with experts helped develop an exhaustive list of potential development barriers. These were then validated through expert interviews and finally consolidated into a working set, (2) BWM Survey: Each expert was asked to do pairwise comparisons by selecting the Best and Worst barrier (from the point of view of significance), and rating the Best over all others and all others over the Worst using the 1–9 scale, as per the BWM methodology. The surveys were held through online forms, emails, and structured interviews for four weeks.
3.5 Data Analysis: The responses of each expert were analysed independently to generate local weights for each barrier. These local weights were then aggregated through the arithmetic mean method to obtain the global weights and final ranking. Consistency ratios for each expert's response were calculated, and all responses with acceptable consistency level ($CR < 0.1$) were considered for the final analysis.

3.6 Ethical Considerations: Participants were informed about the research purpose and confidentiality measures. Informed consent was obtained, and anonymity was maintained throughout the study. The research complied with institutional ethical guidelines.

4. Best-Worst Method (BWM)

The Best-Worst Method (BWM), introduced by Rezaei (2015), is a pairwise comparison-based multi-criteria decision-making (MCDM) method used to derive optimal weights for decision criteria. In this study, BWM is applied to prioritize the development barriers in the F-commerce circular supply chain. The steps are as follows:

Step 1. Define a set of criteria
Let $C = \{c_1, c_2, \dots, c_n\}$ represent the set of n criteria (barriers) identified through literature review and expert input that is used to make a decision about alternatives.

Step 2. Define the best and the worst criterion
At this point, the decision-maker is asked to determine the best (most significant, $c_B \in C$ and the worst (least significant, $c_W \in C$ criterion regarded to their importance.

Step 3. Define the preferences of the best criterion over the other criteria and the preferences of all criteria over the worst criterion

In this step the decision-maker provides preference values from the Best criterion c_B to all other criteria using a scale from 1 to 9, where 1 = equal importance, and 9 = extremely more important. The resulting Best-to-Others vector is:

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$$

where: a_{Bj} represents the preference of c_B over c_j, and $a_{BB} = 1$

Then the decision-maker determines a vector called Other-to-Worst which is similar to the following:

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW})$$

where: a_{jW} represents the preference of c_j over c_W, and $a_{WW} = 1$

Step 4. Formulate the optimization model

The objective is to find the optimal weight vector $w = (w_1, w_2, \dots, w_n)$ such that the maximum absolute differences between the pairwise comparisons and the weight ratios are minimized.
The following linear optimization model is formulated:

$$\min_{W,\xi} \xi$$

subject to:

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \le \xi, \quad \forall_j$$

$$\left|\frac{w_j}{w_W} - a_{jW}\right| \le \xi, \quad \forall_j$$

$$\sum_{j=1}^{n} w_j = 1, \quad w_j \ge 0, \quad \forall_j$$

Step 6: Solve the Optimization Problem

This problem is a convex optimization model that can be converted into a linear programming model for solution. The optimal weights w_j^* are obtained, which satisfy the consistency constraints.

Step 7: Calculate the Consistency Ratio (CR)

To ensure the reliability of the comparisons, BWM provides a Consistency Index (CI) based on the best-to-others and others-to-worst comparisons. The Consistency Ratio (CR) is calculated as:

$$CR = \frac{\xi^*}{\xi_{max}}$$

where, ξ^* is the optimal value obtained from the model, and ξ_{max} is the maximum allowable value for consistency (available in Rezaei's consistency index tables). A CR ≤ 0.1 is generally considered acceptable.

Step 8: Aggregation of Expert Judgments

Once individual weights from all consistent expert responses are computed, the group decision weights are obtained by aggregating the individual weights, typically using the arithmetic mean method:

$$w_j^{(group)} = \frac{1}{k}\sum_{i=1}^{k} w_j^{(i)}$$

where, k = total number of consistent experts, and $w_j^{(i)}$ = weight of criterion j from expert i.

5. Data analysis and result interpretation

Table 2
Best to others for 53 respondents

Expert	Best	A	B	C	D	E	F	G
Expert 1	F	3	5	1	1	9	1	9
Expert 2	A	1	5	7	3	8	2	4
Expert 3	D	1	5	5	7	4	3	9
Expert 4	D	3	5	3	1	4	1	8
Expert 5	F	1	7	2	1	9	1	7
Expert 6	D	2	5	5	1	9	5	3
…	…	…	…	…	…	…	…	…
Expert 50	F	3	5	1	2	9	4	8
Expert 51	D	3	5	4	1	4	3	9
Expert 52	A	1	5	7	3	9	2	4
Expert 53	F	2	6	2	1	9	1	7

Table 3
Others to worst for 53 respondents

Expert	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	…	Expert 50	Expert 51	Expert 52	Expert 53
Worst	G	E	G	E	B	E	…	G	E	E	B
A	7	9	8	7	8	8	…	2	7	9	8
B	6	5	5	5	1	5	…	6	5	5	1
C	7	3	3	6	8	3	…	7	6	3	8
D	7	7	3	7	3	4	…	8	7	8	4
E	1	1	7	1	3	1	…	1	1	1	3
F	4	7	8	7	7	6	…	4	8	7	7
G	1	6	1	3	3	7	…	1	3	5	3

Table 4
Weights of the barriers

	Barriers						
Expert	A	B	C	D	E	F	G
Expert 1	0.1203	0.0722	0.2735	0.2735	0.0266	0.1938	0.0401
Expert 2	0.3073	0.1424	0.0855	0.1424	0.0375	0.1424	0.1424
Expert 3	0.3721	0.1644	0.0986	0.0705	0.0986	0.1644	0.0314
Expert 4	0.1212	0.0727	0.1212	0.2491	0.0337	0.3501	0.0519
Expert 5	0.2363	0.0219	0.2604	0.1510	0.0460	0.2385	0.0460
Expert 6	0.3721	0.1644	0.0986	0.0705	0.0986	0.1644	0.0314
…	…	…	…	…	…	…	…
Expert 50	0.1203	0.0722	0.2735	0.2735	0.0266	0.1938	0.0401
Expert 51	0.1212	0.0727	0.1212	0.2491	0.0337	0.3501	0.0519
Expert 52	0.3073	0.1424	0.0855	0.1424	0.0375	0.1424	0.1424
Expert 53	0.2363	0.0219	0.2604	0.1510	0.0460	0.2385	0.0460
Aggregated	0.2321	0.0942	0.1674	0.1761	0.0491	0.2197	0.0613

A total of seven development barriers were identified through literature review and expert opinions. These include: High cost of initial investment (A), Insufficient IT infrastructure and challenges with data security (B), Lack of understanding regarding the principles of the circular economy (C), Insufficient law enforcement (D), Limited cooperation between partners (E), Stereotypes against product returns due to culture (F), Data-driven monitoring tools are deployed less frequently (G).

Each expert was asked to select the most significant (Best) and least significant (Worst) barrier from the list as shown in table 11 and 12. The expert 1, for example, selected F (stereotypes against product returns due to culture) as the Best Barrier, and G (Data-driven monitoring tools are deployed less frequently) as the Worst Barrier. This step helps narrow the pairwise comparison process to two main references- one positive and one negative.

Then the expert was asked to rate how much more important the Best barrier (F) is compared to each of the other six barriers on a scale from 1 to 9, where 1 indicates equal importance and 9 indicates extreme preference for the Best barrier as shown

in table 11. The values given in this example were- F over A: 3, F over B: 5, F over C: 1, F over D: 1, F over E: 9, and F over G: 9. Thus, the Best-to-Others vector becomes: $A_B = (3, 5, 1, 1, 9, 1, 9)$.

After that the expert rated similarly how much more important each barrier is compared to the Worst barrier (g) - A over G: 6, B over G: 9, C over G: 5, D over G: 7, E over G: 8, and F over G: 4. So, the Others-to-Worst vector is: $A_W = (7, 6, 7, 7, 1, 4, 1)$. Rating for other experts are as shown in table 12

In the next step, using these comparison values, a mathematical optimization model was formulated to calculate the optimal weights for each barrier. The model minimizes the maximum absolute deviation between the actual and expected comparison ratios, subject to the conditions that all weights are positive and sum to 1. This step was performed using Excel Solver, an optimization tool. After solving the model, the expert's preferences were translated into a set of normalized weights for each barrier. The results from the expert 1 were: A (0.1203), B (0.0722), C (0.2735), D (0.2735), E (0.0266), F (0.1938), and G (0.0401). All the weights of the barriers are as shown in table 13. These weights indicate the relative importance of each barrier. A higher value implies greater significance in obstructing the development of a circular supply chain in F-commerce.

To ensure the reliability of the expert's judgment, a input based Consistency Ratio (CR) was calculated after obtaining the weights. In this case, the CR was found to be 0.2917, which is well below the acceptable threshold of 0.3517, indicating a high level of consistency in the pairwise comparisons.
This process was repeated for all experts. Once all individual weight sets were calculated, they were aggregated using arithmetic mean to derive the final group weights for each barrier. For example, aggregated weight of barrier A is $\frac{01203 + 0.3073 + 0.3721 + 0.1212 + 0.2363 + 0.3271 + \ldots + 0.1203 + 0.1212 + 0.3073 + 0.2369}{53} = 0.2321$. This aggregation provides a more robust and generalizable result by incorporating insights from multiple stakeholders.

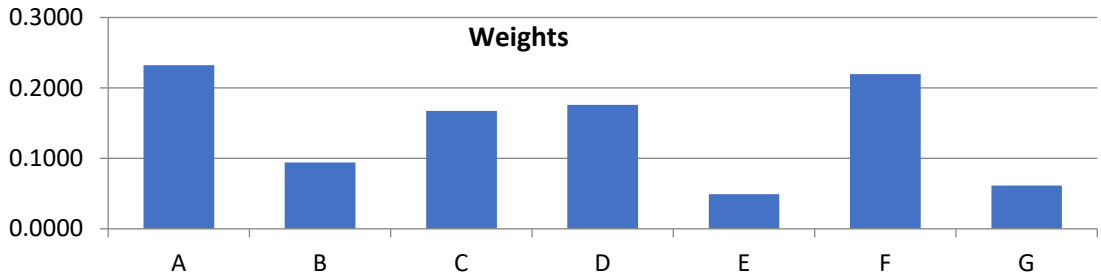

Fig. 1. Weights of the factors

6. Discussion

The use of the BWM has enabled a systematic analysis of top barriers towards promoting closed-loop supply chains within the F-commerce industry. The highest priority barrier is the High cost of initial investment, especially, Stereotypes against product returns due to culture among the SOEs a sharing 91 out of 168 firms. The extremely high entry cost presents a major economic barrier for SMEs, which comprise the major segment for F-commerce. Circular supply chains can require initial investments to incorporate reverse logistics, waste disposal, sustainable packaging, and digital monitoring for F-commerce vendors, working with low margins and few business reserves, the cost of such an outlay simply is not feasible. Recognising this has important implications for effective policy intervention such as subsidies, soft loans or fiscal incentives to reduce the barrier to entry to circularity. The second-highest barrier to shopping, a bias against returns for cultural reasons, shows how entrenched the problem is. Returning or reselling the products is not an option in many cultures, either because it would imply lower quality RGC or because it could be seen as second-hand with an additional stigma or that the seller feels that the costumer is disrespecting the seller in some way. These are negative perceptions that limit consumer participation with return policies and reverse flow mechanisms that are fundamental to circular supply chains. It can be only tackled by such campaigns of public awareness and customer education as are based on local values and behavioural norms. Additional impediments, such as lack of technological infrastructure, weak reverse logistics, and lack of government support were also recognized by the group, although they were assigned low weights, suggesting that although there are operational and systemic enhancements to be pursued, the financial and cultural barriers are the current most pressing threat to the take off of circular F-commerce.

7. Conclusion

The Best-Worst Method (BWM) was used in this work to evaluate and rank the development barriers of circular supply chains in the F-commerce industry. The results showed that the most critical barrier to overcome is the high initial investment, followed by the cultural stereotype about product return. These two obstacles serve to highlight the twin character of the barrier—economic and socio-cultural—to the change form linear to circular in the (digital) commerce perspective.

To overcome the capital constraint, supportive policy environment must be developed such as low interest finance, subsidy and public-private partnership to reduce the capital burden for small and medium F-commerce firms. The cultural market barrier can be addressed with consumer education, changes in behaviour and community-based awareness-building to make circular practices like returns, resale and reuse commonplace.

Other reported obstacles such as infrastructure deficiency and lack of technology were also considered as important, but secondary ones. Economic and cultural resistance will likely make resolution follow.

Nevertheless, the present study is not without its limitations, which must be considered in future studies. The BWM model does not account for a dynamic of expert preferences, that also can change in fast changing markets as F-commerce. Moreover, fuzzy BWM and dynamic MCDM techniques could be used in future research to consider uncertainty and time-variant changes in the attitude of stakeholders. In addition, inter-area and population variations in cultural perception were not studied in greater depth, which leaves ample room for comparative studies.

Finally, addressing the cost and cultural constraints is essential to establish a long-term viable circular supply chain when F-commerce. Such a transformation requires integrated policy making across government, business and consumers, underpinned by future research into the attitudinal, technical and geographical dimensions of the circular economy.

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