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Highlights

- Evaluated reverse logistics in the social commerce platform.
- Developed and used Fuzzy TOPSIS in conjunction with FLINTSTONES.
- Identified the important determinants (criteria) for effective reverse logistics.
- Helped companies devise decision strategies for sustainable reverse logistics.

A Fuzzy TOPSIS Method for Performance Evaluation of Reverse Logistics in Social Commerce Platforms

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Abstract

Reverse logistics initiatives with social commerce not only provide opportunities for firms to create new sources of revenue but also demonstrate their corporate social responsibility via social, green, and environmental activities. Thus, a growing number of companies are attempting to streamline their social commerce platforms to effectively handle reverse logistics. The purpose of this study is to identify the criteria that should be used in designing and evaluating social commerce based reverse logistics processes by firms. We tested the effectiveness of the identified criteria by using them to evaluate the reverse logistics practices of three major global firms that use social commerce platforms. First, we identified the criteria from a thorough review of the literature. Then, we invited five experts to provide (linguistic) ratings of these firms on the selected criteria, using a fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) technique with FLINTSTONES (a software tool) to generate aggregate scores for the assessment and evaluation of reverse logistics practices in social commerce platforms. Sensitivity analysis was also provided to monitor the robustness of the approach. The results of the study identified that four dominant criteria (reverse logistics performance indicators) in the social commerce platform: Customer relationship, Usage risk, Reviews, and Quality control.

Keywords: Fuzzy sets; reverse logistics; social commerce; TOPSIS; sensitivity analysis; FLINTSTONES.

1. Introduction

The forceful drivers for the fast growth of reverse logistics are many, including the increasing shortage of natural resources, environmental law, the realization of backward flow value, e-business development, good reputation requirement, customer satisfaction, and the population of information systems (Škapa & Klapalová, 2012). Rogers and Tibben-Lembke (1999) defined reverse logistics as "The process of planning, implementing, and controlling the efficient, cost-effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal" (Roger & Tibben-Lembke, 1999).

The goal of reverse logistics is to focus on the reverse flow of materials by maximizing their value (G. Kannan, Pokharel, & Kumar, 2009). Products are returned through the supply chain for a variety of reasons: commercial returns, warranty returns, reusable articles, product recalls, end-of-use returns (EOU) and end-of-life returns (EOL) (Han & Ponce-Cueto, 2016). The rate of returns has increased by 57% for retailers and 43% for manufacturers respectively over the past three to five years, as surveyed by Accenture (Zaarour, Melachrinoudis, Solomon, & Min, 2014). Many businesses suffer significantly from poor management of the returns. Only returned products, as reported by CNBC, cost firms more than $260 billion a year and an average profit loss of 10% (McKevitt, 2016).

The efficient implementation of reverse logistics requires an appropriate communication platform. Social commerce, a new business model of e-commerce, makes use of Web 2.0 technologies and social media to support social-related exchange activities. It offers a platform connecting consumers and companies integrating e-business, customer relationship management, technology support, and information systems. Given the enormous effect of returned items on the company‟s bottom line and social commerce´s popularity, an increasing number of firms have made efforts to streamline their reverse logistics process in social commerce platforms (Tavana, Zareinejad, Caprio, & Kaviani, 2016).

This study focuses on identifying the criteria for effective management of returns through social commerce platforms and evaluating the reverse logistics efficiency of top global companies that use social commerce platforms. Firstly, a previous study, based on a thorough review of literature, identified four main criteria with sixteen sub-criteria from social commerce activities (Han & Trimi, 2017). Then, this research invited five experts to evaluate the reverse logistics performance of three top global companies on these criteria. The identification and evaluation of key evaluation criteria will help researchers and managers in strategic decision-making for reverse logistics implementation.

In this study, we applied a fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) technique with FLINTSTONES (a software tool) to assess how efficient companies use social commerce platforms for their reverse logistics process. TOPSIS is based on the notion that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution (Hwang & Yoon, 1981). While effective management of reverse logistics is vital to enhance customer satisfaction and improve organizational performance, it is difficult to evaluate the performance of the system due to lack of measurable standards and limited data. In this study, the fuzzy set theory is introduced to model vagueness and uncertainty, which is combined with TOPSIS to form fuzzy TOPSIS. Fuzzy TOPSIS has become popular among researchers and practitioners because of its numerous advantages as follows:

- It is practical and has the ability to provide solutions with partial or incomplete quantitative information (Awasthi, Chauhan, & Goyal, 2010; Awasthi, Chauhan, Omrani, & Panahi, 2011);
- It allows expressing preferences in the form of natural language parameterized by triangular fuzzy numbers;
- It can compare the best and the worst solutions quantitatively;
- It is easy to implement the algorithm (Chang & Tseng, 2008).

The proposed approach is comprised of three steps as shown in Fig. 1. In Phase 1, we identify the criteria for assessing the reverse logistics process on the social commerce platform. In Phase 2, experts are invited to provide linguistic evaluation ratings of the three global companies against the identified criteria. Fuzzy TOPSIS is adopted to generate aggregate scores for assessment and evaluation of the reverse logistics performance. The sensitivity analysis is also applied for testing the robustness of the method. In Phase 3, software tool FLINTSTONES is used to check and adjust the evaluation result.

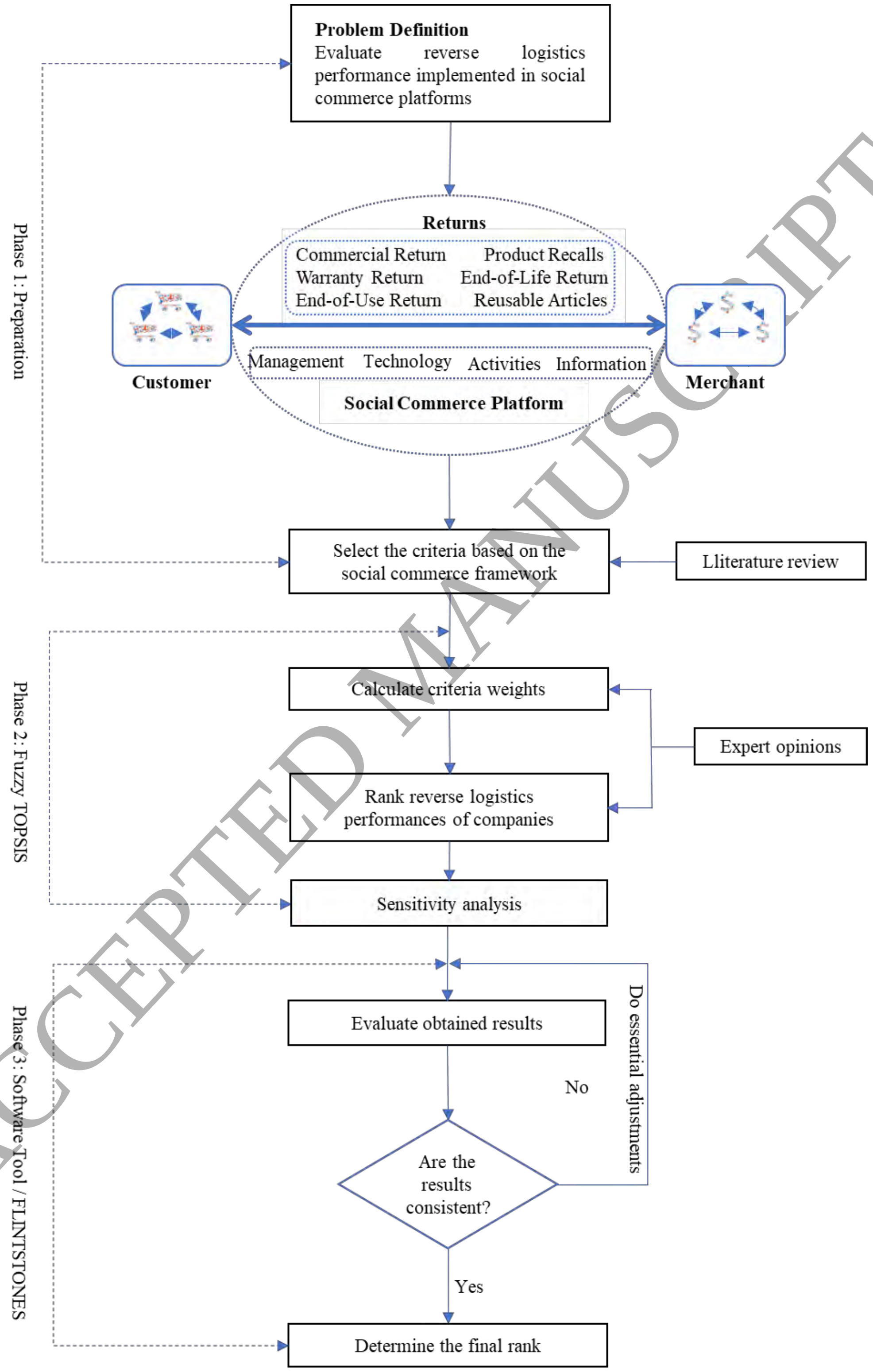

Fig. 1. Schematic diagram of the proposed model.

The rest of the paper is organized as follows. Section 2 presents theoretical background, followed by a note on research methodology in Section 3. Section 4 provides a numerical illustration for the application of fuzzy TOPSIS. Finally, research results and future research needs are discussed in Section 5.

2. Literature review

A review of literature indicates that reverse logistics in social commerce platforms has received only limited attention. Also, fuzzy TOPSIS has not been applied to evaluating reverse logistics performance in the social commerce platform (Behzadian, Otaghsara, Yazdani, & Ignatius, 2012). We reviewed the theoretical background from two aspects: the literature on solving reverse logistics-related problems using fuzzy TOPSIS and commonly used criteria for performance assessment.

2.1. Application of fuzzy TOPSIS to reverse logistics problems

With the growing worldwide attention to sustainable supply chain management, application of fuzzy TOPSIS to reverse logistics problems has received increased attention. Overall, we can classify the approaches of solving reverse logistics problems using fuzzy TOPSIS in three streams:

- **Stream 1:** Selection of the best third-party reverse logistics providers (3PRLPs) or green suppliers.

G. Kannan, Pokharel, and Kumar (2009) developed Interpretive Structural Modeling (ISM) and fuzzy TOPSIS to guide the selection process of best third-party reverse logistics providers. The effectiveness of the model was illustrated using a case study of the battery manufacturing industry in India. Fuzzy AHP was also used for correct evaluation and ranking of the decision criteria/priorities in selecting the best 3PRLPs when a company decides to outsource reverse logistics activities (Tavana et al., 2016). To evaluate and determine green suppliers, Büyüközkan and Çifçi (2012) proposed several strategic environmental considerations in an integrated multiple criteria decision-making model combined with fuzzy TOPSIS. In another study, a framework using fuzzy TOPSIS was proposed for selecting green suppliers for a Brazilian electronics company (D. Kannan, Beatriz, Sousa, José, & Jabbour, 2014). The framework was built on the criteria of green supply chain management (GSCM) practices of 12 suppliers.

- **Stream 2:** Location decision problem

Alimoradi, Yussuf, and Zulkifli (2011) implemented the fuzzy TOPSIS method to find the best place to locate a remanufacturing facility in a discrete space. Ekmekçioĝlu, Kaya, and Kahraman (2010) used a modified fuzzy TOPSIS to select appropriate disposal methods and sites for municipal solid waste.

- **Stream 3:** Reverse logistics process

Hsueh and Lin (2014) constructed a network model to rank alternatives for implementing the sorting process of reverse logistics in the downstream photovoltaic industry. The proposed model combined the benefits, opportunities, costs, and risks and the network concept to construct the framework. Sivapirakasam, Mathew, and Surianarayanan (2011) developed a combination of Taguchi and fuzzy TOPSIS methods to solve multi-response parameter optimization problems in green manufacturing. Awasthi, Chauhan, and Goyal (2010) presented a fuzzy TOPSIS approach for evaluating the environmental performance of suppliers under the fuzzy environment. Later, Awasthi, Chauhan, and Omrani (2011) presented a fuzzy TOPSIS approach for sustainability assessment of urban transportation systems under the fuzzy environment. Nazam, Xu, Tao, Ahmad, and Hashim (2015) used a fuzzy AHP-TOPSIS methodology to rank and assess the risks associated with the implementation of green supply chain management practices under the fuzzy environment. Then the proposed model was applied to a practical case in the textile manufacturing industry.

2.2. Criteria

Evaluation of reverse logistics performance in social commerce platforms is vital to improve operational effectiveness, gain profits and increase customer satisfaction. Table 1 presents lists of important studies that explored information, management, state of art technologies, and social-related exchange activities that are the most commonly referred criteria in performance evaluation of reverse logistics.

Table 1

Commonly used criteria for performance assessment of reverse logistics.

Main Criteria	Reference
Information	Ding (2011); Liao and Kao (2011); Lee, Chiang, and Chen (2012); Erdoğan, Bilişik, Kaya, and Baraçlı (2013); Patil and Kant (2014); Alptekin, Hall, and Sevim (2015) Nagpal, Mehrotra, Kumar Bhatia, and Sharma, (2015); Nazam et al. (2015); Agrawal, Singh, and Murtaza (2016).
Management	Awasthi et al. (2010); Sun (2010); Liao and Kao (2011); Torlak, Sevkli, Sanal, and Zaim (2011); Lee et al. (2012); Hsueh and Lin (2014); Patil and Kant (2014); Alptekin et al. (2015); Nagpal et al. (2015); Nazam et al. (2015); Agrawal et al. (2016); Dixit and Badgaiyan (2016); Lima-Junior and Carpinetti (2016); Tavana et al. (2016).
Technology	G. Kannan et al. (2009); Awasthi et al. (2010); Liao and Kao (2011); Büyüközkan and Çifçi (2012); Patil and Kant (2014); Safari and Ajalli (2014); Nazam et al. (2015).
Activities	Kim, Lee, Cho, and Kim (2011); Torlak et al. (2011); Nagpal et al. (2015).

Information: It is evident that the integration of information flows of reverse logistics is needed to pursue environmental and economic benefits (Agrawal et al., 2016). Through the well configured social commerce platform, enterprises can obtain information that can help secure customer satisfaction. Currently, there is a limited number of enterprises that effectively use information systems in the management of reverse logistics (Alptekin et al., 2015). Information of reverse logistics can be fully shared through a social commerce platform when B2C achieve a „zero distance‟‟ communication (Shi, Li, Yang, Li, & Choi, 2012).

Management: Effective reverse logistics management can help organizational performance by cutting costs, improving customer satisfaction, and enhancing internal processes (Hsueh & Lin, 2014). Changes and improvements brought by social commerce provide new managerial insights for reverse logistics. Specifically, effective management of social commerce can strengthen the functions of reverse logistics systems (Sun, 2010).

Technology: Advances in technology have dramatically influenced the daily lives of individuals, organizations and the way of collecting returned goods over the past several years

(Awasthi, Chauhan, & Omrani, 2011). Technology is the factor that can facilitate innovation and flexibility of reverse logistics. Social media, Web 2.0, cloud computing, and service-oriented architecture are the typical contents of the technology factor. Technology facilitates collecting returns in a social commerce platform in an innovative, flexible and environmentally friendly manner (Gülçin Büyüközkan & Çifçi, 2012).

Social Activities: Social commerce refers to exchange-related social activities that occur in, or are influenced by, an individual's social network in computer-mediated social environments (Nagpal et al., 2015). Reverse logistics through social-related exchange activities in a social commerce platform includes forums and communities, reviews, tagging, M-commerce, and L-commerce, wish lists, and social curation (Torlak et al., 2011).

The advantage of using advanced information systems, effective management strategies, deployment of new technologies, and social-related exchange actives with consumers will all help the implementation of reverse logistics in the social commerce platform.

3. Fuzzy TOPSIS

Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), one of the classic methods for solving multiple criteria decision making (MCDM) problems, was first developed by Hwang and Yoon (1981). The principle of this method is that the most preferred alternative should have the shortest distance from the positive ideal solution (PIS), i.e., the solution that maximizes the benefit criteria and minimizes the cost criteria; and the farthest distance from the negative ideal solution (NIS), i.e., the solution that maximizes the cost criteria and minimizes the benefits criteria (Singh & Benyoucef, 2011).

In classical TOPSIS, the criteria weights and the alternatives performance ratings are given as crisp numerical data. However, under real-life conditions, crisp data is difficult to derive since human opinions are vague and cannot be evaluated with exact numbers (G. Kannan et al., 2009). Therefore, the fuzzy set theory has been combined in numerous MCDM approaches including TOPSIS. Chen and Hwang (1992) first applied fuzzy numeric values to establish fuzzy TOPSIS. In fuzzy TOPSIS all the ratings and weights are given by linguistic variables that are expressed by fuzzy numbers. Recently, fuzzy TOPSIS methods and their applications have spread widely by more scholars (Kelemenis, Ergazakis, & Askounis, 2011).

3.1. Fuzzy set theory

Fuzzy set theory, which was introduced by Zadeh (1965) to deal with problems involving uncertainty and vagueness, utilizes linguistic terms to represent the decision maker‟s choices. Then linguistic terms are converted into triangular fuzzy numbers (TFN). To capture the vagueness of the linguistic assessments and also contribute to the easy usage and computational simplicity, triangular fuzzy numbers are generally applied in practical utilizations (D. Kannan et al., 2014). A triangular fuzzy number can be illustrated as a triplet (a, b, c); the membership function of the fuzzy number $F(x)$ is defined in Fig. 2 and expressed as:

$$F(x) = \begin{cases} \frac{x-a}{b-a}, a \leq x \leq b \\ \frac{c-x}{c-b}, b \leq x \leq c \\ 0, \quad otherwise \end{cases} \quad (1)$$

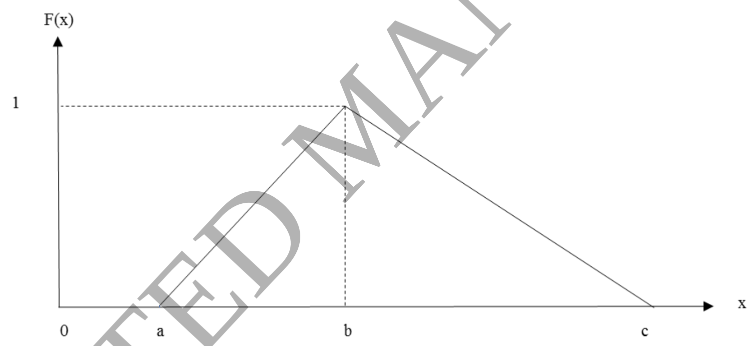

Fig. 2. Membership function of triangular fuzzy number.

In the following, some essential definitions and basic important properties of fuzzy sets are given.

Let $A_1 = (a_1, b_1, c_1)$ and $A_2 = (a_2, b_2, c_2)$ be two triangular fuzzy numbers. Then the functional rules of the two triangular fuzzy numbers are shown below:

$$A_1 + A_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \quad (2)$$

$$A_1 \times A_2 = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2) \quad (3)$$

$$k \times A_1 = (k \times a_1, k \times b_1, k \times c_1) \; where \; k > 0 \quad (4)$$

3.2. Linguistic variable

A linguistic variable is a variable that is expressed in linguistic terms such as artificial words or natural sentences which are then displayed by triangular fuzzy numbers (D. Kannan et al., 2014). In this study, we adopt a range of 1–9 to score the criteria and the alternatives. Table 2 shows the linguistic variables and the corresponding TFN used for the criteria and alternatives respectively.

Table 2

Linguistic terms for criteria and alternatives ratings.

Criteria	Alternatives	
Linguistic term		Triangular fuzzy numbers
Very low (VL)	Very poor (VP)	(1, 1, 3)
Low (L)	Poor (P)	(1, 3, 5)
Medium (M)	Fair (F)	(3, 5, 7)
High (H)	Good (G)	(5, 7, 9)
Very high (VH)	Very good (VG)	(7, 9, 9)

3.3. Fuzzy TOPSIS procedure

The fuzzy TOPSIS procedure includes the following steps:

Step 1: Assign ratings to the criteria and alternatives

Assume there are a group of k experts $(E_1, E_2, \cdots, E_k)$ with m possible alternatives $(A_1, A_2, \cdots, A_m)$, which are to be evaluated against n criteria $(C_1, C_2, \cdots, C_n)$. The criteria weights are denoted by W_{NK} *(N = 1,2, …, n; K = 1,2, …, k)* and the performance ratings of alternatives with respect to criteria by experts are denoted as X_{NKM} *(N = 1,2, …, n; K = 1,2, …, k; M = 1,2, …, m)*.

Step 2: Aggregate the evaluation of the criteria and alternatives

We assume fuzzy ratings W_{NK} and X_{NKM} are describe as triangular fuzzy numbers (a_K, b_K, c_K) (*K = 1,2, …, k*), then, the aggregated importance can be evaluated as:

$$a = min\{a_K\}, b = \frac{1}{k}\sum_{K=1}^{k} b_K, c = max\{c_K\} \qquad (5)$$

Step 3: Normalize triangular fuzzy numbers

The raw data is normalized using linear scale transformation to bring the various criteria scales into a comparable scale.

If W_{NK} represents benefit criteria, then: $\left(\frac{a_K}{c}, \frac{b_K}{c}, \frac{c_K}{c}\right)$ (6)

If W_{NK} represents cost criteria, then: $(\frac{a}{c_K}, \frac{a}{b_K}, \frac{a}{a_K})$ $(a = min\{a_K\}, c = max\{c_K\})$ (7)

Step 4: Compute weighted normalized fuzzy values

${W_{NK}}^*$ becomes W_{NK} after normalization, ${X_{NKM}}^*$ is $new\ X_{NKM}$ after aggregation.

Let the weighted normalized value be V_{NKM}.

$$V_{NKM} = {W_{NK}}^* \times {X_{NKM}}^* \quad (8)$$

Where *N = 1,2, …, n; K = 1,2, …, k; M = 1,2, …, m*; the corresponding triangular fuzzy number of V_{NKM} is $(a_{V_{NKM}}, b_{V_{NKM}}, c_{V_{NKM}})$

Step 5: Calculate fuzzy positive ideal solutions (FPIS) and fuzzy negative ideal solutions (FNIS);

FPIS = (c_V, c_V, c_V) where $c_V = max\{c_{V_{NKM}}\}$ (9)

FNIS = (a_V, a_V, a_V) where $a_V = min\{a_{V_{NKM}}\}$ (10)

Step 6: Calculate the distance of each alternative from FPIS and FNIS;

The distance of each alternative from FPIS (d^+) and FNIS (d^-) is now calculated, respectively, as follows:

$$d^+ = \sqrt{\frac{1}{3}[(a_{V_{NKM}} - c_V)^2 + (b_{V_{NKM}} - c_V)^2 + (c_{V_{NKM}} - c_V)^2\,]} \quad (11)$$

$$d^- = \sqrt{\frac{1}{3}[(a_{V_{NKM}} - a_V)^2 + (b_{V_{NKM}} - a_V)^2 + (c_{V_{NKM}} - a_V)^2\,]} \quad (12)$$

Step 7: Calculate the closeness coefficient (CC_M)

$$CC_M = \frac{\sum_1^n d_{NM}^-}{\sum_1^n d_{NM}^+ + \sum_1^n d_{NM}^-}, N = 1,2,\dots,n;\ M = 1,2,\dots,m \quad (13)$$

4. Application

Fuzzy TOPSIS provides a systematic approach for identifying, evaluating and monitoring reverse logistics performance with a set of criteria. The advantage of the proposed method is its practical applicability and ability to afford a solution when information is poor (partial or limited quantity). To illustrate the proposed approach, this study provides a numerical application.

4.1. Definition of relevant criteria

The focus of this study is the evaluation of reverse logistics performance on the social commerce platform. The proposed method utilizes a set of four main criteria and sixteen sub-criteria from the social commerce framework proposed by Han and Trimi (2017). A social commerce platform, a key element of the social commerce framework, is the linkage component (connecting the other two constituents, Customer and Merchant) through which people communicate, share, and collaborate with four entities: Information, Management, Technology, and Social Activities (the four main criteria).

The main criteria are: Information (C_1), Management (C_2), Technology (C_3) and Social Activities (C_4). Information (C_1) contains two sub-criteria: social networking services/sites (C_{11}) and user-generated contents (C_{12}). Management (C_2) involves customer relationship (C_{21}), quality control (C_{22}), usage risk (C_{23}) and cost (C_{24}). Technology (C_3) includes social media (C_{31}), Web 2.0 (C_{32}), cloud computing (C_{33}), and service-oriented architecture (C_{34}). There are forums and communities (C_{41}), reviews (C_{42}), tagging (C_{43}), M-commerce and L-commerce (C_{44}), wish lists (C_{45}), and social curation (C_{46}) in the fourth main criteria Social Activities (C_4). Table 3 presents the details of these criteria.

The social commerce platform is where information is generated and shared, related to business operations, products/services, or simply social data. Thus, the Information element is the most representative of the uniqueness of social commerce (Shadkam & O'Hara, 2013). Management involves strategies for multi-channeling co-creation and relevant platforms, critical for the purpose of collectively gathering information through a variety of social shopping channels. Technology offers customers user-friendly interface with rich media and clear links for navigation, as a direct marketing tool to support their decision-making processes and social commerce behavior. It refers to the information and communication technology (ICT) infrastructure and applications responsible for the feasibility of social commerce (Shanmugam & Jusoh, 2014). Social Activities are related to the various forms of user-generated contents

(UGCs), support of customers´ decisions by crowdsourcing, and transactions and relationships with customers.

Table 3

Selected criteria for evaluating reverse logistics performance in social commerce platform.

Main Criteria	Sub-criteria	Definition or checklist	Category
Information (C_1)	Social networking services/sites (SNSs) (C_{11})	e.g., Facebook, LinkedIn, and Google+ • Easy to find information on the website • Easy to link to other websites • Fast display of the web page • Effective information delivery service • Correct information displayed • Expert˝s information service • Communication system	B
	User-generated content (C_{12})	e.g., Blogs, wikis, discussion forums, posts, chats, tweets, podcasting, pins, digital images, video, audio files • Accurate • Complete • Relevant • Updates • Usefulness	B
Management (C_2)	Customer relationship (C_{21})	• Problem dealing mechanism: Clear instructions, help functions and feedback • Provide relative information for problem-solving • Response to customer˝s request quickly • Understand individual needs • Provide personalized information • Provide various personalized services	B
	Quality control (C_{22})	• Service Quality • System Quality • Information Quality • Technical quality • Relationship quality	B
	Usage risk (C_{23})	• Privacy security policy • Confidentiality of customer˝s information • Customer˝s information is not stolen	C
	Cost (C_{24})	• Warranty cost • Maintenance cost • Social responsibility cost • Recycle education and promotion cost • Error cost of returned goods	C
Technology (C_3)	Social media (C_{31})	Computer-mediated technologies that allow the creating and sharing of information, ideas, career interests and other forms of expression via virtual communities and networks.	B
	Web 2.0 (C_{32})	World Wide Web websites that emphasize user-generated content, usability (ease of use, even by non-experts), and interoperability (this means that a website can work well with other products, systems and devices) for end users.	B
	Cloud computing (C_{33})	A type of Internet-based computing that provides shared computer processing resources and data to computers and other devices on demand.	B
	Service-oriented architecture (SOA) (C_{34})	A style of software design where services are provided to the other components by application components, through a communication protocol over a network.	B
Social Activities (C_4)	Forums and communities (C_{41})	Develop and invite customers to share their information and experiences about the returned product or service (an example of online forums and communities can be a company˝s Facebook page)	B
	Reviews (C_{42})	Original social commerce toolset that allows people to exchange returns feedback and inform each other's choices with independent views and experiences	B
	Tagging (C_{43})	Content categorization by users˝ tagging (i.e., short description that facilitates searching)	B
	L-commerce and M-commerce (C_{44})	Embed GPS location services tracking and deployment of mobile and smart technologies for returns assistance	B
	Wish lists (C_{45})	Enabling customers to create list of desired services related to returned products, with different privacy settings, such as Listmania lists	B
	Social curation (C_{46})	Combining social features such as sharing, liking, following, and commenting, with the curating capabilities of bookmarking, tagging, and recommending (e.g., Pinterest)	B

B: Benefit (the more the better); **C**: Cost (the less the better)

4.2. Formation of the expert group

Multiple expert opinions were considered when weighting criteria and alternatives. The uncertainty of weights and proxy data were incorporated using the fuzzy concept. In this step, more rational judgments are made by a group of experts rather than by a single professional person. Each expert has a unique educational background and professional expertise compared to that of others. This leads to different levels of knowledge over different aspects of reverse logistics performance. Five professionals, all with Ph.D. degrees and real-world experience, were invited to be in the expert board. The first expert‟s research interests include online marketplaces, E-procurement, E-negotiations, E-health, Web 2.0 and management information systems. The second expert offers expertise in the areas of global business strategies, strategic innovation, technology convergence, ICT for business solutions, operations innovation, and international management. The third is an expert on the application of stochastic methods and data analytics for service improvement and cost reduction in the service sector, such as the airline industry, newly arising supply chain management problems resulting from the use of unmanned aircraft systems technology. The fourth expert focuses on the areas of business/big data analytics, global information systems and supply chain, electronic commerce and data communications and networking. The fifth expert has a broad expertise in business analytics, especially in optimization techniques, computer-based simulations, and Big Data.

4.3. Evaluation of alternatives by fuzzy TOPSIS

Names of these well-known global companies are not disclosed here because of confidentiality. They are referred as $A_1, A_2, and\ A_3$, respectively. The three companies (alternatives) will be evaluated using the social commerce framework criteria (Table 3) by a committee of five experts (*E1, E2, E3, E4,* and *E5*). The experts used linguistic assessments (Table 2) to obtain preference weights for the criteria and to rate the three global companies on the criteria. The results are shown in Tables 4 and 5, respectively.

Table 4

Experts" preference of each criterion weight in the linguistic term.

Criteria	**Experts**				
	E1	*E2*	*E3*	*E4*	*E5*
C_{11}	VH	VH	H	H	M
C_{12}	H	H	H	H	H
C_{21}	VH	VH	VH	VH	VH
C_{22}	H	VH	H	H	VH
C_{23}	H	VH	H	VH	VH
C_{24}	M	VH	M	H	VH
C_{31}	VH	H	H	VH	M
C_{32}	M	H	M	H	VH
C_{33}	L	H	H	H	M
C_{34}	L	H	M	H	H
C_{41}	VH	VH	M	VH	M
C_{42}	VH	H	H	VH	H
C_{43}	H	M	M	VH	M
C_{44}	L	VH	H	VH	VH
C_{45}	M	H	M	H	M
C_{46}	H	H	H	H	M

Key: **VH** – Very High; **H** – High; **M** – Medium; **L** –Low; **LV** – Very Low

Table 5

Experts" ratings of the three companies.

Criteria	**Experts**														
	E1			*E2*			*E3*			*E4*			*E5*		
	A1	A2	A3	A1	A2	A3	A1	A2	A3	A1	A2	A3	A1	A2	A3
C_{11}	F	G	F	VG	G	VG	G	G	G	VG	VG	G	VG	VG	F
C_{12}	G	G	F	P	VG	VG	G	G	VG	VG	G	G	F	G	F
C_{21}	F	VG	VG	G	F	F	VG	G	G	VG	VG	G	G	VG	G

C_{22}	F	VG	VG	VG	G	G	G	G	VG	VG	VG	G	F	VG	G
C_{23}	G	G	F	G	G	F	G	G	G	VG	VG	VG	F	G	G
C_{24}	F	F	F	F	G	G	F	G	G	VG	VG	G	VG	VG	F
C_{31}	VG	G	P	F	VG	G	G	G	G	VG	VG	G	F	F	G
C_{32}	G	F	P	G	P	G	F	VG	G	VG	VG	F	G	F	F
C_{33}	VG	F	F	G	F	F	G	F	G	G	G	VG	F	G	VG
C_{34}	VG	G	VP	VG	G	VP	G	G	VP	VG	G	P	G	VG	P
C_{41}	VG	G	F	G	G	G	VG	F	F	VG	G	G	VG	G	G
C_{42}	G	G	G	VG	G	G	G	F	F	VG	G	G	G	G	F
C_{43}	G	P	P	F	F	F	G	G	G	G	G	G	F	F	F
C_{44}	P	VP	P	VP	F	G	F	G	G	P	P	G	F	P	G
C_{45}	P	VP	P	P	F	G	F	F	F	P	P	G	F	P	G
C_{46}	G	VP	P	G	F	G	G	G	G	VG	P	G	VG	P	F

Key: **VG** – Very Good; **G** – Good; **F** – Fair; **P** –Poor; **LP** – Very Poor

The linguistics terms were then transformed into fuzzy triangular numbers. Then, the aggregated fuzzy weights were calculated using Eq. (5). For example, for criteria C_{11}, the aggregated fuzzy weight is calculated as: a_{11}= min (7,7,5,5,3) =3; $b_{11}=\frac{1}{5}\sum(9+9+7+7+5)=7.4$; c_{11}= max (9,9,9,9,7). The computed results of each criterion and alternatives with respect to criteria are presented in Table 6 and Table 7, respectively.

Table 6

Aggregate fuzzy weights and ranking of each criterion.

Criteria	Aggregate fuzzy weight	Rank
C_{11}	(3, 7.400, 9)	5
C_{12}	(5, 7.000, 9)	4
C_{21}	(7, 9.000, 9)	1
C_{22}	(5, 7.800, 9)	3
C_{23}	(5, 8.200, 9)	2
C_{24}	(3, 7.000, 9)	6
C_{31}	(3, 7.400, 9)	5

C_{32}	(3, 6.600, 9)	7
C_{33}	(1, 5.800, 9)	11
C_{34}	(1, 5.800, 9)	11
C_{41}	(3, 7.400, 9)	5
C_{42}	(5, 7.800, 9)	3
C_{43}	(3, 6.200, 9)	8
C_{44}	(1, 7.400, 9)	10
C_{45}	(3, 5.800, 9)	9
C_{46}	(3, 6.600, 9)	7

Table 7 Fuzzy aggregated decision matrix for companies.

Criteria	A1	A2	A3
C_{11}	(3, 7.800, 9)	(5, 7.800, 9)	(3, 6.600, 9)
C_{12}	(1, 6.200, 9)	(5, 7.400, 9)	(3, 7.000, 9)
C_{21}	(3, 7.400, 9)	(3, 7.800, 9)	(3, 7.000, 9)
C_{22}	(3, 7.000, 9)	(5, 8.200, 9)	(5, 7.800, 9)
C_{23}	(3, 7.000, 9)	(5, 7.400, 9)	(3, 6.600, 9)
C_{24}	(3, 6.600, 9)	(3, 7.400, 9)	(3, 6.200, 9)
C_{31}	(3, 7.000, 9)	(3, 7.400, 9)	(1, 6.200, 9)
C_{32}	(3, 7.000, 9)	(1, 6.200, 9)	(1, 5.400, 9)
C_{33}	(3, 7.000, 9)	(3, 5.800, 9)	(3, 7.000, 9)
C_{34}	(5, 8.200, 9)	(5, 7.400, 9)	(1, 1.800, 5)
C_{41}	(5, 8.600, 9)	(3, 6.600, 9)	(3, 6.200, 9)
C_{42}	(5, 7.800, 9)	(3, 6.600, 9)	(3, 6.200, 9)
C_{43}	(3, 6.200, 9)	(1, 5.400, 9)	(1, 5.400, 9)
C_{44}	(1, 3.400, 7)	(1, 3.800, 9)	(1, 6.200, 9)
C_{45}	(1, 3.800, 7)	(1, 3.400, 7)	(1, 5.800, 9)
C_{46}	(5, 7.800, 9)	(1, 3.800, 9)	(1, 5.800, 9)

Depending on the benefit or cost criteria, we perform normalization of the fuzzy decision matrix using Eqs. (6) and (7). For example, if a criterion belongs to the benefit (B) category, we should use Eq. (6); if a criterion belongs to the cost (C) category, we use Eq. (7). For example, the normalized rating for alternative A1 for criteria C_{11} is given by: a_{11}*= min (3,5,3) =3; c_{11}*= max (9,9,9) =9. We computed the normalized values of the three companies, and the results are shown in Table 8.

Table 8

Normalized fuzzy decision matrix.

Criteria	A1	A2	A3
C_{11}	(0.333, 0.867, 1.000)	(0.556, 0.867, 1.000)	(0.333, 0.733, 1.000)
C_{12}	(0.111, 0.689, 1.000)	(0.556, 0.822, 1.000)	(0.333, 0.778, 1.000)
C_{21}	(0.333, 0.822, 1.000)	(0.333, 0.867, 1.000)	(0.333, 0.778, 1.000)
C_{22}	(0.333, 0.778, 1.000)	(0.556, 0.911, 1.000)	(0.556, 0.867, 1.000)
C_{23}	(0.333, 0.429, 1.000)	(0.333, 0.405, 0.600)	(0.333, 0.455, 1.000)
C_{24}	(0.333, 0.455, 1.000)	(0.333, 0.405, 1.000)	(0.333, 0.484, 1.000)
C_{31}	(0.333, 0.778, 1.000)	(0.333, 0.822, 1.000)	(0.111, 0.689, 1.000)
C_{32}	(0.333, 0.778, 1.000)	(0.111, 0.689, 1.000)	(0.111, 0.600, 1.000)
C_{33}	(0.333, 0.778, 1.000)	(0.333, 0.644, 1.000)	(0.333, 0.778, 1.000)
C_{34}	(0.556, 0.911, 1.000)	(0.556, 0.822, 1.000)	(0.111, 0.200, 0.556)
C_{41}	(0.556, 0.956, 1.000)	(0.333, 0.733, 1.000)	(0.333, 0.689, 1.000)
C_{42}	(0.556, 0.867, 1.000)	(0.333, 0.733, 1.000)	(0.333, 0.689, 1.000)
C_{43}	(0.333, 0.689, 1.000)	(0.111, 0.600, 1.000)	(0.111, 0.600, 1.000)
C_{44}	(0.111, 0.378, 0.778)	(0.111, 0.422, 1.000)	(0.111, 0.689, 1.000)
C_{45}	(0.111, 0.422, 0.778)	(0.111, 0.378, 0.778)	(0.111, 0.644, 1.000)
C_{46}	(0.556, 0.867, 1.000)	(0.111, 0.422, 1.000)	(0.111, 0.644, 1.000)

Then the weights of the evaluation criteria were multiplied with the normalized matrix to form a weighted normalized fuzzy decision matrix (by Eq. (8)). The values from Table 8 and values from Table 6 were used to compute the fuzzy weighted decision matrix for the companies (Table 9).

Table 9 Weighted normalized fuzzy decision matrix for companies.

Criteria	A1	A2	A3
C_{11}	(1.000, 6.413, 9.000)	(1.667, 6.413, 9.000)	(1.000, 5.427, 9.000)
C_{12}	(0.556, 4.822, 9.000)	(2.778, 5.756, 9.000)	(1.667, 5.444, 9.000)
C_{21}	(2.333, 7.400, 9.000)	(2.333, 7.800, 9.000)	(2.333, 7.000, 9.000)
C_{22}	(1.667, 6.067, 9.000)	(2.778, 7.107, 9.000)	(2.778, 6.760, 9.000)
C_{23}	(1.667, 3.514, 9.000)	(1.667, 3.324, 5.400)	(1.667, 3.727, 9.000)
C_{24}	(1.000, 3.182, 9.000)	(1.000, 2.838, 9.000)	(1.000, 3.387, 9.000)
C_{31}	(1.000, 5.756, 9.000)	(1.000, 6.084, 9.000)	(0.333, 5.098, 9.000)
C_{32}	(1.000, 5.133, 9.000)	(0.333, 4.547, 9.000)	(0.333, 3.960, 9.000)
C_{33}	(0.333, 4.511, 9.000)	(0.333, 3.738, 9.000)	(0.333, 4.511, 9.000)
C_{34}	(0.556, 5.284, 9.000)	(0.556, 4.769, 9.000)	(0.111, 1.160, 5.000)
C_{41}	(1.667, 7.071, 9.000)	(1.000, 5.427, 9.000)	(1.000, 5.098, 9.000)
C_{42}	(2.778, 6.760, 9.000)	(1.667, 5.720, 9.000)	(1.667, 5.373, 9.000)
C_{43}	(1.000, 4.271, 9.000)	(0.333, 3.720, 9.000)	(0.333, 3.720, 9.000)
C_{44}	(0.111, 2.796, 7.000)	(0.111, 3.124, 9.000)	(0.111, 5.098, 9.000)
C_{45}	(0.333, 2.449, 7.000)	(0.333, 2.192, 7.000)	(0.333, 3.738, 9.000)
C_{46}	(1.667, 5.720, 9.000)	(0.333, 2.785, 9.000)	(0.333, 4.253, 9.000)

In this phase, the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS) were determined using Eqs. (9) and (10), respectively. For example, for criteria $C_{11,}$ a_v= min (1,1.667,1) =1; c_v=max (9,9,9) =9. The results obtained from the computations are provided in Table 10.

Table 10

FPIS and FNIS.

Criteria	FPIS	FNIS
C_{11}	(9.000, 9.000, 9.000)	(1.000, 1.000, 1.000)
C_{12}	(9.000, 9.000, 9.000)	(0.556, 0.556, 0.556)
C_{21}	(9.000, 9.000, 9.000)	(2.333, 2.333, 2.333)
C_{22}	(9.000, 9.000, 9.000)	(1.667, 1.667, 1.667)
C_{23}	(9.000, 9.000, 9.000)	(1.667, 1.667, 1.667)
C_{24}	(9.000, 9.000, 9.000)	(1.000, 1.000, 1.000)
C_{31}	(9.000, 9.000, 9.000)	(0.333, 0.333, 0.333)
C_{32}	(9.000, 9.000, 9.000)	(0.333, 0.333, 0.333)
C_{33}	(9.000, 9.000, 9.000)	(0.333, 0.333, 0.333)
C_{34}	(9.000, 9.000, 9.000)	(0.111, 0.111, 0.111)
C_{41}	(9.000, 9.000, 9.000)	(1.000, 1.000, 1.000)
C_{42}	(9.000, 9.000, 9.000)	(1.667, 1.667, 1.667)
C_{43}	(9.000, 9.000, 9.000)	(0.333, 0.333, 0.333)
C_{44}	(9.000, 9.000, 9.000)	(0.111, 0.111, 0.111)
C_{45}	(9.000, 9.000, 9.000)	(0.333, 0.333, 0.333)
C_{46}	(9.000, 9.000, 9.000)	(0.333, 0.333, 0.333)

Next, we calculated the distance of each alternative from the fuzzy positive ideal matrix (FPIS) and fuzzy negative ideal matrix (FNIS) using Eq. (11) and Eq. (12). The evaluation results are given in Table 11.

Table 11

Distance for companies.

	d^+			d^-		
	A1	A2	A3	A1	A2	A3
C_{11}	4.854	4.490	5.059	5.577	5.590	5.279
C_{12}	5.439	4.051	4.705	5.462	5.868	5.670
C_{21}	3.958	3.911	4.018	4.834	4.978	4.698
C_{22}	4.560	3.755	3.818	4.938	5.311	5.195
C_{23}	5.287	5.743	5.215	4.366	2.358	4.398
C_{24}	5.711	5.830	5.642	4.787	4.739	4.820
C_{31}	4.984	4.916	5.488	5.915	6.017	5.710

C_{32}	5.130	5.626	5.788	5.733	5.564	5.424
C_{33}	5.635	5.854	5.635	5.555	5.376	5.555
C_{34}	5.326	5.453	7.222	5.943	5.800	2.887
C_{41}	4.378	5.059	5.139	5.811	5.279	5.189
C_{42}	3.818	4.638	4.723	5.195	4.838	4.744
C_{43}	5.365	5.859	5.859	5.509	5.372	5.372
C_{44}	6.364	6.152	5.605	4.269	5.419	5.884
C_{45}	6.378	6.467	5.854	4.038	3.996	5.376
C_{46}	4.638	6.157	5.705	5.942	5.200	5.492
SUM	81.828	83.961	85.476	83.874	81.703	81.693

To rank the reverse logistics performance of the three companies based on their closeness to FPIS and remoteness to FNIS, the closeness coefficient was calculated using Eq. (13). The final results of the fuzzy TOPSIS analysis for evaluating RL performance of firms‟ social commerce are summarized in Table 12.

Table 12

Closeness coefficient for the three companies.

	A1	A2	A3
$\sum_{1}^{n} d_{NM}^{+}$	81.828	83.961	85.476
$\sum_{1}^{n} d_{NM}^{-}$	83.874	81.703	81.693
$\sum_{1}^{n} d_{NM}^{+} + \sum_{1}^{n} d_{NM}^{-}$	165.702	165.664	167.169
CC_M	0.506	0.493	0.489
Ranking	1	2	3

Depending on the maximum closeness of the three companies to FPIS, the three alternatives (companies) were ranked (Table 12): we found A1> A2 >A3. Therefore, we found A1 with the best reverse logistics performance in social commerce.

4.4. Sensitivity analysis

To ensure the feasibility and robustness of the proposed method and its results to the utmost extent as possible, sensitivity analysis can be performed by changing criteria weights. In this study, 16 scenarios were conducted. The weight of one criterion is changed while keeping all other weights the same as shown in Table 13. For example, in scenario 1, the criterion C11 has the highest weight (7,9,9) whereas the remaining criteria have weight (1,1,3). The operation is done for each criterion. The results of sensitivity analysis for 16 criteria are shown in Figure 3.

Table 13

Scenarios for sensitivity analysis.

Scenario No.	Definition	A1	A2	A3	Ranking
1	C11=(7,9,9), the others=(1,1,3)	0,4563	0,4546	0,4421	A1> A2 >A3
2	C12=(7,9,9), the others=(1,1,3)	0,4545	0,4640	0,4535	A2> A1 >A3
3	C21=(7,9,9), the others=(1,1,3)	0,4549	0,4483	0,4435	A1> A2 >A3
4	C22=(7,9,9), the others=(1,1,3)	0,4534	0,4560	0,4525	A2> A1 >A3
5	C23=(7,9,9), the others=(1,1,3)	0,4420	0,4193	0,4330	A1> A3 >A2
6	C24=(7,9,9), the others=(1,1,3)	0,4428	0,4334	0,4339	A1> A3 >A2
7	C31=(7,9,9), the others=(1,1,3)	0,4633	0,4570	0,4449	A1> A2 >A3
8	C32=(7,9,9), the others=(1,1,3)	0,4633	0,4468	0,4420	A1> A2 >A3
9	C33=(7,9,9), the others=(1,1,3)	0,4534	0,4410	0,4435	A1> A3 >A2
10	C34=(7,9,9), the others=(1,1,3)	0,4747	0,4640	0,4149	A1> A2 >A3
11	C41=(7,9,9), the others=(1,1,3)	0,4654	0,4440	0,4406	A1> A2 >A3
12	C42=(7,9,9), the others=(1,1,3)	0,4626	0,4440	0,4406	A1> A2 >A3
13	C43=(7,9,9), the others=(1,1,3)	0,4603	0,4439	0,4420	A1> A2 >A3
14	C44=(7,9,9), the others=(1,1,3)	0,4378	0,4381	0,4449	A3> A2 >A1
15	C45=(7,9,9), the others=(1,1,3)	0,4394	0,4301	0,4434	A3> A1 >A2
16	C46=(7,9,9), the others=(1,1,3)	0,4734	0,4381	0,4434	A1> A3 >A2

From Table 13 and Figure 3 we can see that the ranking of three companies´ reverse logistics performance changed a bit with different weights of criteria in social commerce platforms, but company A1 wins as the best performer for most times (12 times in Scenario 1, 3, 5-13, 16). Company A1 accounts 75% of the winning performance in 16 scenarios.

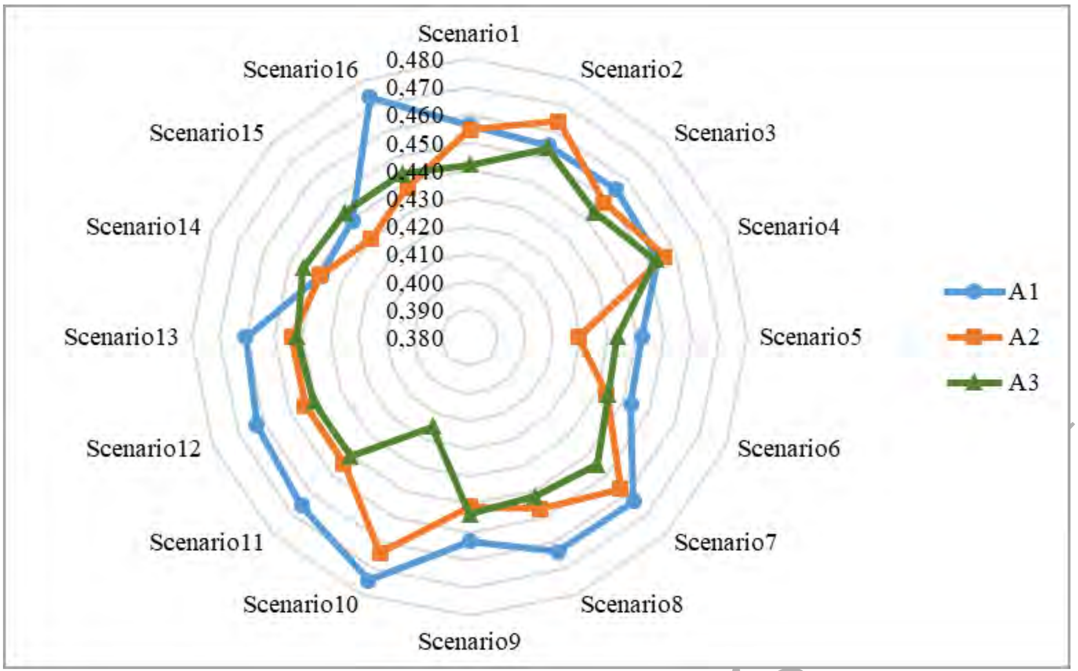

Fig. 3. Result of sensitivity analysis (closeness coefficient scores).

Hence, it can be concluded that our result and the applied method are robust since the best alternative decision (company A1) is relatively insensitive to the changes of criteria weights.

4.5. Checking evaluation results by software FLINTSTONES

FLINTSTONES is a novel decision support suite software for solving linguistic decision-making problems. FLINTSTONES is based on the 2-tuple linguistic model and its extensions, carrying out a linguistic decision analysis scheme and providing linguistic results to facilitate easy human comprehension. FLINTSTONES was developed by the research group Sinbad (Intelligent Systems Based on Fuzzy Decision Analysis) with a double goal: research and education (Estrella, Rodr, Espinilla, & Mart, 2014).

The method we used integrates the selection process based on fuzzy TOPSIS and Hesitant Fuzzy Linguistic Term Set (HFLTS) in FLINTSTONES. The innovative approach which is included in one version of FLINTSTONES is thoroughly functional. We can download this suite from the website (http://sinbad2.ujaen.es/flintstones/?q=software) (Estrella, Rodríguez, & Martínez, 2015).

4.5.1. Framework

In the first process, we define the four elements in FLINTSTONES Framework phase:

Experts: E= {E1, E 2, E3, E4, E5}.

Alternatives: A= {A1, A2, A3}. The domain, Importance, is also set as the special name to overcome the FLINTSTONES limitation.

Criteria: C1= {C11, C12}; C2= {C21, C22, C23, C24}; C3= {C31, C32, C33, C34}; C4= {C41, C42, C43, C44, C45, C46}.

Domains: Alternatives= {VP, P, F, G, VG}; Importance= {VL, L, M, H, VH};

The defined framework is illustrated in Figure 4.

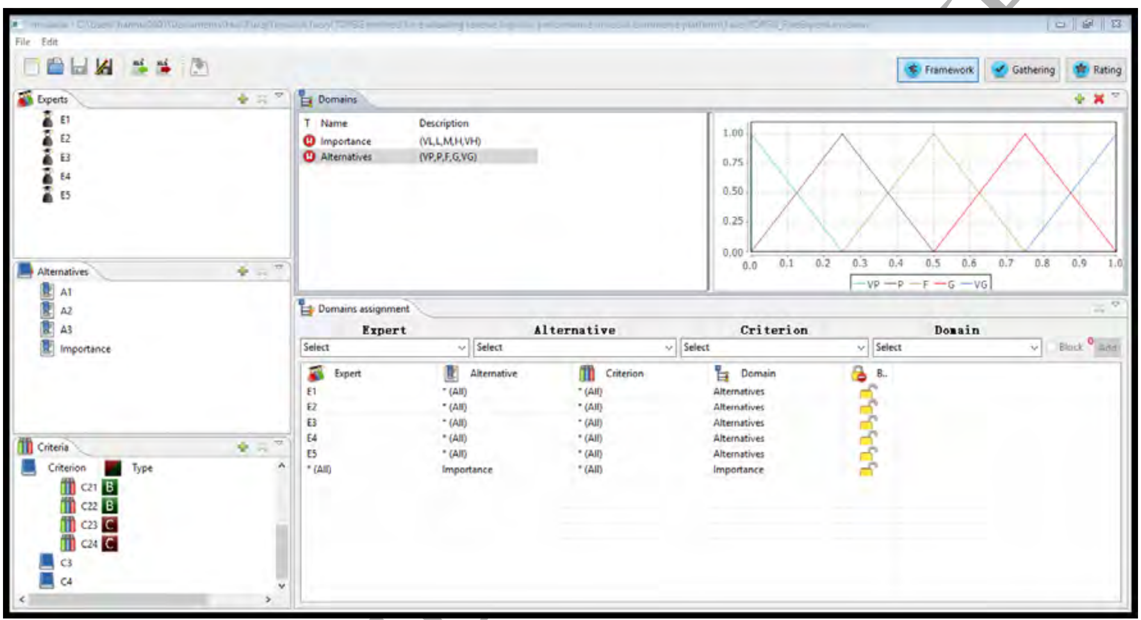

Fig. 4. Framework.

In this study, only two sub-criteria (usage risk C_{23} and cost C_{24}) belong to Cost category (the less the better). While, the main criterion Management C_2 is Benefit category. For example, if we give a lower valuation to C_{23} and a higher valuation to C_2 for one company, it means the company has a lower risk level and a better management system.

In the domains part, we should strictly follow the requirements of the software FLINTSTONES to use names of “Importance” and “Alternatives”. Here, Importance stands for the domain of criteria.

In fuzzy set theory, conversion scales are applied to transform the linguistic terms into fuzzy numbers. Different scholars have used different scales, for example, some researchers used a scale of 0–1 to rate the criteria and the alternatives (Amiri, 2010; Gülin Büyüközkan & Çifçi, 2012; G. Kannan et al., 2009; Kim et al., 2011; Lima-Junior & Carpinetti, 2016; Singh & Benyoucef, 2011). Others used a scale of 1-9 (Awasthi et al., 2010; Awasthi, Chauhan, & Omrani, 2011; Awasthi, Chauhan, Omrani, et al., 2011), while some chose a scale of 1-10 (Erdoğan et al., 2013; D. Kannan et al., 2014; Kelemenis et al., 2011; Liao & Kao, 2011; Sun, 2010). Patil & Kant (2014) used 1-11 for their rating. Although different researchers have their own scale preferences, it will not influence the calculation results. In the software FLINTSTONES system, its automatic scale is between 0-1.

4.5.2. Gathering process

After defining the framework, we continue to gather information. In this step, each expert evaluates criteria and sub-criteria and assesses each alternative against each sub-criterion. Figure 5 shows this gathering process in the software.

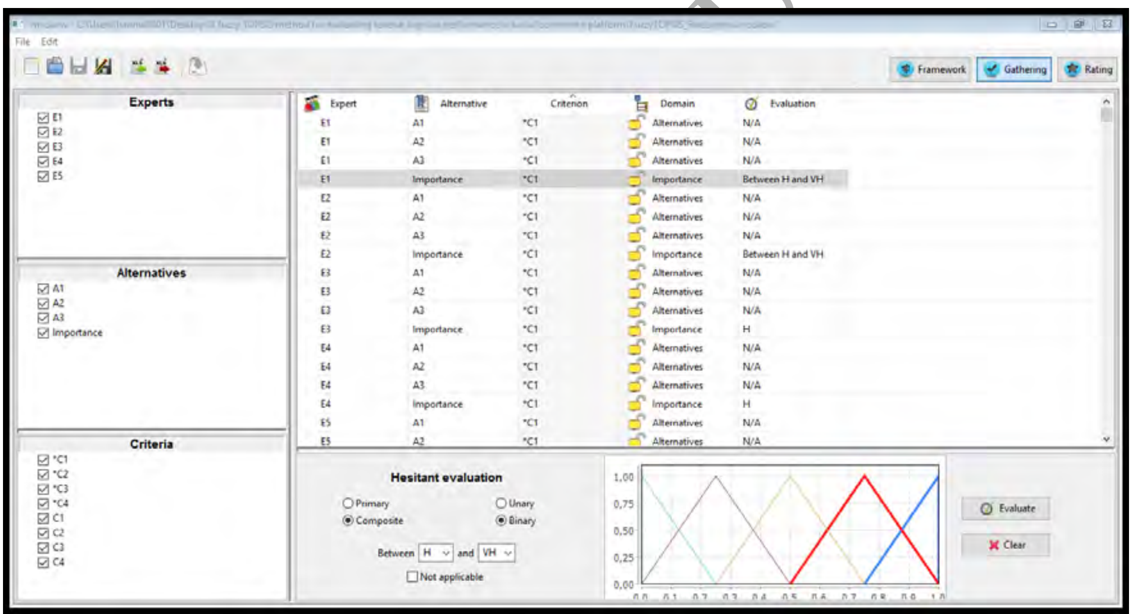

Fig. 5. Information gathering process.

4.5.3. Rating process

Finally, the TOPSIS HFLTS method was applied to execute the rating process in conjunction with FLINTSTONES. In the TOPSIS HFLTS method, the last four steps of the selection process (unification process, computing criteria weights, aggregation process and applying fuzzy TOPSIS) were performed (see Figure 6). The results showed the ranking of the alternatives according to CC: A1 > A2 > A3. The result is the same as that obtained through Fuzzy TOPSIS algorithms.

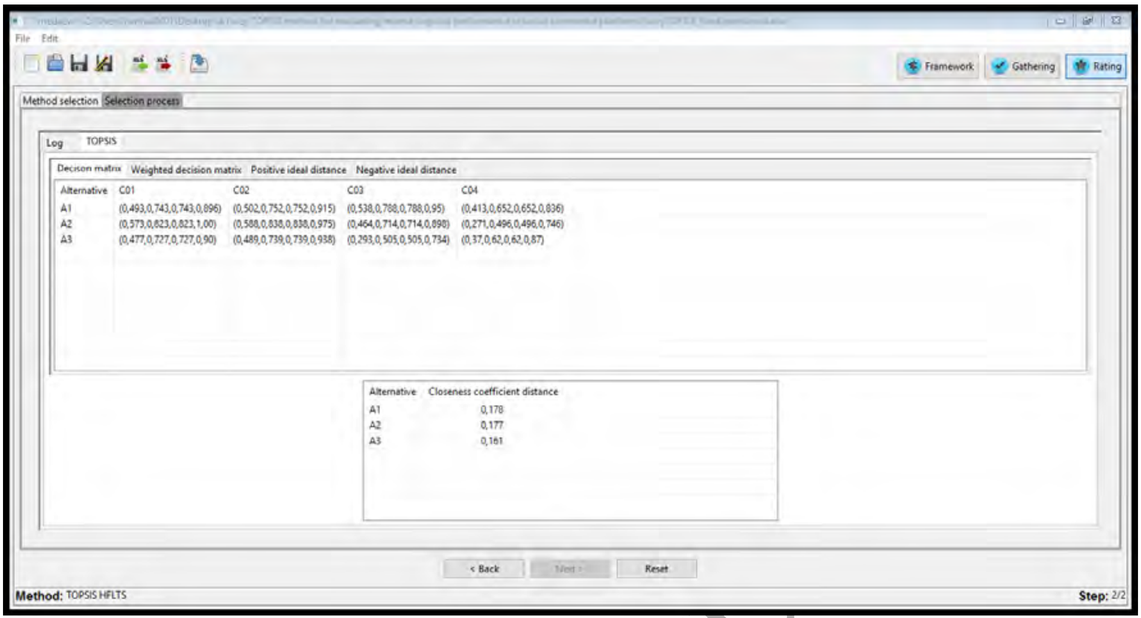

Fig. 6. TOPSIS HFLTS rating results.

5. Discussion

From the results above, we can conclude that firm A1 has the best performance of reverse logistics practices in the social commerce platform. From Table 6, the aggregated fuzzy weights of the Customer relationship (C_{21}), Usage risk (C_{23}), Reviews (C_{42}) and Quality control (C_{22}) are (7, 9.000, 9), (5, 8.200, 9), (5, 7.800, 9) and (5, 7.800, 9) respectively, which rank as $C_{21} > C_{23} > C_{42} = C_{22} > other\ criteria$; while Cloud computing (C_{33}) and Service-oriented architecture (C_{34}) are (1, 5.800, 9) and (1, 5.800, 9) respectively, which rank as $C_{33} = C_{34} < other\ criteria$. Therefore, the findings of this study indicate that Customer relationship (C_{21}), Usage risk (C_{23}), Reviews (C_{42}) and Quality control (C_{22}) are top three factors of importance for reverse logistics in social commerce platforms, while Cloud computing (C_{33}) and Service-oriented architecture (C_{34}) are the least prioritized factors (See Table 6). Besides our findings, other researchers and practitioners also showed that improve customer relationship, usage risk, reviews and quality control have positive influences on the product return rate.

Customer relationship: When companies take actions (such as return service, web site design, customer response system) to improve customer relations, they will bring firms an increased high sales volume as well as decrease return rates. For example, the e-return service helps overcome customer fears and hesitation concerning e-shopping, encourage positive communication, and improve the relationship between customers and retailers, which result in lower return rates (Hsieh, 2013). One customers´ report from Metail (https://metail.com/) shows that its e-return service achieved 3.5 times longer on-site engagement, and crucially, 5% reduction in returns. MetaPacks‟s 2016 State of Ecommerce Delivery report (http://www.metapack.com/state-of-ecommerce-delivery/) found that 72% of consumers are more likely to shop with a retailer that made returns easier.

Usage risk: In an online environment, consumers need to be protected by the return policy to lower the risk perception for purchasing products, as consumers cannot touch, try, or wear products online. For this reason, e-commerce retailers often offer free return shipping if consumers spend more than a specific amount or within a specific period of time (such as Christmas). Therefore, the return policy has its impact on a major/minor return decision intention as the policy might help consumers reduce the perceived risk (Confente, Russo, & Frankel, 2017). Jeng (2017) also agrees that the return policy is of great importance to consumers' purchase and return behaviors. This policy will decrease the return rate (and the costs of handling returns) without decreasing customer purchase intention.

Reviews: According to Forrester Research, about 46% of consumers consider product reviews when deciding on online purchases. Admitting there are abundant advantages of product reviews, when it comes to reducing returns, the essential benefit would be that reviews from peers help consumers better-informed with the products, which in turn minimize the return intention (Wang & Qu, 2017). When Petco (https://www.petco.com/), the pet-supply chain, engaged BazaarVoice to help facilitate customer reviews on its website, the stores' return rate immediately went down 20 percent. The more reviews a product gets, the better. A product with 50 reviews has a 135 percent lower return rate than products with fewer than five reviews. Another study links a wide range of transaction data (2.5 billion-page clicks, 46 thousand different products, 700 brands, 40 product categories, 72 million sold and 33 million returned items) with a large set of online customer reviews (0.9 million). Their results show that positive online customer reviews can lead to lower return rates and higher sales after returns (Lohse, Kemper, & Brettel, 2017).

Quality control: About 93% of all returned products are due to quality and other issues, while only 7% are due to fraud. Product quality issues that stem from supply chains can blindside and lead to unhappy customers and high return rates. The research interestingly shows that product quality has a significantly stronger effect on product returns (Hong & Pavlou, 2014).

6. Conclusion

The return ratio of products has been significantly higher than before the Internet powered digital age (Liu, Chen, Li, & Liu, 2015). At the same time, the rapidly growing social media and Web 2.0 technology have transformed social commerce as an easy and fast tool to effectively manage the reverse logistics process. Social commerce is becoming increasingly popular with technological advances and consumers´ concerns for sustainability (Khor, Udin, Ramayah, & Hazen, 2016). This unique environment brings many opportunities for value creation from reverse logistics. Businesses can obtain a significant competitive advantage if they can leverage social commerce platforms effectively (Alptekin et al., 2015). Therefore, the social commerce platform as an important support system of reverse logistics should be a strategic goal for businesses. To adapt to the reverse logistics market environment, it is imperative to conduct research on the reverse logistics network and highly integrated social commerce platforms (Li, Lu, & Liu, 2014).

From this perspective, evaluating reverse logistics performance in social commerce platforms is important for companies, customers, and researchers. In this study, importance weights of social commerce platform determinants are analyzed by the fuzzy TOPSIS method to evaluate the four main criteria for effective reverse logistics in the social commerce platform.

The study contributes to the literature of reverse logistics in several ways. First, the study results identified the important determinants (criteria) for effective reverse logistics. Secondly, a new methodology for evaluating reverse logistics in the social commerce platform is developed based on fuzzy TOPSIS in conjunction with FLINTSTONES. Here a sensitivity analysis is also performed to verify the robustness of the proposed method. The study results provide new insights to businesses for successful reverse logistics implementation. Social commerce platforms offer new business opportunities to recover value from reverse logistics. The present study may be helpful for companies to devise strategies for sustainable developments. Thus, this study makes important contributions to the fields of sustainability, green management, and reverse logistics.

Although we have devised an effective approach to evaluate reverse logistics practices in the social commerce platform through fuzzy TOPSIS, there still exist some limitations that form the basis for future work. Firstly, the results of this study may be compared with other multi-criteria evaluation techniques such as ELECTRE, PROMETHEE, DEMATEL, DEA, or VIKOR. Secondly, we have not discussed consensus building or interactions among expert group members in the study. Any topic related to group interactions would be an interesting one for evaluating reverse logistics performance. These limitations provide ample opportunities for future research in this growing area of reverse logistics.

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