Int. J. Production Economics 243 (2022) 108350

Contents lists available at ScienceDirect

International Journal of Production Economics

journal homepage: www.elsevier.com/locate/ijpe

Supply chain finance platform evaluation based on acceptability analysis

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ARTICLE INFO

Keywords:
Supply chain finance
Rankings
Acceptability analysis

ABSTRACT

With the rapid development of financial technology, an increasing number of supply chain finance (SCF) service platforms have sprung up to optimize the flows of financial resources, information and materials in the supply chain. The evaluation and selection of SCF platforms have consequently become critical issues not only for platform customers but also for competitors. Although the practices and challenges of SCF have been analyzed in-depth and several studies have investigated the factors that influence SCF platform performance, research on the evaluation of different SCF platforms is scarce. To comprehensively evaluate different types of SCF platforms, this study first identifies critical factors that influence the performance of SCF platforms. A stochastic multicriteria acceptability analysis for group decision-making (SMAA-2) model is then applied to address the SCF platform evaluation problem. Finally, a questionnaire survey is conducted to validate the accuracy of the proposed evaluation model. The empirical results show that the proposed method provides rankings similar to the survey results and thus is accurate and reliable. The evaluation factors and the rankings of SCF platforms can provide references and decision support not only for financial service providers and platform customers but also for regulatory institutions.

1. Introduction

Traditional financing approaches such as bank loans and corporate borrowing have faced great liquidity pressures during the recent economic downturn (Benmelech et al., 2017). Supply chain finance (SCF) is an alternative and preferred financing solution to improve the overall credibility of the whole supply chain, including suppliers, buyers and financial service providers. SCF helps buyers, especially small and medium-size enterprises, alleviate financing difficulties by building a collaborative and innovative framework to provide credit and service with lower interest rates, extended payment terms and more working capital. SCF aims to optimize the flow of capital among organizations via solutions implemented by financial institutions and technology providers that ensure that the flow of funds is consistent with the flow of logistics and information in the supply chain. SCF is a new trend to optimize financial flows along with the flows of goods and information in supply chain management (SCM) and a promising solution for companies (Gelsomino et al., 2016; Wang et al., 2020). Compared with traditional bank loans, the advantages of SCF include low interest rates, flexible payment terms and reduced liability (Wuttke et al., 2016).

SCF service platforms can be classified into three categories according to the dominant industry, i.e., bank-led, core enterprise-led, and technology company-led SCF. In bank-led SCF, banks are the main risk control entity and prefer larger companies with complete capital data when choosing supply chain companies. Under this SCF model, the capital cost borne by chain enterprises is relatively low, and the risk control capability is strong. For example, Ping An Bank has built a supply chain accounts receivable service platform relying on artificial intelligence, blockchain, and cloud computing technology. This SCF platform empowers and upgrades the SCF service model and provides online asset receivable transactions and circulation services for upstream suppliers in the core enterprise industry chain. Core enterprise-led SCF is provided by one of the core companies in the supply chain, such as a business-to-business e-commerce platform or logistics company. This company uses the transaction flow and records on the e-commerce platform to grasp the true operating data of the enterprise

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https://doi.org/10.1016/j.ijpe.2021.108350
Received 14 November 2020; Received in revised form 11 August 2021; Accepted 2 November 2021
Available online 6 November 2021
0925-5273/

and reduce the risks caused by information asymmetry. For instance, one of JD.com's SCF services is an order financing model under the accounts receivable financing model and prepaid financing model. JD.com determines the financing line of suppliers based on financial data such as purchases and sales of merchants on its platform and historical accounts receivable financing data. In technology company-led SCF, the SCF operation model is based on the enterprise resource planning system. For example, the SCF platform of Yonyou Network Technology is connected to the core enterprise's enterprise resource planning system, financial system, procurement platform, sales platform, and other supply chain-related platforms. As a result, the SCF can realize deep penetration and integration of the asset side and the capital side and provide financing services for upstream and downstream small and medium-size enterprises in the supply chain. In a comparison of the finance-oriented and supply chain-oriented perspectives, Lam et al. (2019) concluded that the finance-oriented perspective is associated with financial elements while the supply chain-oriented perspective relates to the business and financing process.

Technology not only promotes the development of SCF but also makes the industry increasingly competitive. SCF platform providers are eager to identify factors affecting platform performance in order to improve the competitiveness of their platforms. Platform clients are also interested in knowing which platforms perform well to aid the selection of a platform for cooperation. Wang et al. (2020) proposed an SCF adoption model to investigate the three drivers of SCF adoption decisions and the performance implications of adoption. Nonetheless, the ranking and evaluation of SCF platforms remains a key issue for supply chain infrastructure, supply chain parties (suppliers, buyers and banks), and supply chain phases since SCF integrates these parties (Chakuu et al., 2019).

Although previous studies have conducted in-depth analyses of the practices and challenges of SCF, empirical studies of the evaluation of different SCF service platforms are scarce (Gelsomino et al., 2016; Martin and Hofmann, 2019). Such evaluations are an important issue for both SCF service providers and small and medium-size enterprises in the supply chain. This research gap motivated us to explore the following two questions: First, what are the SCF factors that impact the performance of different SCF service platforms? Second, how can the SCF platforms provided by different kinds of companies be evaluated?

To address these two questions, this study attempts to build a reasonable and rational framework for evaluating different SCF platforms. Our study makes three contributions to this stream of research. First, based on an analysis of the previous literature, this paper constructs a two-level factor structure named the technology-recognition-organization framework to comprehensively investigate the factors that influence the performance of different SCF platforms. Second, to bridge the gap in evaluating the performance of SCF platforms, this study applies a stochastic multicriteria acceptability analysis for group decision making (SMAA-2) model to address the SCF platform evaluation problem. Third, an online questionnaire survey of specialists from SCF-related industries is conducted. The survey results are analyzed and compared with the rankings generated by the proposed model to further validate the accuracy of the proposed model.

The remainder of this study is structured as follows. Section 2 reviews the related literature. Section 3 analyzes the characteristics that influence the performance of SCF service platforms. In Section 4, the proposed individual decision-making models and the aggregation of individual opinions approach are introduced. Section 5 illustrates and discusses the empirical results. The theoretical and managerial implications are discussed in Section 6. Section 7 summarizes and draws conclusions.

2. Literature review

In this section, studies related to SCF, evaluation theory, the proposed methods and the proposed measure are reviewed.

2.1. Supply chain finance (SCF)

SCF was created as a win-win solution for both service providers and trading partners (Hofmann, 2009; Steeman, 2014; Wuttke et al., 2016): buyers can extend their payment terms by building stable connections with suppliers, and suppliers can obtain immediate payments by selling their company's receivables. SCF platforms treat buyers as reliable partners and provide specific SCF plans to help them participate in global supply chain activities. These plans help both suppliers and buyers meet evolving demands (Hofmann and Belin, 2011; Cavenaghi, 2014). In this way, SCF improves capital flow management from the perspective of the supply chain while promoting the development of the industrial supply chain in a timely and effective manner through financial business innovation and management. The effective use of SCF not only significantly alleviates financial pressure within enterprises but also strengthens the relationships between enterprises and improves the competitive advantage of enterprises and the supply chain. This creates new financial flow innovations compared with traditional supply chain financing approaches.

The rapid development of financial technology (FinTech) is providing more opportunities for SCF, especially in developing countries such as China. In 2005, the Shenzhen Development Bank, which merged with Ping An Bank Co., Ltd in 2012, started the first SCF platform in China. Many different banks have since joined the SCF market and offer many different types of SCF platforms. The integration and application of cutting-edge technologies such as the Internet of Things, big data, and blockchain have also profoundly improved SCF operations (Herath, 2015; Abbasi et al., 2017). SCF has traditionally been provided by commercial banks, but the marketplace is now being entered by non-bank companies that are implementing new technologies, such as the internet and cloud-based technology, to provide their customers advanced working capital financing in both pre- and post-invoice approval processes (More and Basu, 2013; Wuttke et al., 2013; Martin and Hofmann, 2017). For example, the world-renowned Chinese e-commerce companies JD.com and Alibaba have begun to provide SCF services to their online retailers and supply chain members, which sell diverse products through their platforms.

The huge technology and internet revolution since the 1990s has also greatly improved the efficiency of processing financial transactions in SCF by providing easier payment methods to buyers and better financing to suppliers (Zhang et al., 2019; Wuttke et al., 2016). Liebl et al. (2016) described SCF as a key component of the management and regulation of finance flow in all phases of the supply chain. The process of SCF starts with delivery of the product/service from the supplier to the buyer. The buyer's financial institution confirms the delivery and provides the receipt to the supplier. The confirmation receipt allows the supplier to receive payment from the financial institution of the buyer. In this manner, SCF supports the integration of suppliers, buyers and service providers to provide an alternative source of competitive advantage (Caniato et al., 2016; Wuttke et al., 2016). SCF parties manage and coordinate the delivery of financial services and include both primary parties (e.g., suppliers and buyers) and supportive parties (e.g., service providers and banks)(Chod et al., 2010). Li et al. (2020) comprehensively reviewed the most recent literature related to SCF development and future trends.

Several factors that influence SCF have been reported in the literature. Tseng et al. (2018) selected three aspects and 14 criteria based on the fuzzy technique for order preferences by similarity to an ideal solution (TOPSIS) method and found that economic and social aspects are the top two aspects influencing environmental characteristics in the development of SCF for Vietnam's textile industry. Tseng et al. (2019a) constructed a set of measurements and analyzed benefits and costs in the textile industry based on a fuzzy TODIM (an acronym in Portuguese for Interactive Multicriteria Decision-making) method. They found that collaboration value innovation, strategic competitive advantage and financial attributes are the most important aspects for improving firm performance. Ma et al. (2020) studied the importance of factors in supply chain collaboration from the point of view of financial service providers and found that top management support, trust, and IT infrastructure were considered most important. Although Ma et al. (2020) identified the most important factors based on the literature on supply chain collaboration and conducted interviews with practitioners in financial service industries in China, they investigated the collaborative factors from the view of financial service providers. By contrast, the present study mainly focuses on identifying the factors that influence the performance of financial service providers and evaluates these platforms from the customer view.

Researchers in academia are also trying to identify factors influencing the use of specific technologies in SCF, such as blockchain. Orji et al. (2020) evaluated indicators of blockchain technology adoption in the freight logistics industry based on a technology-organization-environment (TOE) framework. They found that the three most important factors influencing the adoption of blockchain technology are "government policies and supports", "infrastructure" and "availability of specific blockchain tools". In a study of blockchain evaluation, Tang et al. (2019) applied an entropy method (Shannon, 2001) to decide the weights of dimensions and chose the TOPSIS model (Hwang and Yoon, 1981) to rank public blockchains and entropy methods (Shannon, 2001) based on two levels of indicators.

2.2. Evaluation theory

Performance measurement can be defined as the process of quantitatively and/or qualitatively evaluating the effectiveness and efficiency of an activity or business process. There are several benefits of evaluating performance, including an improved understanding of key processes, identification of potential problems, and acquisition of insights on possible future improvement actions (Ahi and Searcy, 2015a). Evaluating supply chain performance is a transversal process involving several players and thus is a complex undertaking subject to barriers such as decentralized historical data, a lack of cohesion between metrics and poor communication between reporters and users (Lohman et al., 2004; Naini et al., 2011; Lima-Junior and Carpinetti, 2017).

The literature on supply chain performance evaluation includes conceptual frameworks of metrics (Gunasekaran et al., 2001), surveys identifying the most popular metrics (Gunasekaran et al., 2004), case studies (Cuthbertson and Piotrowicz, 2011) and quantitative models to support performance evaluation (Chithambaranathan et al., 2015). During the past decade, quantitative models have been increasingly applied to support supply chain evaluation using various techniques, including multicriteria decision-making (MCDM) (Chithambaranathan et al., 2015), statistical (Ahi and Searcy, 2015b), mathematical programming (Gong, 2008), artificial intelligence (Ganga et al., 2011) and simulation techniques (Bhaskar and Lallement, 2008). Lima-Junior and Carpinetti (2017) reviewed 84 recent studies and found that most studies evaluate supply chains based on MCDM techniques, among which the Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA) methods are the most frequently used.

Although previous studies have extensively investigated the evaluation of supply chain performance, few studies have attempted to evaluate SCF performance. The ranking and evaluation of SCF platforms are key issues for supply chain infrastructure, supply chain parties (suppliers, buyers and banks), and supply chain phases since SCF integrates these participants. (Chakuu et al., 2019). Among previous efforts, Abdel-Basset et al. (2020) evaluated a set of measurements to provide sustainable SCF in the Egyptian gas industry under uncertainty. Wang et al. (2020) developed an SCF adoption model to investigate the key drivers and corresponding outcomes of SCF adoption decisions. Du et al. (2020) designed a new type of SCF platform based on blockchain technology. Other researchers have discussed the risks of SCF ((Sang, 2021)), SCF strategies for financing farmers ((Yi et al.)), and the financial leverage effect in the supply chain ((Yoo et al., 2021)).

2.3. Proposed methods

Previous studies have primarily applied MCDM techniques for SCF evaluation. MCDM methods find the best evaluation results based on appropriate criteria and are especially useful for supply chain evaluations. Pineda et al. (2018) integrated an MCDM model and data mining to improve airline SCF performance, and Lu et al. (2018) proposed a framework based on Decision-Making Trial and Evaluation Laboratory (DEMATEL) employing Analytical Network Process (ANP) to evaluate the sustainable development performance of international airports. The social sustainability of the supply chain was investigated using the Best-Worst Method by Munny et al. (2019) for a footwear manufacturing company. MCDM techniques have also been applied to the evaluation of supply chain management in cases of uncertainty. Xu et al. (2019) identified the sustainable supplier selection problem according to the Analytical Hierarchy Process under a fuzzy environment. Abdel-Basset et al. (2019) proposed a TOPSIS technique under type-2 neutrosophic number in the supplier selection problem. Rostamzadeh et al. (2018) proposed an efficient Sustainable Supply Chain Risk Management framework based on CRITIC and TOPSIS methods under a fuzzy environment and applied it in a real case company.

Although SCF platforms are typically ranked by a committee or a group of experts with diverse expertise, few previous studies have considered group decision-making characteristics. In other words, most extant methods in the literature assume that the SCF evaluation problem is decided by a single person. As a result, two key issues warrant serious consideration. First, it is difficult to achieve consensus on the precise weights associated with each criterion in decision analysis (Lahdelma and Salminen, 2001), as different normalization schemes and different weight elicitation methods may generate different weights for the same problem (Barron and Barrett, 1996). In addition, the weights determined by different decision-makers usually exhibit considerable variability (Melkonyan and Safra, 2016). Second, in the process of group decision-making with distinct opinions on the same question, the formation of a rational group consensus from different judgments of independent experts remains an unsolved research question deserving significant attention (Yu and Lai, 2011).

The present research attempts to address these two issues by proposing a stochastic multicriteria acceptability analysis for group decision framework (SMAA-2). Unlike traditional group decision-making processes, the proposed method does not require decision-makers to express a preference among experts explicitly or implicitly. Instead, it explores the weight space to describe the valuations that would make each alternative the preferred choice. More specifically, the proposed framework consists of three phases. First, some experts are identified to formulate the group decision-making framework. Then, each expert carries out a standard MCDM process for the SCF evaluation problem independently. Different results may be generated by different experts in this stage. Finally, to consider the weight vectors for any rank from best to worst for each alternative, SMAA-2 produces a holistic acceptability index to measure the overall acceptability of each alternative.

2.4. Proposed measure

A number of researchers have sought to assess the factors that influence supply chain management performance (Tseng et al., 2019b; Liao et al., 2017; Wuttke et al., 2013). Ma et al. (2014) used a complex network modeling approach to construct a supply chain network model to investigate the problem of disruption risk control of the supply chain under the background of globalization. Thomas and Mahanty (2020) presented a dynamic simulation approach for analyzing the well-known emergency sourcing mitigation strategy for a supply chain subject to disruption of its primary supply. By comparison, fewer studies have focused on investigating factors that influence SCF performance, and most have adopted two-level or three-level structure factors (Abdel-Basset et al. (2020); Ma et al. (2020); Lam et al. (2019); Orji et al.

(2020); Tang et al. (2019)). To comprehensively evaluate different types of SCF platforms, here a technology-recognition-organization framework is proposed based on critical factors that have been found to impact the performance of different SCF platforms. The selected factors are shown in Table 1 with references.

As new technologies are developed, they are used to construct or upgrade SCF platforms. Thus, technological factors are an important component of the evaluation of SCF platforms. However, technology is not the only consideration. According to Tang et al. (2019), popularity always plays a key role in evaluating a system or platform, since customers are inclined to choose platforms that are reliable and have good reputations. Based on the analysis of SCF platform evaluation factors in the literature review, two aspects of popularity are considered in this study: recognitive and organizational factors. Recognitive factors measure the degree of acceptance of SCF service providers by customers. The greater the acceptance, the better the SCF platform. Organizational factors represent the financial performance of the SCF service provider. The better the performance of the company providing the SCF service, the more reliable the SCF platform. The three first-level and eleven second-level factors used in this study are shown in Table 1.

Technological factors (F_1) obviously influence the capabilities of different SCF platforms. First, service type (F_{11}) is included to indicate whether the SCF platform is the initial service or a technologically upgraded version. If the technology is an upgraded version, the company has accumulated certain technological capabilities related to the SCF platform, and the platform will therefore be more reliable. Second, number of SCF (F_{12}) denotes how many SCF platforms the company provides. If the company constructs more than one SCF platform, the technological foundation of the platform will be more solid. Third, industry (F_{13}) represents the company's industry. Technology company-led SCF platforms have the advantage of applying advanced technology to their SCF service. Core enterprise-led SCF platforms can access operating data on the supply chain, which is also important in the technological aspect. Bank-led SCF platforms have the advantage of managing capital risk. Fourth, time of SCF (F_{14}) means how long the company has provided the SCF service. The longer the company has provided SCF, the more mature the SCF service of the company.

Recognitive factors (F_2) also impact the performance of SCF platforms. Market value (F_{21}) is the first second-level recognitive factor. The market value of a company is obtained by multiplying the company's stock price by the total equity in the securities market and reflects the company's growth value, profitability value and asset value. The higher the market value of a company, the stronger its capability to construct a reliable SCF platform. Baidu search (F_{22}) is the second second-level recognitive factor. Since Google search is inaccessible in China and Baidu handles approximately 80% of searches in the Chinese search market, the specific term of a company's SCF search heat is chosen as the Baidu search index. The third second-level recognitive factor is the number of followers on Weibo (F_{23}), one of the most popular social networking and online news platforms. Since SCF companies use Weibo accounts to release company news, the number of Weibo followers of a company denotes the size of the audience who cares about the development of the SCF business of the company.

Table 1
References of selected evaluation factors.

Dimensions	Factors	References
Technology (F_1)	Service Type (F_{11})	Tang et al. (2019), Abdel-Basset et al. (2020)
	NO. of SCF (F_{12})	Abdel-Basset et al. (2020), Ma et al. (2020)
	Industry (F_{13})	Orji et al. (2020)
	Time of SCF (F_{14})	Lam et al. (2019)
Recognition (F_2)	Market Value (F_{21})	Tang et al. (2019), Orji et al. (2020)
	Baidu Search (F_{22})	Google Search Tang et al. (2019)
	Followers in Weibo (F_{23})	Followers in Twitter Tang et al. (2019)
Organization (F_3)	Return (F_{31})	Lam et al. (2019)
	Leverage (F_{32})	Lam et al. (2019)
	Number of Employees (F_{33})	Orji et al. (2020)
	Cash Holdings (F_{34})	Lam et al. (2019)

Organizational factors (F_3) describe the characteristics, attributes and resources of the SCF companies, which can either facilitate or impede the development of their SCF platforms. Three firm-level measurements are included in our study as second-level factors to reveal a company's financial ability to develop an SCF service: the company's return (F_{31}), financial leverage (F_{32}) and cash holdings (F_{34}). Number of employees (F_{33}) in the SCF company is chosen as another influential factor in this section since this factor represents the capability of a company to provide manpower in the process of developing and operating the company's SCF platform.

3. Evaluation model

The evaluation of SCF platforms based on critical factors can be treated as a multicriteria problem. An individual decision process may cause biases since the subjective judgments of individual experts are usually ignored (Ma et al., 1999). SCF platforms are usually ranked by a committee or a group of experts rather than a single person not only due to the complexity of the problem but also because of the wider implications of the decision in terms of responsibility. Consequently, in multiple case study settings, it is beneficial to evaluate multicriteria problems using the group decision method.

Because the process of prioritizing and evaluating SCF platforms is a multicriteria, strategic task that involves conflicting choices, MCDM models are required. The factors that influence the evaluation of SCF platforms are interdependent, and thus interactions among these factors should be considered in the decision-making process of prioritization and evaluation. Objective methods determine weights by taking full advantage of mathematical models and are based only on quantifying the intrinsic information of each criterion. In group decision-making, objective methods are considered more appropriate and reliable because they completely eliminate subjectivity in weight determination. Objective methods are therefore extremely useful when experts strongly disagree on the values of criteria weights (Fu et al., 2019). Moreover, Yu & Lai (2011) pointed out that when the weights of criteria values are not consistent with those made by individual experts, weight determination methods can be used. To reduce the decision bias in the decision process, this study proposes an objective approach that identifies individual experts using several objective criteria weight determination approaches.

A number of popular MCDM models have been widely applied in decision-making, such as CRITIC (Diakoulaki et al., 1995), the distance-based approach (Fu et al., 2016), the ideal-point approach(Ma et al., 1999), TOPSIS (Tang et al., 2019), entropy Fu et al. (2019), and AHP (Seidmann et al., 1984). Among these approaches, objective methods are selected to reduce the decision bias. Due to the characteristics of the dataset in this study, some methods, such as entropy, cannot provide an unbiased estimation since some factors cannot be properly processed when their values are zero. Three applicable approaches are retained in this study: the CRITIC approach, distance-based approach, and ideal-point approach. The proposed SCF evaluation method comprises three procedures: identification of individual experts, determination of standard criteria weights for each individual expert, and aggregation of the opinions of individual experts. These procedures are depicted in the flowchart in Fig. 1 and explicitly elaborated in the following subsections.

3.1. Individual decision-making

Assume that m SCF platforms are selected to be evaluated with n criteria. Each criterion can be either subjective or objective. Because of their qualitative nature, subjective criteria need to be converted to

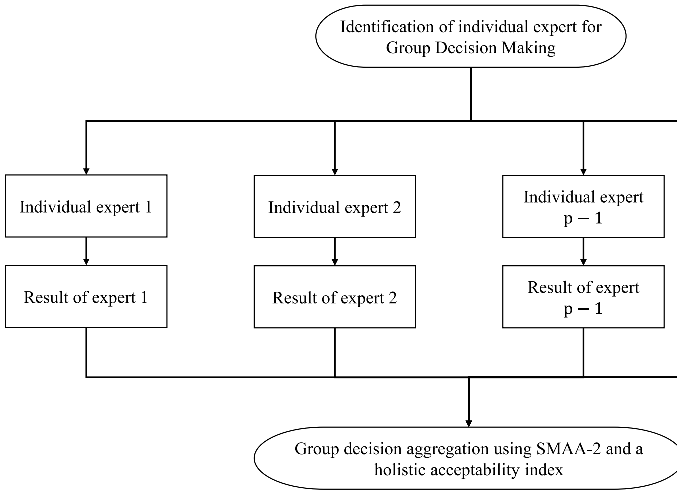

Fig. 1. The evaluation process of SCF platforms.

numerical values via linguistic modeling techniques. By contrast, objective criteria can be described and measured numerically. Let x_{ij}, $i = 1, 2, \ldots, m, j = 1, 2, \ldots, n$ represent the performance of SCF platform i for criterion j. The basic principle of the objective criteria weight determination method is that the importance of a criterion is related to the information expressed by the criterion with respect to the entire set of alternatives. To alleviate the adverse impact of data magnitude and make comparisons across different individual experts feasible, x_{ij}, $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, n$ is normalized by means of

$$\begin{cases} y_{ij} = \dfrac{x_{ij} - \min\limits_i \{x_{ij}\}}{\max\limits_i \{x_{ij}\} - \min\limits_i \{x_{ij}\}}, & \text{for benefit} - \text{type criteria;} \\ y_{ij} = \dfrac{\max\limits_i \{x_{ij}\} - x_{ij}}{\max\limits_i \{x_{ij}\} - \min\limits_i \{x_{ij}\}}, & \text{for cost} - \text{type criteria.} \end{cases} \tag{1}$$

Individual expert k determines the weight associated with criterion $w_j^k, j = 1, 2, \ldots, n$ to maximize the overall performance of SCF i, $i = 1, 2, \ldots, m$:

$$S_{ik} = \sum_{j=1}^{n} y_{ij} w_j^k, i = 1, 2, \ldots m. \tag{2}$$

3.1.1. CRITIC approach

According to Diakoulaki et al. (1995), objective criteria weights can be determined by the CRITIC method based on the following two characteristics of MCDM: the conflicts between and contrast intensity of the evaluation criteria. The working process of the CRITIC approach can be described as follows.

1. Standardize the input data based on Equation (1).
2. Calculate the standard deviation σ_j of criterion j. Since the contrast intensity of the criterion can be quantified by the corresponding standard deviation σ_j, σ_j is recognized as a reasonable measurement of criterion j's value in the process of decision-making.
3. Build an $n \times n$ symmetric matrix with element r_{jk}, which denotes the linear correlation between criteria j and k. The value of r_{jk} is negatively related to the discordance of the scores of the alternatives in criteria k and j. As a result, $\sum\limits_{k=1}^{n} (1 - r_{jk})$ measures the conflict produced by criterion j associated with the decision-making condition specified by the other criteria.
4. Compute the level of information. Since the information in the MCDM model consists of the conflicts between and contrast intensity of the evaluation criteria, the amount of information I_j can be computed by the following product formula: $I_j = \sigma_j \cdot \sum\limits_{k=1}^{n} (1 - r_{jk})$.
5. Calculate the weight of each criterion. The weight w_j of criterion j is denoted by the following: $w_j = \frac{I_j}{\sum_{j=1}^{n} I_j}, j = 1, 2, \ldots, n$. Larger values of I_j indicate that criterion j provides more information and thus is more important in the evaluation process.
6. Optimize the overall performance of SCF platforms using (2).

3.1.2. Distance-based approach

The logic of the distance-based approach is to minimize the discrepancy between peer evaluation and self-evaluation. This discrepancy can be treated as noise or information redundancy during the evaluation process, but these discrepancies need to be reduced and eliminated to provide reasonable evaluation results (Fu et al., 2016). When the discrepancy is smaller, the agreement between peer evaluation and self-evaluation is stronger, resulting in a better evaluation method. y_{ij} denotes the performance of alternative i relative to criterion j and thus can be treated as the value of self-evaluation. Moreover, for alternative i, the value of peer evaluation can be represented by the arithmetic average of y_{ij}, i.e., $\overline{y}_i = \frac{1}{n} \sum\limits_{j=1}^{n} y_{ij}, i = 1, 2, \ldots, m$.

Step 1. Build the distance function. The Euclidean distance can be applied to measure the discrepancy between peer evaluation and self-evaluation. For each alternative, the discrepancy can be optimized as follows:

$$f_i = \min \sum_{j=1}^{n} \left[\left(y_{ij} - \overline{y}_i \right)^2 w_j^2 \right] \tag{3}$$

$$s.t. \sum_{j=1}^{n} w_j = 1 \tag{4}$$

Step 2. Solve the optimization problem. From a systematic perspective, the performance optimization problem of all alternatives can be solved by the following multiple-objective programming model:

$$\left\{\begin{array}{l} \left\{\begin{array}{l} f_1 = \min \sum_{j=1}^{n}\left[\left(y_{1j}-\bar{y}_1\right)^2 w_j^2\right] \\ f_2 = \min \sum_{j=1}^{n}\left[\left(y_{2j}-\bar{y}_2\right)^2 w_j^2\right] \\ \vdots \\ f_m = \min \sum_{j=1}^{n}\left[\left(y_{mj}-\bar{y}_m\right)^2 w_j^2\right] \end{array}\right. \\ s.t. \sum_{j=1}^{n} w_j = 1 \end{array}\right. \tag{5}$$

Then, the following single-objective programming model is proposed to sum the multiple objectives with equal weights:

$$\left\{\begin{array}{l} F = \min \sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(y_{ij}-\bar{y}_i\right)^2 w_j^2\right] \\ s.t. \sum_{j=1}^{n} w_j = 1 \end{array}\right. \tag{6}$$

Based on the above quadratic programming (6), the following Lagrange function is obtained:

$$L = \sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(y_{ij}-\bar{y}_i\right)^2 w_j^2\right] + \lambda\left(\sum_{j=1}^{n} w_j - 1\right) \tag{7}$$

The Hessian matrix of L relative to w_j is as follows:

$$H = \begin{bmatrix} \frac{\partial^2 L}{\partial w_1^2} & \frac{\partial^2 L}{\partial w_1 \partial w_2} & \cdots & \frac{\partial^2 L}{\partial w_1 \partial w_n} \\ \frac{\partial^2 L}{\partial w_2 \partial w_1} & \frac{\partial^2 L}{\partial w_2^2} & \cdots & \frac{\partial^2 L}{\partial w_2 \partial w_n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial^2 L}{\partial w_n \partial w_1} & \frac{\partial^2 L}{\partial w_n \partial w_2} & \cdots & \frac{\partial^2 L}{\partial w_n^2} \end{bmatrix},$$

in which the diagonal elements are positive and the others are zero. Therefore, the Hessian theorem suggests that the Lagrange function L has a minimum value.

Step 3. Obtain the optional solution. By solving $\left\{\begin{array}{l} \frac{\partial L}{\partial \lambda} = 0 \\ \frac{\partial L}{\partial w_j} = 0 \end{array}\right.$, the optimal solution to the single-objective programming model (6) is obtained as follows:

$$w_j = \frac{1}{\sum_{j=1}^{n}\left[\sum_{i=1}^{m}\left(y_{ij}-\bar{y}_i\right)^2\right]^{-1} \times \sum_{i=1}^{m}\left(y_{ij}-\bar{y}_i\right)^2}. \tag{8}$$

The overall performance of SCF platforms is then optimized using (2).

3.1.3. Ideal-point approach

The principle of the ideal-point approach is to minimize the distance between alternatives and the ideal point (Ma et al., 1999). This approach is attractive because the alternative that seeks to maximize performance will be chosen.

Step 1. Build the distance function. According to Ma et al. (1999), a weighted decision matrix $\left[Y_{ij}\right]_{m\times n}$ with $Y_{ij} = w_j y_{ij}$ is built. As a result, the ideal-point approach can be represented by $Y^* = \left\{Y_1^*, Y_2^*, \ldots, Y_n^*\right\}$, where

$$Y_j^* = \max_i \left\{Y_{ij}\right\} = \max_i \left\{w_j y_{ij}\right\} = \max_i \left\{y_{ij}\right\} w_j = y_j^* w_j. \tag{9}$$

The ideal values of criterion j are denoted as $y_j^* = \max_i \left\{y_{ij}\right\}$. The ideal point is particularly considered as an achievable goal.

The following Euclidean distance function is applied to measure the difference between alternative i and the ideal point:

$$D_i = \sum_{j=1}^{n}\left(Y_{ij}-Y_j^*\right)^2 \tag{10}$$

$$= \sum_{j=1}^{n}\left[\left(y_{ij}-y_j^*\right)^2 w_j^2\right] \tag{11}$$

Step 2. Solve the optimization problem. From a systematic perspective, the problem of performance optimization of all alternatives can be solved by the following multiple-objective programming model:

$$\left\{\begin{array}{l} \left\{\begin{array}{l} g_1 = \min \sum_{j=1}^{n}\left[\left(y_{1j}-y_j^*\right)^2 w_j^2\right] \\ g_2 = \min \sum_{j=1}^{n}\left[\left(y_{2j}-y_j^*\right)^2 w_j^2\right] \\ \vdots \\ g_m = \min \sum_{j=1}^{n}\left[\left(y_{mj}-y_j^*\right)^2 w_j^2\right] \end{array}\right. \\ s.t. \sum_{j=1}^{n} w_j = 1 \end{array}\right. \tag{12}$$

Step 3. Obtain the optional solution. In a process analogous to the distance-based approach, the optimal solutions to model (12) are obtained as follows:

$$w_j = \frac{1}{\sum_{j=1}^{n}\left[\sum_{i=1}^{m}\left(y_{ij}-y_j^*\right)^2\right]^{-1} \times \sum_{i=1}^{m}\left(y_{ij}-y_j^*\right)^2}. \tag{13}$$

The overall performance of the SCF platforms is then optimized using (2).

3.2. Aggregation of individual opinions

In the presence of various opinions from different individual experts, to reach group consensus, the results of individual experts should be aggregated, which is not possible under group decision-making. Stochastic multicriteria acceptability analysis (SMAA) is therefore proposed as a multicriteria decision support model to explore the weights to determine the valuations that make each alternative the first choice (Lahdelma and Salminen, 2001). SMAA-2 further extends the SMAA model by considering the information of other rankings and thus represents a good compromise method. This approach is especially meaningful in cases of extreme alternatives that receive the best rankings from some experts but very poor rankings from others. The aggregation of experts' opinions helps solve the problem of the uncertainty of the preferences of these experts.

Step 1. Construct the utility function. Assume p experts are providing decisions for m SCF platforms, i.e., S_{il}, $l = 1, 2, \ldots, p$, $i = 1, 2, \ldots, m$. Table 2 clearly shows the decision process of p experts for m.

The real-valued utility function $u(x_i, \lambda)$ is used to measure the pref-

Table 2
A group decision-making framework for SCF platform evaluation.

SCF Platforms	Expert 1	Expert 2	⋯	Expert p
hline 1	S_{11}	S_{12}	⋯	S_{1p}
2	S_{21}	S_{22}	⋯	S_{2p}
⋮	⋮	⋮	⋮	⋮
m	S_{m1}	S_{m2}	⋯	S_{mp}

erences of different experts. According to the weight vector λ, the utility function is applied to map alternative x_i to utility value

$$u_i(\lambda) = u(x_i, \lambda), \tag{14}$$

to quantify each preference in various decisions. In addition, a more general situation where both weights and input data are not given is considered. A stochastic variable ζ_{il} with density function $f(\zeta)$ and estimated joint probability distribution in space X can be used to represent the imprecise and uncertain input data. A weight distribution with density function $f(\lambda)$ in the feasible weights set Λ is applied to denote the partially known or even unknown preferences, where

$$\Lambda = \left\{ \lambda \in \Re^p : \lambda \geq 0, \sum_l \lambda_l = 1 \right\} \tag{15}$$

Therefore, the feasible weights set is a $p - 1$ dimensional simplex. Then, the constructed utility function is applied to map the weight distribution and stochastic input data in the utility distribution $u(\zeta_i, \lambda)$.

Step 2. Compute favorable weights. The total loss of weight knowledge is expressed as a uniform weight distribution of Λ in a "Bayesian" manner with density function

$$f(\lambda) = \frac{1}{vol(\Lambda)} = \frac{(p-1)!}{\sqrt{p}}. \tag{16}$$

In the SMAA model, the favorable weights set of each alternative $\Lambda_i(\zeta)$ is denoted by the following:

$$\Lambda_i(\zeta) = \{ \lambda \in \Lambda : u(\zeta_i, \lambda) \geq u(\zeta_k, \lambda), \forall k \} \tag{17}$$

According to the ranking function

$$rank(\zeta_i, \lambda) = 1 + \sum_k \varphi(u(\zeta_k, \lambda) > u(\zeta_i, \lambda)), \tag{18}$$

in which $\varphi(false) = 0$ and $\varphi(true) = 1$, the ranking of each alternative is denoted by an integer from worst ($= m$) to best ($= 1$).

In the SMAA-2 model, the favorable weights set of alternative $\Lambda_i^r(\zeta)$ is denoted by the following:

$$\Lambda_i^r(\zeta) = \{ \lambda \in \Lambda : rank(\zeta_i, \lambda) = r \} \tag{19}$$

In this way, the weight $\lambda \in \Lambda_i^r(\zeta)$ assigns utility to alternative x_i to rank rth among all the alternatives.

Step 3. Compute the rank acceptability index. The rank acceptability index b_i^r is defined as the expected value of the favorable weights set. The rank acceptability index is an effective way to measure various valuations so that alternative x_i receives the rth ranking. In the meantime, the rank acceptability index is computed by the multidimensional integral of the favorable ranking weights and input data distribution as follows:

$$b_i^r = \int_X f(\zeta) \int_{\Lambda_i^r(\zeta)} f(\lambda) d\lambda d\zeta. \tag{20}$$

The rank acceptability can be directly applied in the process of evaluating alternatives. The iterative process is also adopted to deal with large-scale problems. In each iteration k, the acceptability of the k best ranking positions (kbr) is denoted as follows:

$$a_i^k = \sum_{r=1}^{k} b_i^k, \tag{21}$$

in which a_i^k measures various valuations that assign any of k best ranking positions to the alternative x_i.

Step 4. Compute the holistic acceptability index. To compare alternatives by rank acceptabilities, a comprehensive approach is proposed that includes the rank acceptabilities in the holistic acceptability index a_i^h for each alternative, i.e.,

$$a_i^h = \sum_r \beta^r b_i^r, \tag{22}$$

where β^r are metaweights, which are non-increasing, normalized and non-negative when rank increases, i.e., $\beta^1 \geq \beta^2 \geq \cdots \geq \beta^m \geq 0$.

4. Empirical results

Consistent with a previous study (Lam et al., 2019), the official websites of Chinese companies listed on the Shanghai and Shenzhen Stock Exchanges and public media, including Baidu, Weibo, Sohu and Toutiao, were searched to identify SCF platform businesses. As SCF is a relatively new business mode, the search dates were January 2010 to August 2020. In total, 178 SCF announcements were obtained. Of these, 36 platforms were excluded because of confounding events such as mergers and acquisitions, and 16 SCF platforms were removed due to missing financial data during this period, resulting in a final size of 126. However, ranking 126 platforms is complex, and it would be difficult to display the results. Thus, only representative companies of each industry were considered in this study.

Twelve representative SCF platforms were included from three different industries: bank-led (Agricultural Bank of China (ABC), CITIC Bank (CITIC), Industrial and Commercial Bank of China (ICBC), Ping An Bank (PAB), Shanghai Pudong Development Bank (SPDB), and Bank of Shanghai (BS)); core enterprise-led (Lakala INC. (LKL), S.f.Holding (SF), Suning.com (Suning), Eternal Asia Supply Chain Management (EASCM), and Xiamen Xiangyu (XMXY)); and technology company-led (YGSOFT INC.(YGS)). Among these companies, ABC and ICBC are representative state-owned commercial banks, PAB, SPDB, and CITIC are representative joint-stock commercial banks, and BS is a representative city commercial bank. Moreover, LKL, SF, Suning, EASCM, and XMXY are representative of payment, logistic, E-commerce, supply chain, and transportation companies, respectively. Finally, YGS is a representative technology company.

A numerical illustration is provided to demonstrate the implementation process of our method for the evaluation of SCF platforms. Eleven second-level factors are considered, and the input data of these factors were drawn from the Wind database and Baidu and Weibo searches in August 2020. Table 3 displays part of the raw data of these eleven factors from August 2020.

In Table 3, Service Type indicates whether the platform provides an initial service or upgraded service. If it is the initial service, the value is set to 0. Otherwise, it is set to 1. No. of SCF represents the number of SCF platforms the company provides. Industry denotes which industry the company belongs to. If it is a bank-led platform, Industry is set to 1. If it is a core enterprise-led platform, Industry is set to 2. If it is a technology-led platform, Industry is set to 4. Time of SCF represents how many years the platform has been running. The values of the other variables are easy to understand and do not require further explanation.

4.1. Three individual approaches

According to the process described in Section 3, the decisions of three individual approaches, namely, the CRITIC approach, distance-based approach and ideal-point approach, are implemented. To better compare the empirical results, the SCF platform criteria weights of the three individual stakeholders are presented in Table 4 and Fig. 2. For the CRITIC approach, the weights of technology, recognition and organization are 46.79%, 23.9% and 29.32%. For the distance-based approach, the weights of technology, recognition and organization are 30.46%, 35.99% and 33.56%. For the ideal-point approach, the weights of technology, recognition and organization are 27.08%, 16.75% and 56.16%. On average, the weights of technology, recognition and organization are 34.78%, 25.55% and 39.68%, respectively, meaning that the ranking of these three factors in order of decreasing importance is

Table 3
Raw data of supply chain finance.

Company	Service Type	No.of SCF	Industry	Time of SCF	Market value	Baidu Search	Follower in Weibo	Return	Leverage	Employees	Cash Holdings
ICBC	0	3	1	5	17927.24	3940000	280000	2762.86	1.0807551	445106	887.14
ABC	0	1	1	2	11374.5	2550000	350000	1931.33	1.0728848	464011	8276.98
CITIC	1	3	1	2	2578.87	2420000	1440000	374.72	1.0791897	57045	3379.15
PAB	1	3	1	6	2685.78	3020000	3920000	100.72	1.0594059	33440	37.31
SPDB	1	2	1	1	3117.2	1430000	1100000	488.64	1.088141	58253	1100.44
BS	0	1	1	2	1200.45	8290000	204000	103.86	1.0659341	12699	759.35
LKL	1	1	1	2	303.21	632000	1740000	4.64	2.2265048	3640	6.99
SF	0	3	2	1	3112.97	9440000	600000	44.64	2.068096	114813	152.99
Suning	1	2	2	2	1031.55	11200000	4890000	55.85	1.8940287	42196	265.34
EASCM	1	1	2	4	128.64	1290000	5787	4.68	1.2465654	13264	36.97
XMXY	0	1	2	2	144.12	435000	433	11.23	1.4395296	5660	33.29
YGS	1	1	3	1	118.52	284000	537	1.21	10.08046	4749	4.41
MIN	0	1	1	1	118.52	284000	433	1.21	1.0594059	3640	4.41
MAX	1	3	3	6	17927.24	11200000	4890000	2762.86	10.08046	464011	8276.98
GAP	1	2	2	5	17808.72	10916000	4889567	2761.65	9.0210538	460371	8272.57

Table 4
Criteria weights from three individual stakeholders.

Method	Service Type	No. of SCF	Industry	Time of SCF	Market value	Baidu Search	Followers in Weibo	Return	Leverage	Employees	Cash Holdings
CRITIC	0.1650	0.1055	0.1204	0.0770	0.0648	0.0904	0.0838	0.0709	0.0698	0.0782	0.0743
Distance-based	0.0313	0.0708	0.0612	0.1413	0.1405	0.1018	0.1176	0.1107	0.0280	0.1047	0.0922
Ideal-point	0.0872	0.0671	0.0545	0.0620	0.0498	0.0631	0.0546	0.0470	0.4194	0.0498	0.0454
Sum	0.2835	0.2434	0.2361	0.2803	0.2551	0.2553	0.2560	0.2286	0.6023	0.2327	0.2119

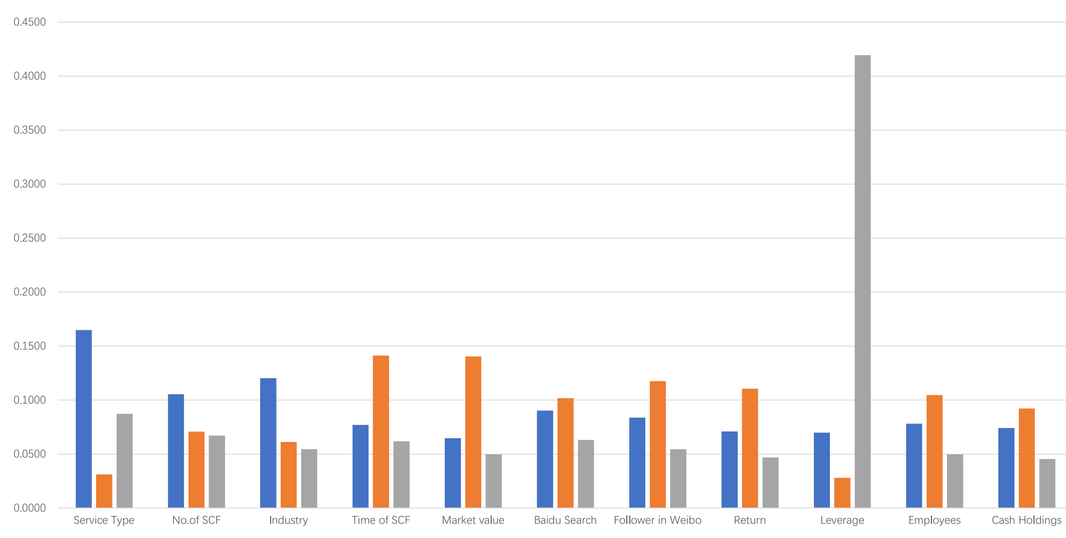

Fig. 2. Comparison of criteria weights.

organization, technology and recognition. The weights are obtained by step v in the CRITIC approach, Equation (8) and Equation (13), respectively.

The criteria weights from the above analysis and the normalized input data for the evaluation of SCF platforms are used in Equation (2) to derive the evaluation results of the three individual stakeholders, which are presented in Table 5. The second, third and fourth columns of the table show the evaluations of these twelve platforms with the CRITIC, distance-based and ideal-point approaches, respectively. It is obvious that the different MCDMs result in different rankings. The larger the value, the better the performance of the SCF platform. Thus, to reach agreement, SMAA-2 is applied to obtain a holistic acceptability index.

4.2. Holistic acceptability index

Given the uncertain preference of the evaluation results obtained from the above three experts, the evaluation results are taken into consideration as input data for SMAA-2. With the help of the toolbox provided by Tervonen (2014), the rank acceptability index is obtained as shown in Fig. 3 and Table 6. To further calculate the precise holistic acceptability index, the rank-order centroid approach (ROC) is applied to compute metaweights, i.e.,

$\beta^r = \frac{1}{10}\sum_{t=r}^{10}\frac{1}{t}, r = 1, 2, \ldots, 10$ (Barron and Barrett, 1996).

The exact values of the holistic acceptability index can be applied to rank SCF platforms effectively (Lahdelma and Salminen, 2001). Table 7

Table 5
Evaluation results of three individual stakeholders.

Name	CRITIC	Distance-based	Ideal-point
ICBC	0.4905	0.1745	0.2570
ABC	0.3528	0.1444	0.3462
CITIC	0.4558	0.0952	0.2892
PAB	0.5244	0.1818	0.2609
SPDB	0.3582	0.0670	0.3558
BS	0.1698	0.0664	0.4760
LKL	0.2746	0.0649	0.4410
SF	0.3460	0.1186	0.3642
Suning	0.5444	0.1685	0.2480
EASCM	0.3502	0.1014	0.3868
XMXY	0.1447	0.0430	0.5152
YGS	0.2855	0.0918	0.8580

and Fig. 4 clearly report the ranking of the SCF platforms and compare this ranking with the rankings of the individual stakeholders. According to the holistic acceptability index, the top three SCF platforms in August 2020 are PAB, Suning and YGS. Table 7 also clearly shows that different criteria result in different rankings. For example, ICBC ranks third, second and eleventh among the twelve SCF platforms in the CRITIC, distance-based and ideal-point approaches, respectively, but fourth in the holistic ranking.

4.3. Further validation

This section presents the results of an online questionnaire survey conducted to further validate the accuracy of the proposed model. The survey was powered by wjx.com, and the questionnaires were distributed only to specialists in the SCF industry, i.e., banks, supply chain companies, technology companies and related research institutions. A total of 200 copies of the questionnaire were distributed to these specialists, and 135 were returned, corresponding to a return rate of 67.5%. Among all returned questionnaires, 106 were effective, giving an effective ratio of 78.5%.

The questionnaire included three types of questions related to the respondent's current employer, personal basic information and assessment of selected SCF platforms. Table 8 displays the statistical data of the background of the respondents and employer information. Among the respondents, 61.32% were younger than 32 years of age, and 87.74%

Table 7
Individual and holistic rankings.

Name	CRITIC	Distance-based	Ideal-point	Proposed method
ICBC	3	2	11	4
ABC	6	4	8	5
CITIC	4	7	9	7
PAB	2	1	10	1
SPDB	5	9	7	10
BS	11	10	3	11
LKL	10	11	4	9
SF	8	5	6	6
Suning	1	3	12	2
EASCM	7	6	5	8
XMXY	12	12	2	12
YGS	9	8	1	3

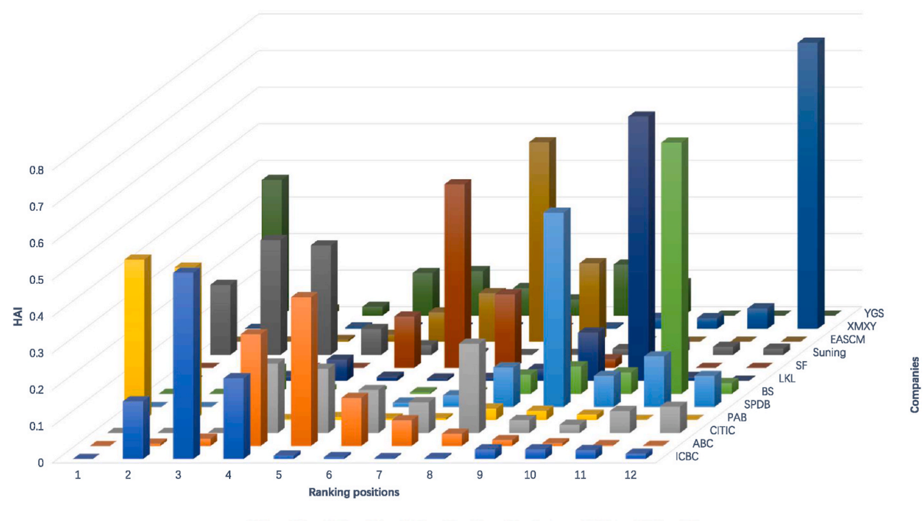

Fig. 3. Rank acceptability index.

Table 6
Rank acceptability index and holistic acceptability index.

Name	b^1	b^2	b^3	b^4	b^5	b^6	b^7	b^8	b^9	b^{10}	b^{11}	b^{12}	a_i^h
ICBC	0.0000	0.0277	0.0680	0.0233	0.0008	0.0004	0.0001	0.0001	0.0009	0.0006	0.0004	0.0001	0.1224
ABC	0.0000	0.0012	0.0027	0.0323	0.0345	0.0090	0.0038	0.0014	0.0005	0.0002	0.0000	0.0000	0.0856
CITIC	0.0000	0.0000	0.0000	0.0201	0.0149	0.0080	0.0046	0.0104	0.0011	0.0005	0.0009	0.0005	0.0610
PAB	0.1133	0.0730	0.0075	0.0003	0.0007	0.0003	0.0003	0.0013	0.0008	0.0003	0.0000	0.0000	0.1977
SPDB	0.0000	0.0000	0.0000	0.0000	0.0009	0.0008	0.0017	0.0046	0.0170	0.0019	0.0020	0.0006	0.0296
BS	0.0000	0.0000	0.0092	0.0013	0.0007	0.0003	0.0002	0.0022	0.0024	0.0013	0.0100	0.0002	0.0278
LKL	0.0000	0.0006	0.0018	0.0062	0.0010	0.0004	0.0004	0.0014	0.0043	0.0165	0.0002	0.0000	0.0328
SF	0.0000	0.0000	0.0000	0.0000	0.0119	0.0343	0.0109	0.0057	0.0008	0.0000	0.0000	0.0000	0.0636
Suning	0.0494	0.0550	0.0400	0.0075	0.0022	0.0003	0.0001	0.0001	0.0005	0.0008	0.0003	0.0001	0.1564
EASCM	0.0000	0.0001	0.0007	0.0021	0.0068	0.0091	0.0297	0.0091	0.0000	0.0000	0.0000	0.0000	0.0577
XMXY	0.0000	0.0147	0.0005	0.0004	0.0003	0.0003	0.0001	0.0002	0.0010	0.0007	0.0008	0.0054	0.0242
YGS	0.0959	0.0030	0.0033	0.0124	0.0104	0.0052	0.0024	0.0060	0.0028	0.0000	0.0000	0.0000	0.1413

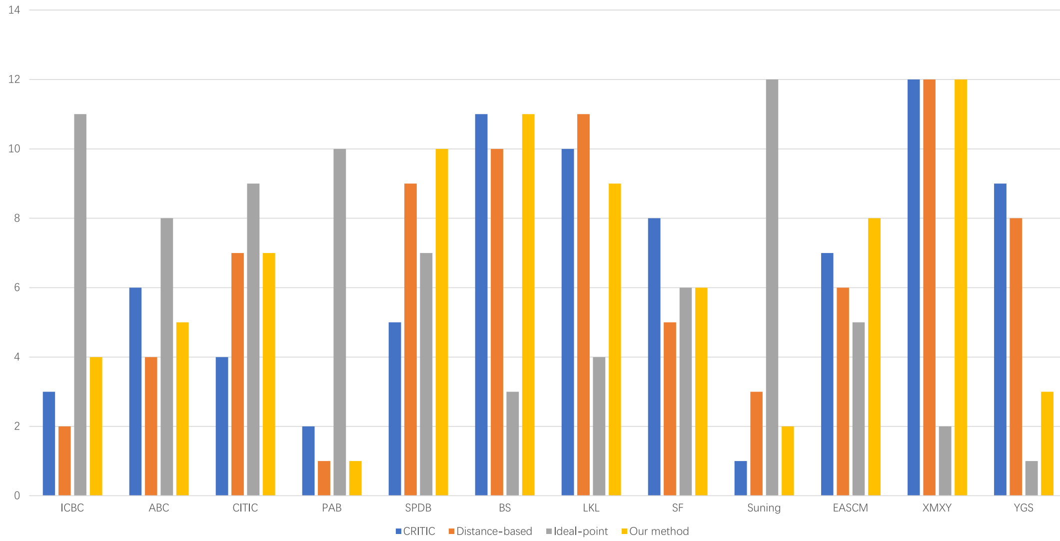

Fig. 4. Individual and holistic rankings.

Table 8
Personal and employer information of the respondents.

Category	Option	Frequency	Percentage
Gender	Male	72	67.92%
	Female	34	32.08%
Age	≤ 24	20	18.87%
	25–32	45	42.45%
	33–40	21	19.81%
	40–48	16	15.09%
	≥ 49	4	3.77%
Education	(Post)Doctorate	13	12.26%
	Master	45	42.45%
	Bachelor	35	33.02%
	College	8	7.55%
	Below College	5	4.72%
Industry	Banks	56	52.83%
	Supply chain company	16	15.09%
	Technology company	9	8.49%
	Related research institutions	7	6.60%
	Others	18	16.98%
Working Years	< 1	21	19.81%
	1–3	32	30.19%
	4–5	35	33.02%
	6–10	13	12.26%
	> 10	5	4.72%
Familiarity with SCF	Never heard of	18	16.98%
	Partially understand	29	27.36%
	Understand well	38	35.85%
	Familiar	16	15.09%
	Very familiar	5	4.72%

held at least a bachelor's degree. Thus most practitioners in the SCF industry are young and highly educated. Moreover, among the five industries, 52.83% of the respondents were employed by banks, 15.09% by supply chain companies, 8.49% by technology companies, 6.60% by related research institutions and 16.98% in other industries.

To assess the specialist's familiarity with SCF platforms, a 5-stage assessment method was adopted. The response format was designed as a 5-point Likert scale with the following meaning: 5 = very familiar, 4 = familiar, 3 = understand well, 2 = partially understand and 1 = never heard of. Based on their responses, the specialists were divided into five groups, each of which was assigned a different weight when calculating the overall scores, i.e., 40% for a response of 5, 30% for 4, 20% for 3, 10% for 2 and 0% for 1.

Based on the technology-recognition-organization framework, each selected SCF platform was also assessed in terms of three aspects (technology, recognition and organization) with a 5-point Likert scale in which 5 points was the highest score, corresponding to a platform that performs best in this aspect, while 1 point was the lowest score, indicating a platform that performs worst in this aspect. A specialist's score for a SCF platform was calculated by averaging the technology score (TS), recognition score (RS) and organization score (OS). Then, the overall score of the SCF platform was obtained based on the weights of the different specialist groups as follows:

$$Overallscore_j = \sum_{i=1}^{5} \frac{w_i \cdot \left(TS_i^j + RS_i^j + OS_i^j\right)}{3}. \tag{23}$$

where $Overallscore_j$ is the final survey score of SCF platform j assessed by the investigated specialists; w_i represents the weight of specialist group i, i.e., $w_1 = 0\%$, $w_2 = 10\%$, $w_3 = 20\%$, $w_4 = 30\%$ and $w_5 = 40\%$; and TS_i^j, RS_i^j and OS_i^j represent the average technology score, recognition score and organization score of SCF platform j given by specialists in group i, respectively.

The technology score, recognition score, organization score and calculated overall score for each SCF platform are displayed in Table 9. Table 9 also summarizes the survey rankings and compares the survey rankings with the rankings from our proposed model. Fig. 5 plots the comparison of the rankings for the twelve SCF platforms. The trends of the two ranking methods are relatively similar. Among the twelve selected SCF platforms, PAB, Suning, ICBC, ABC, SF, EASCM and XMXY receive the same rankings by the two ranking systems. Furthermore, the survey increases the ranking of CITIC, SPDB, and BS and decreases the ranking of YGS and LKL. This may reflect bias due to the composition of the group of surveyed specialists, as the largest share were from the bank industry (52.38%) and the smallest share were from technology companies (8.49%). In summary, the results of our proposed ranking model are similar to the survey rankings. Despite some differences between the two rankings, our proposed model is accurate and reliable.

5. Implications

In this section, the theoretical implications and managerial implications are discussed.

5.1. Theoretical implications

This research contributes to the literature by exploring decisive factors and offers comprehensive insights on dealing with SCF platform

Table 9
Ranking comparisons.

Name	Technology score	Recognition score	Organization score	Overall score	Survey ranking	Proposed ranking
ICBC	3.65	3.78	3.73	3.72	4	4
ABC	3.62	3.94	3.65	3.66	5	5
CITIC	3.68	3.91	3.62	3.77	3	7
PAB	4.08	3.88	3.96	3.97	1	1
SPDB	3.58	3.32	3.49	3.43	9	10
BS	3.32	3.64	3.3	3.39	10	11
LKL	3.34	3.49	3.23	3.37	11	9
SF	3.58	3.75	3.55	3.60	6	6
Suning	3.82	3.88	3.81	3.83	2	2
EASCM	3.43	3.51	3.52	3.47	8	8
XMXY	3.21	3.23	3.25	3.23	12	12
YGS	3.68	3.55	3.36	3.51	7	3

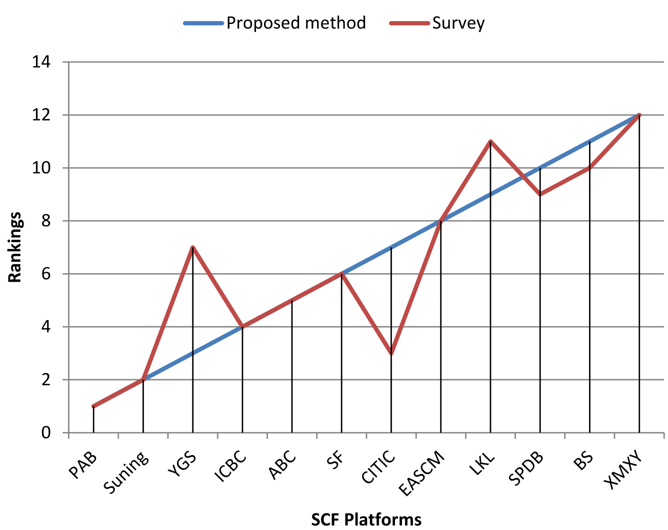

Fig. 5. Ranking comparisons.

evaluation problems. Studies of the factors influencing the performance of SCF platforms are scarce in the literature. This study seeks to provide and inspire a clear perspective by identifying and analyzing the significant factors that influence the performance of SCF platforms. Moreover, this study considers relevant main contexts, namely technology, recognition and organization, to increase the accuracy of the evaluation of the significant factors. Under the technology-recognition-organization framework constructed in this study, eleven second-level factors are analyzed.

Moreover, this study bridges the gap in the evaluation of the performance of SCF platforms. SCF platforms are becoming an important tool for businesses and their supply chains and can facilitate financial transparency and stronger cooperation among members. However, SCF companies are still struggling to understand which kinds of factors influence SCF platform performance and how to rank the performance of existing SCF platforms. This study extends the SMAA-2 model to address the SCF platform evaluation problem and constructs a holistic acceptability index to identify the overall performance of each SCF platform. This study is the first to explore the rankings of SCF platforms.

5.2. Managerial implications

This study analyzes three first-level and eleven second-level factors that can influence SCF platform performance. SCF companies can utilize the proposed research model and the current findings to improve their performance. The empirical results in Table 4 and Fig. 2 list the three first-level factors in order of importance: organization, technology and recognition. Leverage is the most important factor in evaluating the performance of SCF platforms. Thus, SCF service providers should pay attention to leverage and reduce their leverage if they want to improve the performance of their SCF platforms. In addition, service type and time of the SCF in the category of technology and Baidu search and followers in Weibo in the category of recognition have relatively large weights and should also be taken into consideration. Hence, SCF providers are recommended to start their SCF business as soon as possible and update the technology efficiently. The development of efficient strategic plans for the use of search engines and social media to promote online marketing of the SCF business is also recommended.

Furthermore, the empirical findings of this study can provide support for the decision-making process in the selection of SCF platforms. This study applies the SMAA-2 model to evaluate the performance of 12 popular SCF platforms. The empirical results suggest that the rankings of these 12 SCF platforms from best to worst are PAB, Suning, YGS, ICBC, ABC, SF, CITIC, EASCM, LKL, SPDB, BS and XMXY. Companies in the supply chain can select suitable SCF platforms according to these empirical results. These companies can also apply the proposed framework to evaluate SCF platforms using different criteria.

Finally, regulatory institutions can allocate the resources of SCF platforms as a whole according to the empirical results. Specific financial incentives could be formulated to reduce the perceived high cost of investment in SCF technologies and help SCF companies update the latest technology efficiently. Moreover, regulatory institutions can enact policies to coordinate regulations and consolidate legal systems to encourage firms in the supply chain to adopt SCF platforms. In addition, the rankings of the SCF platforms in this study can help regulatory institutions supervise the financial risk levels of different SCF businesses.

Based on these contributions, the current study provides practical insights and also introduces new opportunities for future studies by filling voids in the literature on the evaluation of SCF platforms.

6. Conclusions

Based on an analysis of the previous literature, this study constructed a technology-recognition-organization framework of critical factors that influence the performance of SCF platforms. Furthermore, to bridge the gap in evaluating the performance of SCF platforms, multicriteria group decision-making was applied. The entire evaluation process included (i) identifying individual experts, (ii) executing the stylized MCDM process and (iii) obtaining the group decision. In particular, the three approaches for determining objective weights, i.e., the ideal point, CRITIC and distance-based approaches, represented three individual experts. The individual experts can act as think tanks in helping decision-makers evaluate SCF platforms. Because the preferences of the different individual experts remained uncertain, SMAA-2 was used to obtain holistic evaluations to reach a good compromise. To evaluate SCF platform performance, a comparative analysis was performed to show the differences in evaluation results between the holistic evaluation and individual experts. Finally, a questionnaire survey was conducted to demonstrate the validity and effectiveness of our proposed methodology.

The average weights of technology, recognition and organization were 34.78%, 25.55% and 39.68%, respectively, meaning that organization was most important in evaluating SCF platforms, followed by technology and recognition. Moreover, the rankings and holistic acceptability index indicated that PAB, Suning and YGS ranked as the top three among the twelve selected SCF platforms, with index values of 0.1977, 0.1564, and 0.1413, respectively. Although the survey increased the rankings of three banks and decreased the rankings of two technology companies, the survey rankings were similar to those of the proposed model, supporting its accuracy and reliability.

This study sought to comprehensively evaluate the SCF platforms from multiple dimensions. The evaluation factors and the rankings of the SCF platforms can provide references and decision support not only for SCF platform companies and companies who need financial support in supply chains but also for regulatory institutions. SCF companies can utilize the findings of this study to improve their performance, and companies who need financial support can choose SCF platforms based on the evaluation results. Regulatory institutions can also allocate the resources of SCF platforms as a whole according to the empirical results.

The selection of factors in this study relied on the literature on SCF, and only three first-level and eleven second-level factors were selected for analysis. Thus, future studies can include more factors that may influence the performance of SCF platforms. Moreover, due to data availability, this study focused only on twelve Chinese listed firms that provide SCF services. Future studies can consider a larger sample of SCF platforms and evaluate the performance of SCF platforms in other countries.

Acknowledgement

The authors would like to sincerely thank the editor and other anonymous referees for their helpful and valuable comments that greatly improved the paper. The authors are listed in alphabetical order and contributed equally to the manuscript. This work is supported by the National Natural Science Foundation of China (NSFC No. 72002088, 72103083), Jiangxi Natural Science Fund (20192BAB207010), Jiangxi Province Department of Education Key Science and Technology Research Projects (GJJ190292, GJJ180245), Ministry of Human Resources and Social Security of the People's Republic of China (20YJA790062), Humanities and Social Sciences Project in Jiangxi Province of China (JJ18207, JD18094) and Jiangxi Province Social Science Planning Project (19Y12).

Appendix. Key measures in the questionnaire survey

1. What is your Gender? a. Male b. Female
2. What is your age? a. Below 25 b. 25–32 c. 33–40 d. 41–48 e. Above 48
3. What is your education level? a. (Post)Doctorate b. Master c. Bachelor d. College e. Below College
4. Which industry do you work in? a. Banks b. Supply chain company c. Technology company d. Related research institutions e. Others
5. How long have you been working in this industry? a. less than 1 year b. 1–3 years c. 4–5 years d. 6–10 years e. more than 10 years
6. Please indicate your familiarity with SCF platforms. a. Never heard of b. Partially understand c. Understand well d. Familiar e. Very familiar
7. Please rate the technology of the following 12 companies. 1 is the lowest score, 5 is the highest score.
8. Please rate the recognition of the following 12 companies. 1 is the lowest score, 5 is the highest score.
9. Please rate the organizational development level of the following 12 companies. 1 is the lowest score, 5 is the highest score.

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