Evaluating risks of supply chain finance in a cross-border e-commerce context: An improved TOPSIS approach with loss penalty

Jinzhao Shi[a*], Maolin Sun[a], Xiao Yang[a], Kin Keung Lai[b*]

[a] *School of Economics and Management, Chang'an University, Middle Section of South Second Ring Road, Xi'an 710064, China;*

[b] *International Business School, Shaanxi Normal University, Xian, China*

***Corresponding author:** Jinzhao Shi and Kin Keung Lai

Affiliation: School of Economics and Management, Chang'an University

Detailed permanent address: Middle Section of South Second Ring Road, Xi'an 710064, PR China

Email address: jzshi@chd.edu.cn (J. Shi); 2021123026@chd.edu.cn (M. Sun); 2022123066@chd.edu.cn (X. Yang); mskklai@snnu.edu.cn (K.K. Lai).

Jinzhao Shi (*PhD)* is a lecturer in the School of Economics and Management at Chang'an University, Xi'an, China. He received his Ph.D degree from Xi'an Jiaotong University and the City University of Hong Kong in 2019. His research interests include supply chain finance, and low-carbon supply chain management. He has published articles in *International Journal of Production Economics, Journal of the Operational Research Society, Computers & Industrial Engineering, Expert Systems with Applications*, and others.

Kin Keung Lai (*PhD)* is a Distinguished Professor in the International Business School, Shaanxi Normal University, China. Prior to his current post, he was a Chair Professor in Department of Management Sciences at City University of Hong Kong. Professor Lai is also a Changjiang Scholar Chair Professor in China as well as an academician of the International Academy for Systems and Cybernetic Sciences. His research interests are operations and supply chain management, financial and business intelligence modelling. He serves as Editor-in-Chief or Associate Editor for several international journals. He has published more than 500 papers in international journals and conferences.

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Abstract: The rapid development of cross-border e-commerce (CBEC) has put forward urgent requirements for efficient capital coordination among cross-border supply chain members, and the emerging cross-border e-commerce supply chain finance (CBEC-SCF) is seen as an effective solution. Based on the classification of traditional supply chain finance and the characteristics of CBEC, this paper systematically proposes three types of operational modes of CBEC-SCF, namely the CBEC-based warehouse receipt financing, CBEC-based order financing and CBEC-based factoring. Risks of CBEC-SCF are analyzed from different aspects such as credit, market, operational and legal risks. Evaluating the overall risk levels of different CBEC-SCF modes is a typical multi-criteria decision-making problem, where various sub-risks are criteria. Given the truth that decision-makers like banks are usually risk averse, this paper theoretically proposes an improved TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method with loss penalty to rank the overall risk levels of different CBEC-SCF modes. The boundary conditions for the improved method to change the ranking of alternatives is theoretically proved, and case studies are carried out to verify the applicability and significance of the proposed method. To fit more application scenarios, the improved TOPSIS with loss penalty is further extended to cases with multi-level criteria and "experts" as criteria, and this shows that the risk ranking of the CBEC-SCF modes may change with the risk aversion degree of the bank.
Keywords: cross-border e-commerce; supply chain finance; TOPSIS; risk aversion

1. Introduction

With the rapid development of Internet and acceleration of economic globalization, Cross-border E-commerce (CBEC) has flourished in recent years and is becoming an important channel for promoting international trade (Zhu et al., 2019a). Relevant data indicates that the scale of China's CBEC market has grown from 5.4 trillion yuan in 2015 to 14.2 trillion yuan in 2021, with an average annual growth rate of more than

15%.[1] Meanwhile, the booming CBEC has resulted in the need for effective coordination of logistics, information and capital flow among cross-border supply chains (Wang et al., 2020a). Most extant studies of CBEC focus on solving the cross-border logistics problems (Ren et al., 2020; Wang et al., 2021) and information flow management issues (Zhu et al., 2019a; Elia et al., 2021). In practice, China has developed many cross-border import and export e-commerce trading platforms, e.g., AliExpress, DHgate, Lightinthebox, Tmall Global, etc., which has greatly improved the information exchange (Wang et al., 2020a). What's more, China has been making efforts to solve the logistics problems faced by CBEC, including construction of the CBEC comprehensive pilot zone (Wang et al., 2022), overseas warehouses (Wang et al., 2021) and "China-Europe freight train" (Zhang et al., 2020), and so on.

In contrast, optimization of capital flow in CBEC supply chains, especially the financial support for SMEs (Small and Medium-sized Enterprises), has become a more urgent need in the context of slowing global economic growth. There is no doubt that most CBEC traders are SMEs with the characteristics of "pure trade" (Wang et al., 2020a), which makes it difficult for them to obtain bank loans through fixed assets mortgage, thus creating huge liquidity pressure. In addition, at present, financial services for CBEC businesses in China comprise largely of cross-border payments and settlements, income and expenditure declaration and transaction guarantee (Wang et al., 2020a), and there is still a lack of systematic solutions for CBEC supply chain financing.

Supply Chain Finance (SCF), a new financing method based on the real trade and current assets in the supply chain, aims to optimize supply chain capital flow with the aid of core enterprise credit and helps SMEs upstream and downstream of supply chain to obtain short-term operating funds (Wuttke et al., 2013). In essence, it is a kind of current asset pledge financing, which provides convenient financing for SMEs by revitalizing liquid assets such as inventories, prepayments, accounts receivable, and so on (Wang et al., 2020b). With the rapid development of CBEC, the notion of using SCF method to solve the financing needs of cross-border traders is gaining growing acceptance. In China, there are already some channels providing Cross-border E-commerce Supply Chain Finance (CBEC-SCF), for instance, JD International (the cross-border B2C platform of JD.COM) provides movable property financing and

[1] www.100ec.cn/zt/wmds

accounts receivable financing for suppliers through its platform.[2] However, these practices are still in the initial stage, and a complete CBEC-SCF is yet to grow into a smooth and mature system. As a result, this paper attempts to take the lead in proposing "three categories and five modes" of the CBEC-SCF, namely CBEC-based warehouse receipt financing ("import-bonded zone" mode and "export-overseas warehouse" mode), CBEC-based order financing ("import-purchasing" mode and "export-production" mode) and CBEC-based factoring, to provide a relatively full picture for mode development of the industry.

Although SCF offers some unique advantages in financing of SMEs (Wuttke et al., 2013), banks may face many risks such as credit, market, operational and other risks (Yu et al., 2021; Sang, 2021). In the context of CBEC, these risk factors become more complicated. For example, the cross-border logistics, cross-border goods supervision, cross-border settlement and other new risks appear and these need some extra attention. Therefore, determining how to accurately identify the potential risks of CBEC-SCF and evaluate the overall risk levels of different CBEC-SCF modes is the way for commercial banks to choose appropriate operational modes and exercise effective risk control. Given the truth that risk assessment of CBEC-SCF modes is an MCDM (Multi-Criteria Decision Making) problem and the banks are usually risk averse (Kahneman and Tversky, 1979), this paper proposes an improved TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method with loss penalty to evaluate the overall risk levels of different CBEC-SCF modes. The improved TOPSIS is also extended to cases with multi-level criteria and "experts" as criteria, respectively. All the experimental studies in this paper verify the practicability and significance of the proposed method for the MCDM problem risk aversion decision-makers need to resolve, showing the great potential of this method for risk aversion banks to assess the risks of different CBEC-SCF modes.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the improved TOPSIS with loss penalty. Section 4 proposes three modes of the CBEC-SCF and analyzes their risk factors. Section 5 introduces the application of the improved TOPSIS in evaluating risks of CBEC-SCF modes, and further extends the method to cases with multi-level criteria and "experts" as criteria. Section 6 concludes the paper.

[2] https://baijiahao.baidu.com/s?id=1741955235191481627&wfr=spider&for=pc

2. Literature review

Since this paper focuses on a new research objective, i.e., CBEC-SCF, and proposes an improved TOPSIS method, the literature review mainly includes two parts. The first part reviews the studies related to CBEC and SCF, while the second reviews the TOPSIS method.

2.1 CBEC and SCF

2.1.1 CBEC

CBEC is viewed as the process of selling goods to overseas consumers via online channels (Zhu et al., 2019a). From the perspective of import and export trade, it can be divided into export-oriented CBEC and import-oriented CBEC. From the perspective of trading partners, CBEC can be divided into B2B-CBEC (Wang et al., 2020a) and B2C-CBEC (Wang et al., 2021), etc. With acceleration of economic globalization, CBEC has become a new mode of cross-border trade (Zhu et al., 2019a), which has effectively shortened the supply chain, providing consumers with low-price and multi-category goods, as well as expanding the channels for sales (Kim et al, 2017). Because of this, CBEC is becoming a new growth point of foreign trade in China (Zhu et al., 2019a), with many e-commerce giants such as Tmall, JD, NetEase having established their CBEC platforms (Wang et al., 2020a), and more and more traditional foreign trade enterprises are shifting to these platforms.

However, notwithstanding the rapid development of CBEC, there are still many restrictive factors, such as language and culture (Kim et al, 2017), distance (Yan et al., 2023), communication technology (Elia et al., 2021), online payment (Wang et al., 2020a), and so on. To address such problems, scholars have made attempts mainly from the perspectives of information and material/logistics management (Zhu et al., 2019a; Liu and Li, 2020; Ren et al., 2020; Elia et al., 2021; Wang et al., 2021). For instance, Liu and Li (2020) proposed a blockchain-based framework to improve the information flow coordination level of the CBEC supply chain, while Ren et al. (2020) applied a deep learning approach for inventory optimization and demand forecasting for the CBEC-related third-party-forwarding logistics. At the same time, although financial services for CBEC, e.g., the cross-border payment and settlement, income and expenditure declaration and transaction guarantee (Wang et al., 2020a), have been widely used, there is still a lack of systematic solutions for CBEC supply chain financing, especially financial products that specifically address the short-term financing of foreign trade SMEs. The CBEC-based Supply Chain Finance (CBEC-

SCF), as addressed in the current study, may provide a solution.

2.1.2 SCF operational modes

Supply Chain Finance (SCF) aims at optimizing supply chain capital flow with the aid of core enterprise's credit and helping SMEs in the chain to obtain short-term operating funds (Wuttke et al., 2013). Different from the traditional fixed-assets-based financing, SCF focuses on revitalizing the current assets in supply chains, e.g., accounts receivable, prepayment, inventory, etc., with close control of the physical (products/logistics) and financial (capital/cash) flows in the financing system (Shi et al., 2020a). Gelsomino et al. (2016) categorized the studies of SCF from the perspectives of "finance oriented" and "supply chain oriented", where the former focused on the current-assets-based short-term financial services provided by financial institutions, while the latter emphasized on optimization of working capital finance for supply chain members. Specifically, in the "supply chain oriented" perspective, Chakuu et al. (2019) systematically reviewed the related studies on SCF and pointed out that such financing services are conducted mainly based on three kinds of collateral, i.e., accounts payable, accounts receivable and inventories. In general, the main operational modes of SCF include the following three types: prepayment financing or ordering financing (Wang et al., 2020b; Shi et al., 2023), accounts receivable financing or factoring (Yan et al., 2021), and inventory pledge financing (de Matta and Hsu, 2022).

With the ever-widening applications of information technology and the explosive growth of Internet finance, the so-called online SCF has become the main trend (Shi et al., 2020b). Some non-bank investors have begun to act as financial service providers and carry out online SCF business (Ma et al., 2020). For example, some e-commerce giants in China, such as Alibaba and JD, have started to provide SCF services to traders on their platforms (Lam et al., 2019). On the other hand, commercial banks, such as Ping An Bank and Bank of China, have also launched their online SCF services independently or jointly with other e-commerce enterprises (Lam et al., 2019). As a result, the traditional SCF has been extended to a series of new online SCF modes, e.g., online order financing (Shi et al., 2020b), online factoring (Yan et al., 2021), online inventory financing (Yu et al., 2021), etc. On the basis of online SCF, this paper further considers the new business scenario of CBEC to study the operational mode and risk assessment of the CBEC-based SCF.

2.1.3 SCF risk evaluation

SCF aims at financing SMEs on the basis of the core enterprise's credit worthiness in the supply chain (Shi et al., 2020a), and usually with the current assets (e.g., accounts receivable, prepayment, inventory, etc.) in the chain as collateral (Wang et al., 2020b). For example, small suppliers can use accounts receivables or orders from the core enterprises to get finance from the banks (Yan et al., 2021; Shi et al., 2023), or small dealers can fulfill the prepayment through bank loans as long as the seller as core enterprise provides buyback guarantee (Shi et al., 2020a). Thus, financial service providers such as banks play a pivotal role in SCF activities, which are considered as the main risk bearers (Ma et al., 2020). Because SCF is real-trade-oriented and advocates credit transfer among supply chain members, banks usually face various risks when providing such financial services to SMEs, such as credit, operational, market, and policy risks (Yu et al., 2021; Sang, 2021). Among these risks, credit risk is the most common and has been the focus of most research (Ma et al., 2020; Wu and Liao, 2020; Sang, 2021).

In order to assess the credit risk in the SCF business, scholars have adopted various advanced models, such as FAD (Wu and Liao, 2020), BP neural network (Sang, 2021), SVM (Zhao and Li, 2022), ensemble machine learning (Zhu et al., 2019b), and grey correlation model (Huang et al., 2021). In addition, Wu and Liao (2020) proposed an improved MCDM method called the utility-based hybrid FAD to compare the credit risk of a limited number of alternative borrowers in the SCF business. To improve the accuracy of prediction, Zhu et al. (2019b) applied an integrated method of random subspace and MultiBoosting to evaluate SMEs' credit risk. However, it is not difficult to see that most of the existing studies focus on the credit risk faced by the banks in SCF business. In contrast, *this paper takes the emerging CBEC-SCF as the research objective, and makes a comprehensive evaluation of the credit, market, operational, legal, and other risks that the banks face. More importantly, an improved TOPSIS method is proposed to take the risk aversion of banks into account*.

2.2 TOPSIS

MCDM problems usually involve many conflicting criteria, which may put significant pressure on decision makers (Kuo, 2017). Many classic MCDM methods such as WSM (Weighted Sum Model), WPM (Weighted Product Model), SAW (Simple Additive Weighting), AHP (Analytic Hierarchy Process), ELECTRE (Elimination Et Choice Translating Reality), and TOPSIS have been developed. While WSM, WPM, SAW, and AHP help decision makers find a single optimal solution, ELECTRE and TOPSIS further help them obtain a ranked list of alternatives.

Among many MCDM methods, TOPSIS is popular and widely applied because of its more intuitive and clear logic (Kuo, 2017). In the decades since TOPSIS was proposed, a large number of improved versions of the method have been used to solve different MCDM problems.

(1) *Integration of TOPSIS with other methods*. With the increasing complexity of research questions, the integration of TOPSIS with other methods such as ANP (Tavana et al., 2013), SPA (Yuan and Luo, 2019), GRA (Kirubakaran and Ilangkumaran, 2016), OWA (Cheng et al., 2023), AHP (Amrita et al., 2022), VIKOR (Bakioglu and Atahan, 2021), etc., has become a solution. For example, Tavana et al. (2013) combined the Analytical Network Process (ANP) and TOPSIS to evaluate the community's overall e-government readiness, while Yuan and Luo (2019) embedded the Set-Pair Analysis (SPA) into the TOPSIS to assess China's regional energy security. Kirubakaran and Ilangkumaran (2016) constructed a hybrid MCDM model by integrating Grey Relational Analysis (GRA) and TOPSIS to select appropriate equipment maintenance strategies.

(2) *Fuzzy TOPSIS*. The MCDM problems usually involve people's subjective judgments when scoring the alternatives or determining weights of criteria (Salih et al., 2019), thus embedding fuzzy set theory into MCDM methods is necessary (Prabhu et al., 2020), and fuzzy TOPSIS is one of them. Fuzzy sets such as the triangular fuzzy membership function (Zenouz et al., 2021), trapezoidal fuzzy membership function (Zhao et al., 2023), intuitionistic fuzzy sets (Prabhu et al., 2020; Singh et al., 2023), interval-valued fuzzy sets (Joshi and Kumar, 2016; Mathew et al., 2022), Pythagorean fuzzy sets (Rani et al., 2022), have been combined with TOPSIS to solve different problems. For instance, Prabhu et al. (2020) proposed the interval-valued triangular fuzzy TOPSIS method to find the factors that determine the manufacturing performance, while Joshi and Kumar (2016) extended TOPSIS by integrating the interval-valued, intuitionistic, and hesitant fuzzy sets. For more literature on fuzzy TOPSIS, we refer the reader to Salih et al. (2019).

(3) *Improvement of relative closeness coefficient in TOPSIS*. The above two ways to improve TOPSIS are essentially hybridization of TOPSIS with other methods and theories, which means *external improvement* of TOPSIS. Another way is the *internal improvement* of TOPSIS, which mainly focuses on improving the calculation of relative closeness coefficient in TOPSIS. In the traditional TOPSIS, the calculation of relative closeness coefficient ignores the weight issues of distances between alternatives from

the positive and negative ideal solutions. To address this, Kuo (2017) and Dwivedi et al. (2018) proposed new methods for calculation of relative closeness coefficient with the form of linear combination and exponent respectively. Sun et al. (2018) proposed the similarity-like positive and negative correlation coefficient decision making factors and constructed four types of relative closeness coefficients in TOPSIS.

Although the above studies have improved the relative closeness coefficient in TOPSIS, characteristics of its economic implications are still unclear. This paper proposes a new improved relative closeness coefficient in TOPSIS that incorporates the risk aversion of decision makers, providing a more effective decision-making tool for banks.

3. The improved TOPSIS with loss penalty

3.1 MCDM problem

An MCDM problem can be expressed as a decision matrix whose elements indicate the evaluated values of all alternatives with respect to each criterion. Let $A=\{A_1, A_2, \ldots, A_m\}$ be a set of m feasible alternatives and $C=\{C_1, C_2, \ldots, C_n\}$ be a finite set of n criteria. Then, the MCDM problem can be concisely described in matrix format as

$$X=\left[x_{ij}\right]_{m\times n}=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}, \qquad (1),$$

where each of elements x_{ij} means the rating of alternative A_i with respect to criterion C_j.

3.2 The original TOPSIS

The TOPSIS approach was initially developed by Hwang and Yoon (1981), which aims to identify the best solution from a finite set of alternatives, and its core principle is that the best solution should be the nearest to the positive ideal solution (PIS) and be the remotest from the negative ideal solution (NIS) simultaneously. The process of TOPSIS can be described as follows.

Step 1. Normalize the decision matrix $X=\left[x_{ij}\right]_{m\times n}$ to the matrix $R=\left[r_{ij}\right]_{m\times n}$. The normalized value r_{ij} can be calculated as

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}. \quad (2).$$

Step 2. Calculate weighted normalized matrix $V = \left[v_{ij}\right]_{m\times n}$. The weighted normalized value v_{ij} can be calculated as

$$v_{ij} = w_j r_{ij}. \quad (3),$$

where w_j is the weight of each criterion, which satisfies $\sum_{j=1}^{n} w_j = 1$ and $w_j \in [0,1]$.

Step 3. Determine the PIS and the NIS, denoted by V^+ and V^- respectively, as

$$V^+ = \left\{v_1^+, v_2^+, ..., v_n^+\right\} = \left\{\max_{1\le i\le m}\left(v_{ij}\right)\middle| j \in J^+, \min_{1\le i\le m}\left(v_{ij}\right)\middle| j \in J^-\right\} \quad (4),$$

$$V^- = \left\{v_1^-, v_2^-, ..., v_n^-\right\} = \left\{\min_{1\le i\le m}\left(v_{ij}\right)\middle| j \in J^+, \max_{1\le i\le m}\left(v_{ij}\right)\middle| j \in J^-\right\} \quad (5),$$

where J^+ and J^- are the sets of benefit criteria and cost criteria, respectively.

Step 4. Calculate the Euclidean distance. The distances of alternative A_i from the PIS and NIS are given, respectively, as

$$d_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2} \quad (6)$$

and

$$d_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}, \quad (7).$$

Step 5. Calculate the relative closeness coefficient. The relative closeness of alternative A_i with respect to the PIS is defined as

$$RC_i = \frac{d_i^-}{d_i^+ + d_i^-}. \quad (8).$$

Step 6. Rank the alternatives A according to RC_i.

3.3 The improved TOPSIS with loss penalty

Although we can get the ranking of alternatives by their relative closeness values (RC_i) in the original TOPSIS, this may not satisfy the decision makers since the deeper economic implications behind d_i^+ and d_i^- in RC_i are not captured in the original TOPSIS method. In reality, people usually have different attitudes or tolerance towards benefits and losses when making decisions; for instance, people typically exhibit greater sensitivity to losses than to equivalent gains, which is called *loss aversion* (Kahneman and Tversky, 1979; Tom et al., 2007). Based on this, the current paper improves the original TOPSIS and enhances its applicability by taking into account the psychological preference of decision makers, namely *loss aversion*.

The main idea is to introduce an extra term of *loss penalty* into the calculation of the relative closeness in the original TOPSIS method to provide for the *loss aversion* of the decision makers, i.e.,

$$RC_i^{LP} = \frac{d_i^-}{d_i^+ + d_i^-} - \lambda \frac{D - d_i^-}{D}, \qquad (9),$$

where RC_i^{LP} is the improved relative closeness coefficient of A_i; d_i^+ and d_i^- are the distances of alternative A_i from the PIS and NIS, respectively; D is the distance between PIS and NIS; and $\lambda \geq 0$, called the *loss penalty factor,* which measures the degree of loss aversion of the decision maker.

In Eq. (9), $-\lambda \frac{D - d_i^-}{D}$ is exactly the term of *loss penalty*, where λ is the *loss penalty factor*, while $\frac{D - d_i^-}{D}$ is the *adjusted loss value* of alternative A_i. Obviously, $\frac{D - d_i^-}{D}$ increases with the decrease of d_i^-, which means that the closer the alternative is to the NIS, the greater is the loss value, and thus the greater is the loss penalty under a given λ. Further, as $0 \leq d_i^- \leq D$ always holds, $\frac{D - d_i^-}{D} \in [0,1]$ establishes, unifying the dimensions of $\frac{d_i^-}{d_i^+ + d_i^-}$ and $\frac{D - d_i^-}{D}$ in Eq. (9). When the alternatives are closer to PIS, RC_i^{LP} is closer to 1, i.e., $\lim_{d_i^- \to D} RC_i^{LP} = 1$; when the alternatives are closer to NIS, RC_i^{LP} is closer to $-\lambda$, i.e., $\lim_{d_i^- \to 0} RC_i^{LP} = -\lambda$. Given RC_i^{LP} increases with d_i^- from Eq. (9), we have $RC_i^{LP} \in [-\lambda, 1]$, and a higher RC_i^{LP} means a higher ranking of A_i.

For the improved TOPSIS with loss penalty, RC_i^{LP} in Eq. (9) has the following properties.

Proposition 1. *In the original TOPSIS, the sufficient condition of* $RC_1 > RC_2$ *is*

$$d_1^- d_2^+ - d_2^- d_1^+ > 0 \tag{10}$$

while in the improved TOPSIS, the sufficient condition of $RC_1^{LP} > RC_2^{LP}$ *changes into*

$$d_1^- d_2^+ - d_2^- d_1^+ > \frac{\lambda\left(d_2^- - d_1^-\right)\left(d_1^+ + d_1^-\right)\left(d_2^+ + d_2^-\right)}{D} \tag{11}$$

Proof of Proposition 1. In the original TOPSIS, it is easy to verify that when Eq. (10) is true, $RC_1 > RC_2$ establishes (Kuo, 2017). In the improved TOPSIS, if Eq. (11) is true, we have $\frac{d_1^-}{d_1^+ + d_1^-} - \frac{d_2^-}{d_2^+ + d_2^-} > \lambda \frac{D - d_1^-}{D} - \lambda \frac{D - d_2^-}{D}$, implying $RC_1^{LP} > RC_2^{LP}$. □

Proposition 2. *For a pair of alternatives* A_1 *and* A_2 *that satisfy* $d_1^- d_2^+ > d_2^- d_1^+$,

(a) If $d_2^- > d_1^-$, *there always exists a unique positive*

$$\tilde{\lambda} = \frac{\left(d_1^- d_2^+ - d_2^- d_1^+\right) D}{\left(d_2^- - d_1^-\right)\left(d_1^+ + d_1^-\right)\left(d_2^+ + d_2^-\right)} \tag{12}$$

and when $\lambda < \tilde{\lambda}$, $RC_1^{LP} > RC_2^{LP}$ *holds; when* $\lambda > \tilde{\lambda}$, $RC_1^{LP} < RC_2^{LP}$ *holds.*

(b) If $d_2^- < d_1^-$, $RC_1^{LP} > RC_2^{LP}$ *always holds.*

Proof of Proposition 2. For part (a). Let $a_1 = RC_1 = \frac{d_1^-}{d_1^+ + d_1^-}$, $a_2 = RC_2 = \frac{d_2^-}{d_2^+ + d_2^-}$, $b_1 = \frac{D - d_1^-}{D}$, $b_2 = \frac{D - d_2^-}{D}$, then $RC_1^{LP} = a_1 - b_1\lambda$, $RC_2^{LP} = a_2 - b_2\lambda$. If $d_1^- d_2^+ > d_2^- d_1^+$, we have $a_1 > a_2$ based on Proposition 1; and if $d_2^- > d_1^-$ holds, we have $b_1 > b_2$. By viewing both RC_1^{LP} and RC_2^{LP} as functions concerning λ, curves of the two functions intersect only once over $\lambda \in (0,+\infty)$, and the abscissa of the intersection point can be solved as $\tilde{\lambda}$ in Eq. (12) through letting $RC_1^{LP} = RC_2^{LP}$. Further, when $\lambda < \tilde{\lambda}$, $RC_1^{LP} > RC_2^{LP}$ holds; and when $\lambda > \tilde{\lambda}$, $RC_1^{LP} < RC_2^{LP}$ holds.

For part (b). If $d_2^- < d_1^-$ holds, we have $b_1 < b_2$, and then the curves of RC_1^{LP} and RC_2^{LP} have no intersection point over $\lambda \in (0,+\infty)$, implying that $RC_1^{LP} > RC_2^{LP}$ always holds. □

Proposition 2 theoretically proves that the improved TOPSIS with loss penalty in this paper may change the ranking of alternatives, compared with the original TOPSIS. When $d_1^- d_2^+ > d_2^- d_1^+$, we undoubtedly have $RC_1 > RC_2$ through the original TOPSIS from Proposition 1, while we may have $RC_1^{LP} < RC_2^{LP}$ through the improved TOPSIS if $d_2^- > d_1^-$ and $\lambda > \tilde{\lambda}$ are further satisfied, as shown in Proposition 2(a). This shows the great significance of the improved TOPSIS, as it may provide a new and more reasonable ranking of alternatives for a loss-averse decision maker in an MCDM problem. In this paper, we tackle decisions of banks that tend to be risk averse in SCF (Ma et al., 2020), thus it is more appropriate to employ the improved TOPSIS with loss penalty to rank the overall risk levels of different CBEC-SCF modes.

4. Modes and risks of CBEC-SCF

We use the improved TOPSIS with loss penalty in Section 3 to measure the overall risk levels of CBEC-SCF modes that banks encounter. The problem is an MCDM problem where alternatives and criteria are financing modes and risk types respectively, as elaborated as follows.

4.1 CBEC-SCF modes

The main principle to design CBEC-SCF operational modes is to solve the short-term liquidity problems faced by traders in the cross-border e-commerce import and export trading activities, with current assets such as inventory, accounts receivable, prepayments, etc. as the guarantee. Given that the practice of CBEC-SCF in the industry is till at the initial stage of exploration, we take the lead in systematically proposing three types of operational modes of CBEC-SCF, namely CBEC-based warehouse receipt financing, CBEC-based order financing and CBEC-based factoring. It is not difficult to find that CBEC-SCF is an extension of online SCF in the new context of CBEC, and it is still evolved from the three types of traditional SCF modes, as shown in Fig. 1.

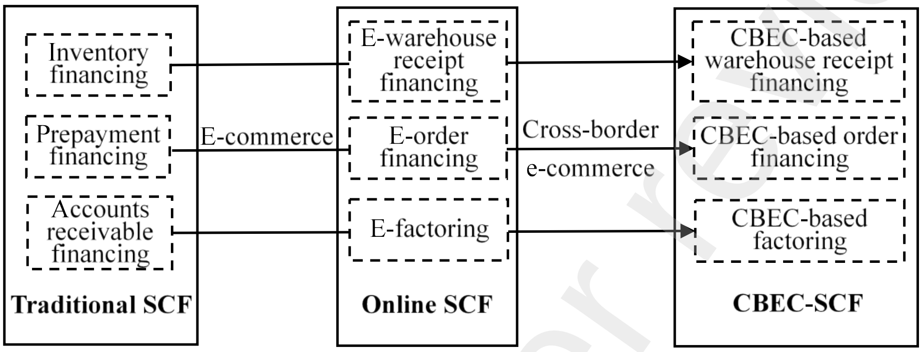
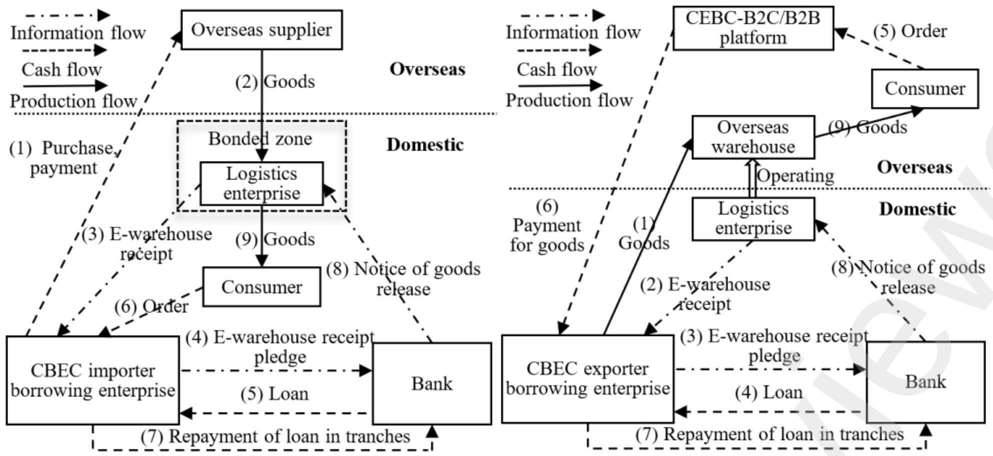


Fig. 1. The evolution path of CBEC-SCF modes.

4.1.1 CBEC-based warehouse receipt financing

The CBEC-based warehouse receipt financing mode realizes the function that domestic CBEC platform enterprises or enterprises stationed on the platform pledge their goods in the bonded area or overseas warehouse to banks to obtain financing. The goods are supervised by the 3PLs (third-party logistics enterprises) recognized by banks and electronic warehouse receipts issued by the 3PLs are used as financing guarantees. It is evolved from the traditional inventory pledge financing (de Matta and Hsu, 2022) and integrates many new features of online financing and CBEC (Yu et al., 2021), aiming at revitalizing the role of inventory assets in CBEC activities and accelerating the capital turnover efficiency of borrowing enterprises. According to the characteristics of import and export in CBEC activities, the CBEC-based warehouse receipt financing mode can be further subdivided into the "*import-bonded zone type*" and the "*export-overseas warehouse type*", where the former revitalizes the inventories of the CBEC importers in the bonded area while the latter activates that of the CBEC exporters in the overseas warehouses, as shown in Fig. 2.

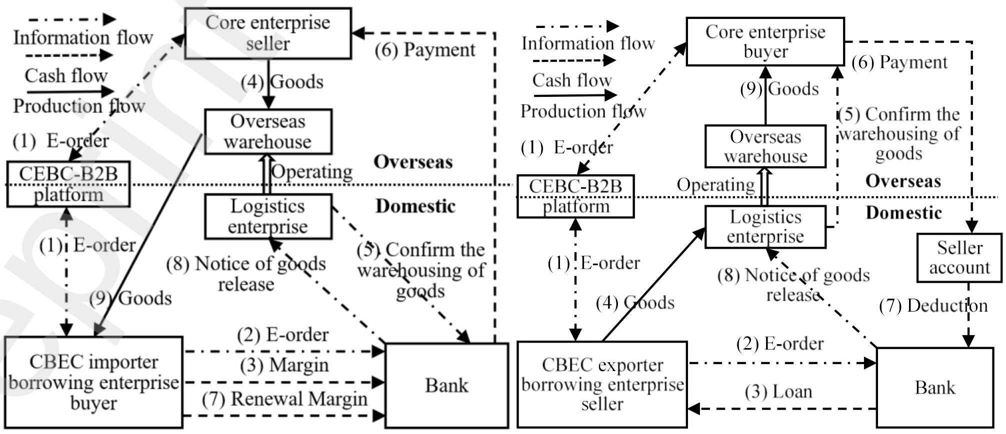


(a) The "import-bonded zone type" (b) The "export-overseas warehouse type"

Fig. 2. The operational processes of CBEC-based warehouse receipt financing.

4.1.2 CBEC-based order financing

The CBEC-based order financing mode encourages domestic enterprises stationed on CBEC platforms to apply to banks for financing by virtue of electronic purchase or production orders signed with overseas core enterprises and certified by the platforms. It is evolved from the traditional prepayment/order financing (Wang et al., 2020b), and aims to solve the shortage of purchasing and production funds in the import and export activities of CBEC supply chains. Generally speaking, counterparties of the borrowing firms are the creditworthy overseas enterprises and such a mode emphasizes the closed-loop control of the production (refers to goods in overseas warehouse) and capital flows. The CBEC-based order financing mode can also be divided into two subtypes, i.e., the "*import-purchasing type*" and the "*export-production type*", where the former solves the shortage of procurement funds for CBEC importers while the latter addresses the problem of production funds for CBEC exporters, as shown in Fig. 3.



(a) The "import-purchasing type" (b) The "export-production type"

Fig. 3. The operational processes of CBEC-based order financing.

4.1.3 CBEC-based factoring

The CBEC-based factoring mode allows domestic borrowing enterprises (exporters) to transfer their accounts receivables, generated by CBEC activities, to banks to obtain financing. It is evolved from the traditional factoring (Yan et al., 2021), and is beneficial to the advance realization of accounts receivables of CBEC exporters, as shown in Fig. 4.

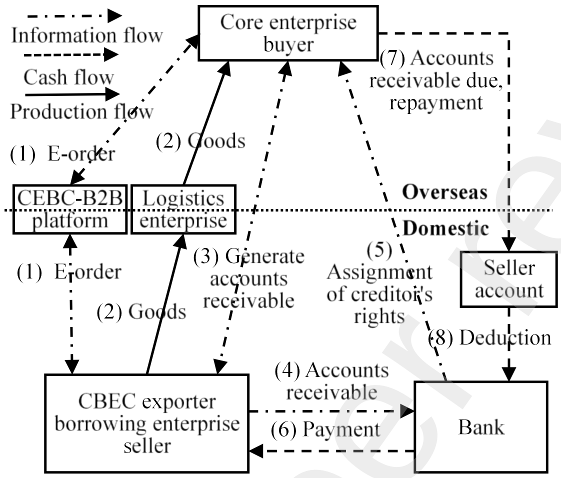


Fig. 4. The operational process of CBEC-based factoring.

4.2 CBEC-SCF risks

Since banks and other financial services providers play a pivotal role in SCF activities, they are considered as the main risk bearers (Ma et al., 2020). When providing financial services to SMEs, they may face many kinds of risks such as credit, market, operational, and policy risks (Yu et al., 2021; Sang, 2021). In this paper, the risks of CBEC-SCF are examined from the perspective of banks, and the CBEC-SCF modes are taken as the evaluation objects rather than individual borrowers.

4.2.1 Credit risk

Most literature on SCF risk evaluation focuses on the credit risk, and mainly takes the operating ability (e.g., operating status, scale, profitability, solvency, etc.) and financial credit status (e.g., tax, debt repayment, credit rating, guarantee status, etc.) of the borrowing enterprises and their counterparties (core enterprises in supply chains) as evaluation indicators (Zhu et al., 2019b; Wu and Liao, 2020; Sang, 2021; Zhao and Li, 2022). Obviously, the better the operating ability and credit status of the borrowing enterprises and the core enterprises, the lower the possibility of the borrowers' default. However, in the context of CBEC, the e-credit status of the borrowing enterprises, e.g., historical orders, transaction networks, customer comments, etc., is another important criterion to consider. In addition, in CBEC-SCF, the credit granting to borrowers has partly changed into "overseas credit granting". For example, banks face new challenges in investigation of overseas core enterprises and inventories in overseas warehouses, which bring credit risks to banks in terms of loan approval, structure and pricing. Finally, moral hazard cannot be ignored, such as the moral hazard of internal staff of the banks and joint fraud of supply chain members based on false orders or warehouse receipts (Yu et al., 2021).

4.2.2 Market risk

On the one hand, the market risk of CBEC-SCF comes from health of the industry in which the borrower operates and the collateral provided. In addition to development prospects of the industry (Zhu et al., 2019b; Zhao and Li, 2022), fluctuations in tariff rates and exchange rates in case of CEBC-SCF may lead to termination of cross-border transactions, resulting in defaults and losses of banks. The collateral risk mainly comes from a decline in value of pledged goods (Zhu et al., 2019b) and accounts receivable (Zhu et al., 2019b; Sang, 2021). On the other hand, the stability of cross-border supply chain directly affects production and sales of the borrowing enterprises and the guarantee realization of core enterprises (Zhao and Li, 2022), which is another major market risk factor. The more stable the cross-border supply chain is, the less likely it is to cause economic losses. Besides, the level of cooperation between e-commerce platforms and banks is crucial since the platforms can sense in advance or predict the potential market risks of the industry and supply chain where the borrowers are located by using its technical advantages. They can warn banks about risks.

4.2.3 Operational risk

The first is the operational risk brought by cross-border transportation and storage. In the transportation stage, in addition to the traditional risk of loss of goods in transit (Yu et al., 2021), there are also many new risks, such as unreliable/weak distribution by overseas logistics firms, or the low level of information sharing among the overseas logistics, e-commerce platforms and banks, which may lead to difficulties in monitoring overseas in-transit distribution activities. Besides, in the CBEC-based warehouse receipt or order financing, the pledge of goods (Ma et al., 2020; Yu et al., 2021) is still one of the main risk control methods used by banks. Therefore, appropriate measures should be taken to effectively "check" the pledged goods in the bonded area and overseas warehouses. The second is the operational process risk. The design of CBEC-SCF modes emphasizes the closed-loop control of logistics and capital flow, meaning operational procedures should be strictly obeyed. For example, logistics enterprises must be required to release the pledged goods after receiving the bank's instructions. The last is the risk of online operation, such as the risk of information tampering and disclosure caused by insecure networks (Yu et al., 2021), the application risk of electronic credit rating technology caused by the low-ability of bank staffs, and the risk of cross-border payments.

4.2.4 Legal risk

Legal risk mainly includes pledge, cross-border capital flow and legal uncertainty. First of all, in the context of CBEC, frequent trade of goods in bonded areas and overseas warehouses and other factors aggravate the risk of ownership and legitimacy of pledged goods. Besides, the ownership and legitimacy of receivables as collateral may be problematic due to violation of non-transferable agreement and repeated pledge (Yu et al., 2021). Secondly, some segmentation modes of CBEC-SCF involve cross-border capital flow, and the risk of cross-border money laundering cannot be ignored. Finally, due to the cross-border trade, CBEC-SCF faces different legal systems in different countries, which may lead to the risk of applicability of laws, such as the legitimacy of electronic technologies (e.g., electronic signatures) and electronic bills (e.g., electronic warehouse receipts, electronic orders and electronic contracts) in different countries.

5. Case study and extensions

5.1 Case study

As CBEC-SCF is an emerging financial service, few banks have systematically examined or implemented the financing modes this paper has proposed. We use a virtual case to illustrate how to apply the method put forward in Section 3 to evaluate the overall risk levels of different CBEC-SCF modes, and to clarify the potential and significance of this method.

Assuming the PA Bank is about to launch CBEC-SCF business, it needs to rank the overall risk levels of the three CBEC-SCF modes based on the four sub-risks (criteria), as listed in Section 4. Five industry/academic experts, marked as $\{E1, E2, E3, E4, E5\}$, are invited to grade the risk levels for each financing mode on the scale in Table 1, and the original decision matrix is given in Table 2. Since the dimensions of each criterion (sub-risk) are unified, it is not necessary to normalize the original decision matrix in this example.

Table 1

CBEC-SCF risk rating scale.

Rating	Low	Moderately Low	Medium	Moderately High	High
Score	0.0~1.0	1.0~2.0	2.0~3.0	3.0~4.0	4.0~5.0

Table 2

Experts' original decision matrix.

Modes (Codes)	Experts	Criteria			
		Credit risk ($R1$)	Market risk ($R2$)	Operational risk ($R3$)	Legal risk ($R4$)
CBEC-based warehouse receipt financing ($M1$)	$E1$	4.5	4.5	3	2
	$E2$	3.5	2	3	1
	$E3$	4	4.5	2	2.5
	$E4$	3	4	3	2
	$E5$	4	3.5	1	1.5
CBEC-based order financing ($M2$)	$E1$	5	5	3	1.5
	$E2$	4.5	3.5	3	2
	$E3$	4.5	4	2	1
	$E4$	2	3.5	2	2
	$E5$	5	4	2	1.5
CBEC-based factoring ($M3$)	$E1$	5	1	1.5	4.5
	$E2$	4.5	1	1	3
	$E3$	4.5	2	0.5	4
	$E4$	4	1	1	4
	$E5$	4.5	1	1.5	4.5

Supposing the relative weights assigned by the experts are $(0.1, 0.2, 0.2, 0.1, 0.4)$, then the original decision matrix in Table 2 can be reduced as that in Table 3. Then, the relative weights of criteria (sub-risks) can be determined. There are various subjective and objective weighting methods, while in this paper the entropy method (Chen, 2021) is used as one of the objective weighting methods. Its principle is to assign weights to the criteria based on the degree of dispersion of all alternatives' scores under a certain criterion, that is, the more discrete the alternatives' scores under a certain criterion are, the higher is the degree of variations among the alternatives, and therefore a higher weight should be assigned to the criterion. According to the method of Chen (2021), the weight of the four sub-risks can be calculated as $(0.01, 0.41, 0.16, 0.42)$ based on Table 3, and then the weighted decision matrix can be obtained as Table 4.

Now, Eq. (4)-(9) are used to calculate the relative closeness coefficients of the alternatives. When applying Eq. (4) and (5) to determine the PIS and NIS, it should be noted that the criteria (risks) in this example is the cost criteria rather than the benefit criteria. Then the distances between each alternative and the PIS, NIS can be calculated using Eqs. (6) and (7), as shown in Table 5. Given the truth that the distance between the PIS and NIS is $D = 1.56$, Eq. (9) is employed to calculate the relative closeness coefficient of each alternative (Table 6), considering two different loss penalty factors, i.e., $\lambda=0$ and $\lambda=2$, where the former corresponds to the case of original TOPSIS calculated by Eq. (8).

Table 3

The reduced decision matrix.

Modes \ Risks	$R1$	$R2$	$R3$	$R4$
$M1$	3.85	3.55	2	1.7
$M2$	4.5	3.95	2.3	1.55
$M3$	4.5	1.2	1.15	4.05

Table 4

The weighted decision matrix.

Modes \ Risks	$R1$	$R2$	$R3$	$R4$
$M1$	0.0385	1.4555	0.32	0.714
$M2$	0.045	1.6195	0.368	0.651
$M3$	0.045	0.492	0.184	1.701

Table 5

Distances from PIS and NIS.

Modes	d_i^+	d_i^-
$M1$	0.98	1.00
$M2$	1.14	1.05
$M3$	1.05	1.14

Table 6

Relative closeness coefficients and ranking of modes.

Modes	$\lambda=0$		$\lambda=2$	
	RC_i^{LP}	Rank	RC_i^{LP}	Rank
$M1$	0.51	*2*	-0.20	*3*

$M2$	0.48	*3*	-0.17	*2*
$M3$	0.52	1	-0.01	1

The results in this case show that under the original TOPSIS, the priority of the modes that the banks should choose is $M3 \succ M1 \succ M2$, while under the improved TOPSIS with loss penalty, the priority becomes $M3 \succ M2 \succ M1$. This shows that the improved TOPSIS can change the decisions and choices of banks, and has the potential for banks with risk/loss aversion to make decisions more accurately and reasonably. In addition, it is not difficult to see that in the improved TOPSIS, the loss penalty factor λ plays a key role in ranking of alternatives. In this example, the simulation results show that when the factor exceeds a critical value less than 1, the ranking of $M1$ and $M2$ will change, as shown in Fig. 5 which confirms Proposition 2. Therefore, in practice, decision-makers should reasonably choose the value of λ according to the degrees of risk/loss aversion.

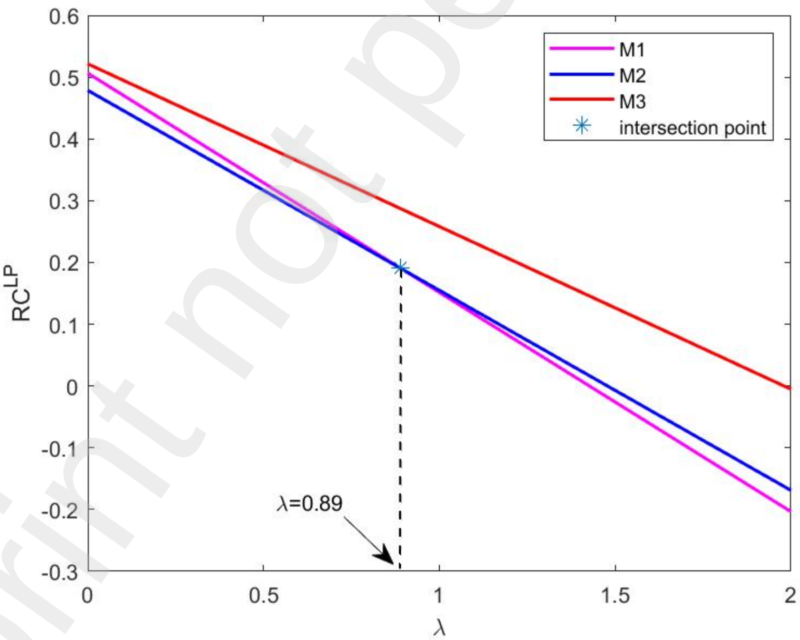


Fig. 5. Change of RC_i^{LP} with λ.

5.2 Extensions

Section 3 describes the most general decision scenario of the improved TOPSIS with loss penalty. In reality, the evaluation index system may be more complicated, showing that the criterion is not single-level but multi-level. Therefore, we extend the improved

TOPSIS to the case with multi-level criteria in Section 5.2.1. Another example is that when determining the weight of the criteria (risks), the risk/loss aversion of decision-makers is required to be considered, for which we further propose an improved TOPSIS method with "experts" as criteria in Section 5.2.2.

5.2.1 The case with multi-level criteria

In the MCDM problem, multi-level criteria decision-making problem is very common. Taking the CBEC-SCF risk evaluation in this paper as an example, there are often sub-criteria under the main criteria like the credit, market, operational and legal risks. For example, the credit investigation risk and moral hazard can be set under credit risk, and the collateral risk, industry risk, supply chain risk as well as exchange rate risk can be set under market risk.

To solve such problems, various comprehensive evaluation methods can be nested on the basis of the improved TOPSIS proposed in Section 3. For example, evaluated values of the main criteria can be obtained by iteration of the multi-level grey evaluation method (Wang et al., 2007), and the weight of each sub-criterion can be determined by AHP (Satty, 2003), entropy method (Chen, 2021) and others. Once the evaluated values of the main criteria are obtained, the problem is transformed into a single-level criteria problem, which can be further processed using the method described in Section 3 of the current paper.

5.2.2 The case with "experts" as criteria

In the improved TOPSIS (Section 3), there is no special emphasis on the processing method of weighting criteria. In the example in Section 5.1, we use the entropy method to assign weights to criteria. However, this method fails to incorporate the risk/loss aversion idea advocated in this paper when the "cost criterion" is weighted. Therefore, in this section, we further propose a new model that takes both CBEC-SCF modes and risks as alternatives, and "experts" as criteria. This new model can simultaneously take into account the risk aversion of the decision-maker when weighting the risks and selecting the final modes. It can also be used to deal with the problem with multi-level criteria in Section 5.2.1. The processes of the proposed method are as follows.

Step 1. Construct the "risks-experts" decision matrices ($Y^{(k)}=\left[y_{ij}^{(k)}\right]_{m\times n}$, $k=1,2,\ldots,q$) under each CBEC-SCF mode.

$$Y^{(k)}=\left[y_{ij}^{(k)}\right]_{m\times n}=\begin{bmatrix} y_{11}^{(k)} & y_{12}^{(k)} & \cdots & y_{1n}^{(k)} \\ y_{21}^{(k)} & y_{22}^{(k)} & \cdots & y_{2n}^{(k)} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1}^{(k)} & y_{m2}^{(k)} & \cdots & y_{mn}^{(k)} \end{bmatrix} \quad (12).$$

Step 2. Calculate the weightings of risks in each CBEC-SCF mode ($w_i^{(k)}$). Take "experts" as cost criteria, calculate the relative closeness coefficients of risks ($RC_i^{LP(k)}$) through the improved TOPSIS with loss penalty, and standardize them as

$$w_i^{(k)}=\frac{1-RC_i^{LP(k)}}{\sum_{i=1}^{m}(1-RC_i^{LP(k)})}. \quad (13).$$

Step 3. Construct the "modes-experts" decision matrix ($Z=\left[z_{kj}\right]_{q\times n}$) through $z_{kj}=\sum_{i=1}^{m}w_i^{(k)}y_{ij}^{(k)}$.

$$Z=\left[z_{kj}\right]_{q\times n}=\begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1n} \\ z_{21} & z_{22} & \cdots & z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ z_{q1} & z_{q2} & \cdots & z_{qn} \end{bmatrix} \quad (14).$$

Step 4. Take "experts" as cost criteria, calculate the relative closeness coefficients of CBEC-SCF modes (RC_k^{LP}) through the improved TOPSIS with loss penalty.

Then, we still use the case in Section 5.1 to illustrate the new model. Based on the scoring matrix (Table 2), the "risks-experts" decision matrices under each CBEC-SCF mode are constructed (Tables 7-9). Taking "experts" as criteria, the relative closeness coefficients can be calculated from the improved TOPSIS in Section 3.3 and the weightings of risks can be obtained by Eq. (13), as shown in Table 10. In Table 10, we give results under two different loss penalty factors, i.e., $\lambda=0$ and $\lambda=2$, and it can be seen that the ranking on weightings of risks may change with the loss penalty factor.

Based on Steps 3 and 4 of the model, the "modes-experts" decision matrix can be constructed and the ranking of alternatives can be obtained, as shown in Tables 11 and 12 respectively. From Table 12, when the risk aversion is not considered ($\lambda=0$), the priority of the financing mode that the bank should choose is $M1\succ M3\succ M2$. When the risk aversion of the bank is considered with $\lambda=2$, the priority changes into

$M1 \succ M2 \succ M3$. Fig. 6 further gives a decision-making panorama of the case, where the number shows the ranking of risks in each level. It intuitively shows that considering risk preference may change the optimal options of the decision-maker, and also shows the great importance of the improved TOPSIS with loss penalty in this paper.

Table 7

The "risks-experts" decision matrix under mode $M1$.

Modes	Risks	Experts				
		$E1$	$E2$	$E3$	$E4$	$E5$
$M1$	$R1$	4.5	3.5	4	3	4
	$R2$	4.5	2	4.5	4	3.5
	$R3$	3	3	2	3	1
	$R4$	2	1	2.5	2	1.5

Table 8

The "risks-experts" decision matrix under mode $M2$.

Modes	Risks	Experts				
		$E1$	$E2$	$E3$	$E4$	$E5$
$M2$	$R1$	5	4.5	4.5	2	5
	$R2$	5	3.5	4	3.5	4
	$R3$	3	3	2	2	2
	$R4$	1.5	2	1	2	1.5

Table 9

The "risks-experts" decision matrix under mode $M3$.

Modes	Risks	Experts				
		$E1$	$E2$	$E3$	$E4$	$E5$
$M3$	$R1$	5	4.5	4.5	4	4.5
	$R2$	1	1	2	1	1
	$R3$	1.5	1	0.5	1	1.5
	$R4$	4.5	3	4	4	4.5

Table 10

Relative closeness coefficients and rankings of risks under each CBEC-SCF mode.

Modes	Risks	$\lambda=0$			$\lambda=2$		
		$RC_i^{LP(k)}$	$w_i^{(k)}$	Ranking	$RC_i^{LP(k)}$	$w_i^{(k)}$	Ranking
$M1$	$R1$	0.09	0.44	1	-1.7	0.467	1
	$R2$	0.23	0.37	2	-1.26	0.389	2
	$R3$	0.75	0.12	*3*	0.59	0.069	*4*

	$R4$	0.84	0.07	*4*	0.56	0.075	*3*
$M2$	$R1$	0.08	0.49	1	-1.74	0.49	1
	$R2$	0.26	0.39	2	-1.19	0.40	2
	$R3$	0.78	0.12	3	0.39	0.11	3
	$R4$	1	0	4	1	0	4
$M3$	$R1$	0	0.48	1	-2	0.497	1
	$R2$	0.85	0.07	*3*	0.73	0.045	*4*
	$R3$	0.89	0.05	*4*	0.71	0.047	*3*
	$R4$	0.16	0.40	2	-1.48	0.411	2

Table 11

The "modes-experts" decision matrices under different loss penalty factors.

Modes	$\lambda=0$				
	$E1$	$E2$	$E3$	$E4$	$E5$
$M1$	4.13	2.70	3.83	3.29	3.27
$M2$	4.76	3.93	4.01	2.58	4.25
$M3$	4.33	3.46	3.91	3.63	4.09
	$\lambda=2$				
$M1$	4.20	2.69	3.94	3.31	3.41
$M2$	4.78	3.93	4.02	2.59	4.27
$M3$	4.45	3.56	3.99	3.72	4.20

Table 12

Relative closeness and ranking of each mode.

Modes	$\lambda=0$		$\lambda=2$	
	RC_k^{LP}	Rank	RC_k^{LP}	Rank
$M1$	0.86	1	0.79	1
$M2$	0.18	*3*	-1.28	*2*
$M3$	0.24	*2*	-1.41	*3*

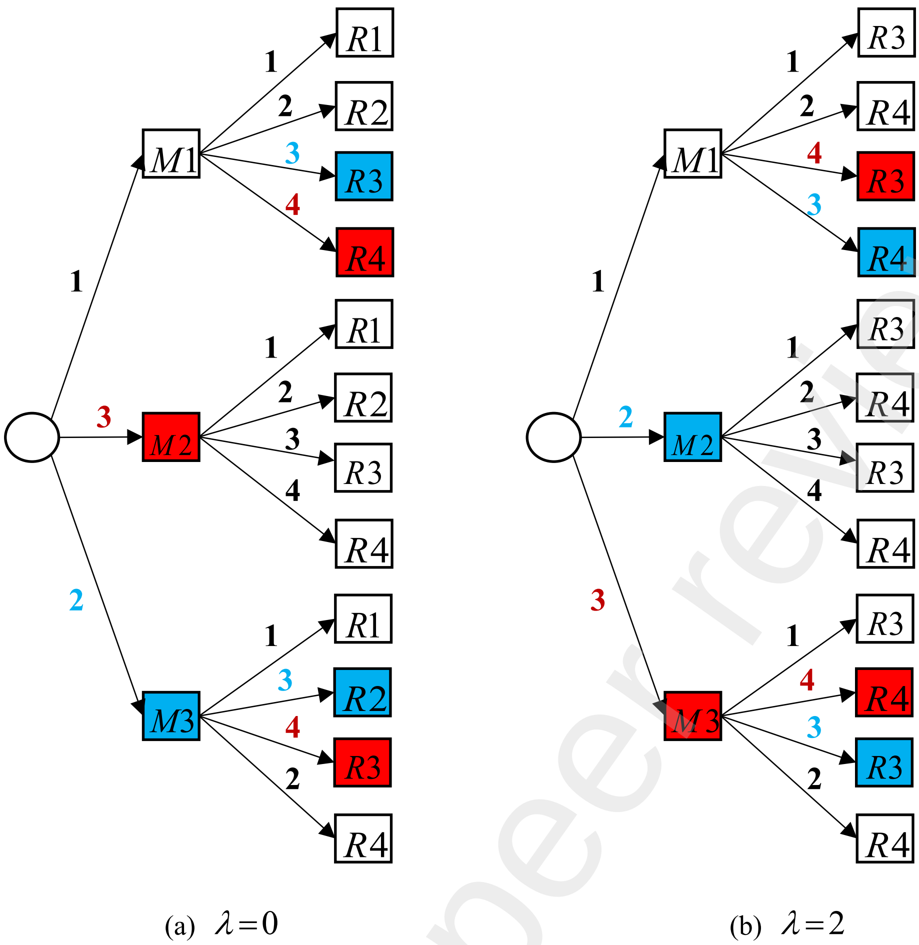


Fig. 6. Decision-making panorama under different loss penalty factors.

6. Conclusion

Rapid development of CBEC has resulted in urgent requirements for high-efficiency capital flow coordination among cross-border supply chain members. Based on classifications of the traditional SCF and the characteristics of CBEC, this paper proposes three types of operational modes for the emerging Cross-border E-commerce Supply Chain Finance (CBEC-SCF), namely the CBEC-based warehouse receipt financing, CBEC-based order financing and CBEC-based factoring, and analyzes the risks of CBEC-SCF from four aspects, i.e., credit, market, operational and legal risks. Given the truth that risk assessment of CBEC-SCF modes is an MCDM problem and decision-makers like banks are usually risk averse, this paper proposes an improved TOPSIS with loss penalty to estimate the overall risk levels of different CBEC-SCF modes. The improved TOPSIS is also extended to cases with multi-level criteria and "experts" as criteria. Finally, case studies are conducted to verify the practicability and values of the proposed method for the MCDM problem with a risk averse decision-maker, showing that the risk ranking of CBEC-SCF modes may change with the risk aversion degree of the bank.

The most important managerial insight provided by this study is that the risk preference of decision makers is proved to change the ranking of alternatives in an improved TOPSIS under certain circumstances. In terms of the issue of CBEC-SCF risk assessment this paper tackles, the risk-aversion degree of the bank will change its priority for selecting CBEC-SCF modes. This paper provides a multi-criteria decision-making tool that can take into account the risk aversion of decision makers, providing the banks and others a methodological reference for accurate and scientific decision-making.

The limitation of this paper mainly lies in that CBEC-SCF is an emerging business, and commercial banks that have fully implemented the CBEC-SCF panoramic modes that we propose have not yet been found in the Chinese market. Therefore, we use virtual cases to validate the practicability and significance of the improved TOPSIS. In the future, as this business gradually matures, real cases can be applied to study the true ranking of risk levels of CBEC-SCF modes, providing more effective guidance for the industry.

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