A Data-Driven Weighting Method Based on DEA Model for Evaluating Innovation Capability in Banking

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Abstract. The innovation capability evaluation is in fact a multi-criteria decision-making problem that requires aggregating multiple innovation management practices into a composite innovation capability index. In such multi-criteria decision-making, assigning appropriate weights to criteria is a critical and difficult task. However, the literature related to innovation capability evaluation mainly used the weighting methods based on subjective expert opinions. These conventional methods have problems when dealing with complex multi-criteria data. This study aims to develop a method for automatically determining the weights of multiple innovation management practices for evaluating innovation capability in banking based on data envelopment analysis (DEA) model without input. The results will show the typical importance weights of innovation management practices for each bank which are then used to derive an aggregated index objectively representing the innovation capability level of each bank. A case study of three banks in Vietnam was adopted from the prior study to show the applicability of the proposed method.

Keywords: Data-driven weighting · Data envelopment analysis (DEA) · Innovation capability · Banking

1 Introduction

The fourth industrial revolution with digitization and the explosion of many new technologies such as artificial intelligence, big data, and cloud computing brings great opportunities for the development in the production and business processes. Organizations across sectors have been putting many efforts into exploiting new technologies to innovate their products/services in order to survive in the digital economy. The pivotal role of innovation in the competitive advantage and success of a company is firmly confirmed in the literature [1,2]. According to [3], a company can only effectively innovate if it has innovation capability (IC). IC is a significant determinant of continuous innovations to respond to the dynamic market environment and also firm performance [4,5]. Therefore, the IC evaluation is a serious problem that organizations must consider to comprehend their IC levels and find out important areas in the innovation management process that should

K. Honda et al. (Eds.): IUKM 2022, LNAI 13199, pp. 53–66, 2022.
https://doi.org/10.1007/978-3-030-98018-4_5

be focused on to improve the IC level for achieving better innovative performance as well as higher business performance.

Because IC is a multidimensional process [6,7], the IC evaluation can be considered as a multi-criteria decision-making (MCDM) problem which requires taking into account multiple criteria (in this study, multiple innovation management practices (IMPs)). Some of the IMPs used for measuring IC in the prior studies are strategic planning [8,9], organization [10,11], resource management [12,13], technology management [14,15], research and development (R&D) [16,17], knowledge management [13,18], network and collaboration [8,19]. In MCDM, weighting and aggregating of criteria are major tasks in developing composite indicators [20]. Especially, different sets of weights lead to different ranking outcomes, so the weighting method should be fair. To derive an overall evaluation on the IC of a company, we first need to determine the weights of different IMPs for each company that are then used for computing the composite innovation capability index ($CICI$) of that company.

In the literature on the IC evaluation, the widely used weighting methods have been relied on subjective opinions from experts such as the analytic hierarchy process (AHP) [10], fuzzy measures [17,21]. However, it is difficult, time-consuming, and even costly to get such information from experts, especially in case there are complex and changing multiple criteria. One of the common subjective weighting methods is the AHP which requires subjective judgments of experts to make pairwise comparisons among criteria from which the weights of criteria are obtained. When the number of criteria is high, the experts may face difficulties to deal with many comparisons, sometime they may be confused. It is the reason why the weighting methods that require external or prior information was criticized by [22]. Moreover, the prior studies only applied the same set of weights for different companies. This may cause disagreement among the companies because each company may have its own business strategies that lead to different preferences in developing particular IMPs. To overcome the shortcomings of subjective weighting methods, further consideration can be placed on developing objective weighting methods that can endogenously drive the weights of criteria based on data without referring to any prior or external information. Up to now, far too little attention has been paid to applying data-driven weighting methods in the IC evaluation. This indicates a need to develop a weighting method based on the collected data of IMPs to be applied in evaluating the IC of companies. Several data-driven weighting methods such as DEA, or Genetic Algorithm (GA) can be considered.

The purpose of this paper is to develop a data-driven weighting method based on DEA to determine the typical set of weights of IMPs for each bank or the IMPs focused/ignored by each bank and thereby compute an overall IC evaluation ($CICI$) for each bank based on aggregating multiple IMPs and sub-IMPs. DEA is one of the popular methods for developing composite indices in MCDM, it can select the best possible weights of IMPs for each bank by giving higher weights for better IMPs and therefore give objective evaluations on the IC of banks. To illustrate the applicability and validity of the proposed method, the data of IMPs and sub-IMPs on a case study of three banks in Vietnam was taken from the literature [23]. The data on sub-IMPs were first averaged to obtain the scores of IMPs. The data-driven weighting method developed based on DEA model was then employed to determine the weights of IMPs for each bank that were finally used to aggregate IMPs into a composite index ($CICI$). The research findings could be used as a basis for benchmarking the most innovative banks and potentially support bank managers in proposing effective strategies for properly allocating innovation resources in order to upgrade their IC and achieve better innovative performance.

This study makes two contributions to the innovation literature as well as the practices of innovation management. First, this study can be considered as one of the first attempts that apply a data-driven weighting method (DEA without input) for evaluating IC. Second, this study will contribute to a deeper understanding of the important IMPs that each bank is focusing on and the corresponding IC levels of banks, based on which some useful lessons can be drawn for innovation management in banking.

The remaining part of this paper proceeds as follows: Sect. 2 reviews theories of IC evaluation and DEA models. Section 3 is concerned with the proposed method by this study. The empirical results of using the proposed IC evaluation method in the case study of three banks in Vietnam are displayed in Sect. 4. Section 5 presents the conclusions of this study.

2 Literature Review

2.1 IC Evaluation

Innovation can be defined as beneficial changes in organizations to create new or improved products/services and thereby to improve business performance [24–27]. Successful innovations require a wide combination of many different assets, resources, and capabilities that facilitate the development of new or improved products/services to better satisfy market needs (also known as IC) [16,28–31]. According to [32], IC refers to the capability of utilizing innovation strategies, technological processes, and innovative behaviors. Lawson and Samson proposed seven constructs in developing IC including strategy, competence, creative idea, intelligence, culture, organization, and technology [14]. As IC is a complex concept that is multi-dimensional and impossible to be measured by a single dimension [33], multiple IMPs must be considered to evaluate the IC of a company.

On account of the role of improving IC for successful innovation, IC evaluation has become one of the dominant streams in the innovation research literature. The common approach for evaluating IC in the previous works was based on multiple IMPs to comprehensively apprehend all necessary capabilities for organizations to effectively innovate. However, particular authors may adapt different IMPs according to the research contexts and also used different techniques to aggregate all IMPs into a single index showing the IC level of a firm. Wang et al. [17] applied a non-additive measure and fuzzy integral method to evaluate the overall performance of technological IC in Taiwanese hi-tech companies. Five factors including innovation-decision, manufacturing, capital, R&D, and marketing capabilities with various qualitative and quantitative criteria were considered in their research. Cheng and Lin [21] proposed a fuzzy expansion of the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to measure the technological IC of Taiwanese printed circuit board firms taking into account seven criteria comprising planning and commitment of the management, knowledge and skills, R&D, marketing, information and communication, operation, and external environment. Wang and Chang [10] presented a hierarchical system to diagnose the innovation value of hi-tech innovation projects considering five main dimensions (strategy innovation, organization innovation, resource innovation, product innovation, and process innovation) and their fifteen secondary dimensions. By adopting the AHP, the main dimensions are found in the descending order of importance to the firm's innovation performance: process innovation, resources innovation, product innovation, strategic innovation, and organizational innovation. Boly et al. [9] adopted a multi-criteria approach and value test method to measure the IC of French small and medium-sized manufacturing companies based on 15 IMPs: strategies management, organization, moral support, process improvement, knowledge management, competence management, creativity, interactive learning, design, project management, project portfolio management, R&D, technology management, customer relationship management, and network management. The evaluated companies were then categorized into four innovative groups (proactive, preactive, reactive, passive) based on their IC levels.

The literature review reveals that many attempts have been made to evaluate IC in manufacturing sectors [9,17,21]. However, there are limited numbers of studies that focus on IC evaluation in the service sector, particularly in the banking sector. In fact, banks are also keenly focusing on innovating their services by adopting new technologies to promptly deliver their services, improve banking experiences for customers, and thereby stay competitive in the market [34]. Innovation becomes a core business value of banks nowadays, it helps banks to explore new opportunities for stable development, and long-term success [35,36]. It is widely approved that innovation in each sector has different unique characteristics [37]; therefore, banks cannot apply the same innovation management policies as manufacturing sectors when developing their new services. Thus, there is an emerging need for a study dedicated to evaluating the IC of banks. In an effort to fill this gap, this study will contribute a method for IC evaluation in banking by investigating the importance weights of IMPs in the banking context as well as determining the overall IC level of banks to be evaluated.

2.2 DEA Models

DEA, proposed by [38], is used to measure the efficiency of decision-making units (DMUs) that is obtained as the maximum of a ratio of a weighted sum of outputs to a weighted sum of inputs. For each particular DMU, the weights are chosen to maximize its efficiency. For example, to calculate the efficiency of a DMU k in a set of all DMUs to be measured K:

$$\text{Maximize: } e_k = \frac{\sum_{i=1}^{n} w_i \mathrm{y}_{ik}}{\sum_{j=1}^{m} u_j \mathrm{x}_{jk}} \tag{1}$$

subject to

$$e_{k'} = \frac{\sum_{i=1}^{n} w_i \mathrm{y}_{ik'}}{\sum_{j=1}^{m} u_j \mathrm{x}_{jk'}} \leq 1; \quad \forall k' \in K$$

$$w_i, u_j \geq 0; \quad i = 1, ..., n; \quad j = 1, ..., m$$

where e_k and $e_{k'}$ are the efficiency of DMU k and DMU k', k and $k' \in K$; n and m are the number of outputs and the number of inputs, respectively; w_i and u_j are the weight of the i-th output ($i = 1, ..., n$) and the weight of the j-th input ($j = 1, ..., m$), respectively; $\mathrm{y}_{ik'}$ is the value of the i-th output of DMU k'; $\mathrm{x}_{jk'}$ is the value of the j-th output of DMU k'. The maximization (Eq. (1)) selects the most favorable set of weights for the DMU k whose score is being optimized while the constraints allow. To compute the efficiency of the other DMUs, it just needs to change what to maximize in Eq. (1). The advantage of the DEA model is that it can endogenously derive the different preference profiles for each DMU and thus provide a more objective evaluation for DMUs than the approaches that determine weights based on subjective information from experts.

DEA has become one of the commonly used techniques that can resolve the subjectivity problem in developing composite indicators. Although the original DEA requires outputs and inputs to be specified, several authors have proposed DEA-like models to solve the problems that there is no input. For instance, Zhou et al. [39] presented the best practice model in which a DEA-like model without input was used to obtain the different weights for each DMU. Their approach allows each DMU to pick its own most favorable weights to maximize its aggregated score. However, extreme weighting of sub-indicators may occur, so this approach becomes unrealistic and comes with low discriminating power. To alleviate this shortcoming, Hatefi and Torabi [40] proposed a common weights approach, the same weights are applied to compute scores for all DMUs, to improve discriminating power. The authors used an optimization model to select the weights that minimize the largest deviation among the scores' deviations from 1. This means the selected weights will maximize the lowest score. Thus, this approach has a drawback as the worst performing DMU controls the final weights.

3 Data-Driven Weighting Method Based on DEA Model

In this study, a data-driven weighting method based on DEA model is proposed to compute composite indices representing IC levels of banks ($CICI$). However, in our formulation, the proposed DEA model has no input and several revisions in constraint conditions compared with the original DEA model.

The IC evaluation in banking follows the two-level hierarchy: the upper level contains IMPs and the lower level comprises the sub-IMPs related to each IMP in the upper level. The sub-IMPs are assessed using a five-point Likert scale (from 1-very bad to 5-very good) to show how efficiently those practices are achieved at the evaluated banks. Accordingly, there are two levels of aggregation to calculate the $CICI$ of these banks. The first level of aggregation (lower level aggregation) is to aggregate sub-IMPs of an IMP to determine the development degree of this

IMP at each bank. The second level of aggregation (upper level aggregation) aims to aggregate IMPs to derive the overall IC of each bank ($CICI$).

3.1 Lower Level Aggregation

Let B be the set of all banks to be evaluated. Considering a bank $b \in B$, the development degree of IMP i at bank b is determined as follows:

$$\bar{x}_i^{(b)} = \frac{1}{N_i} \sum_{j=1}^{N_i} x_{ij}^{(b)}, \quad i \in \{1, ..., N\} \tag{2}$$

where $\bar{x}_i^{(b)}$ is the development degree of IMP i at bank b, $\bar{x}_i^{(b)} \in [1, 5]$; $x_{ij}^{(b)}$ is the score of the j-th sub-IMP of the i-th IMP of bank b, $x_{ij}^{(b)} \in [1, 5]$; N_i is the number of sub-IMPs associated with IMP i; N is the number of IMPs.

According to Eq. (2), the development degree of an IMP is obtained by averaging the scores of all sub-IMPs related to this IMP, in other words, the weights of sub-IMPs are equal. Equal weighting is applied because the relation between IMPs and their measurement items (sub-IMPs) is not causal [9]. Moreover, we prioritize to determine the different weights of IMPs in the upper level of aggregation to specify critical IMPs that much decide the IC of banks.

3.2 Upper Level Aggregation

For the upper level aggregation, we first determine the optimal set of weights of IMPs for each bank so that it will maximize the $CICI$ of the bank being evaluated. The optimal weights for each bank is calculated based on the data of IMPs obtained in the lower level aggregation.

Considering a bank $b \in B$ (B is the set of all banks to be evaluated), let $W^{(b)} = \{w_1^{(b)}, \ldots, w_N^{(b)}\}$ be the optimal set of weights for maximizing the $CICI$ of bank b, $CICI^{(b)} \in [1, 5]$. The optimal set of weights for bank b is determined by solving the optimization problem below:

$$\text{Maximize} \quad CICI^{(b)} = \sum_{i=1}^{N} \bar{x}_i^{(b)} \times w_i^{(b)} \tag{3}$$

subject to

$$0 \leq w_i^{(b)} \leq 1 \quad \text{and} \quad \sum_{i=1}^{N} w_i^{(b)} = 1, \quad i \in \{1, ..., N\} \tag{4}$$

where $\bar{x}_i^{(b)}$ is the development degree of IMP i at bank b, $\bar{x}_i^{(b)} \in [1, 5]$; $w_i^{(b)}$ is the weight of IMP i in the optimal set of weights $W^{(b)}$ for bank b; N is the number of IMPs. The above optimization problem is converted into a linear programming problem that can be solved by a linear programming solver (such as Scipy package for Python).

It is worth noting that the most ideal $CICI$ value that a bank can reach is 5, but in practice, the $CICI$ values are usually lower than 5. Therefore, we set the threshold of $CICI$ as $5 - \epsilon, \epsilon \in [0, 4]$. One more constraint condition is added to solve the above optimization problem: The $CICI$ values of all banks in the set B must be equal or lower than $5 - \epsilon$ when applying the optimal weights for bank b being optimized.

$$\sum_{i=1}^{N} \bar{x}_i^{(b')} \times w_i^{(b)} \leq 5 - \epsilon; \quad \epsilon \in [0, 4]; \quad \forall b' \in B \tag{5}$$

It is clear that, if the value of ϵ is low, extreme weighting may occur with higher weights for better IMPs, which leads to a high standard deviation of weight values. When ϵ is increased, the standard deviation of weight values will be reduced. At the standard deviation of weight values equals 0, equal weighting happens. The selection of ϵ is optional, depending on the evaluator's preference. ϵ can be chosen so that the corresponding standard deviation of weight values is in the range between its highest value and its lowest value. If the evaluator prefers the weights toward extreme weighting to clearly show the best practices of each bank, ϵ is selected at the corresponding standard deviation of weight values near its highest value. In contrast, in case the evaluator prefers the weights toward equal weighting, ϵ is chosen so that the corresponding standard deviation of weight values is close to its lowest value. In this study, we tend to choose the standard deviation of weight values in the middle area of its possible range to balance extreme weighting and equal weighting.

The optimal set of weights for a bank can disclose which IMPs that this bank is focusing on. By comparing with other banks, we can explore the strengths and weaknesses of each bank on different IMPs.

4 An Illustrated Example

This example is adopted from the research of [23] on evaluating the IC of three banks in Vietnam. The concept of IC in their research was defined based on the Pareto analysis - a statistical technique to select the major tasks which the management should put more effort into. As a result, 11 IMPs were chosen as critical practices in innovation management process: managing strategy (MS), managing resource (MR), organizing (OR), managing idea (MI), improving process (IP), marketing (MA), R&D (RD), interactive learning (IL), managing portfolio (MP), managing knowledge (MK), and managing technology (MT). The 44 measurement items/sub-IMPs measuring the 11 IMPs were adapted from [8–13, 15, 16, 19, 41–47], which ensures the reliability and validity of the measurement scale as they were verified through peer-reviewed previous research (see Table 1). In their data collection [23], five experts in banking fields individually responded to the questionnaire to rate the development degrees of sub-IMPs in the three evaluated banks, enormously called Bank a, Bank b, and Bank c, using a five-point Likert-scale ranging from 1 (very bad) to 5 (very good). The final scores of 44 sub-IMPs for the three banks (shown in Table 2) were obtained by averaging the assessment scores of the five experts.

Table 1. IMPs and sub-IMPs

No	IMPs	Sub-IMPs
1	MS	MS1: Set clear innovation goals in business strategies MS2: Widely disseminate innovation strategies throughout the bank MS3: Managers dedicatedly encourage innovation practices MS4: Effective use methods supporting decision making to create business strategies
2	MR	MR1: Provide proper resources for innovation MR2: Manage adaptive and diverse capital sources MR3: Concentrate on employing talented employees MR4: Regularly schedule training programs for providing necessary knowledge to develop new services
3	OR	OR1: Organizational culture and atmosphere assist innovative activities OR2: Reward employees for their innovation achievements OR3: Tolerate failures in doing something new OR4: Develop interactive communication systems among employees in the bank
4	MI	MI1: Have a validated process to gather ideas from various divisions in the bank MI2: Collaborate with outside organizations for idea development MI3: Have a quick procedure to evaluate new ideas MI4: Use a test markets before launching new services
5	IP	IP1: Structure innovation processes IP2: Assign facilitators supporting innovation activities IP3: Schedule regular meetings to inspect innovation activities IP4: Managers usually examine the development of innovation projects
6	MA	MA1: Keep great associations with clients MA2: Have capable sales employees MA3: Evaluate the levels of customer satisfaction after sales MA4: Create a positive brand image in clients' minds
7	RD	RD1: Structure R&D programs RD2: Upgrade funds for R&D activities RD3: Enhance cooperation across different functional departments RD4: Hold regular meetings to discuss R&D subjects
8	IL	IL1: Boost interactive learning activities IL2: Assign managers who are responsible for interactive learning activities IL3: Hole meetings to evaluate the completed innovation projects IL4: Disseminate experiences obtained from past projects all through the bank
9	MP	MP1: Business strategies fit with investment portfolios MP2: Analyze all proceeding projects based on multiple criteria MP3: Have periodic reports on the allocation of resources to projects MP4: Assure the balance between long-term and short-term, and high-risk and low-risk projects
10	MK	MK1: Identify and update employees' knowledge to satisfy job requirements MK2: Encourage knowledge sharing at work MK3: Classify and store knowledge for employees to easily access MK4: Adapt knowledge dissemination methods
11	MT	MT1: Increase the integration of new technologies into banking products as a key success factor MT2: Plan scenarios to predict the trend of new technologies MT3: Capture the technologies competitors are using MT4: Technologies acquired from the external fit the infrastructures and operations of the bank

Table 2. Scores of 44 sub-IMPs for three banks in Vietnam

Bank	MS1	MS2	MS3	MS4	MR1	MR2	MR3	MR4	OR1	OR2	OR3	OR4	MI1	MI2	MI3	MI4	IP1	vIP2	IP3	IP4	MA1	MA2
a	4.4	4.2	3.8	4.0	3.4	4.2	4.0	3.4	3.8	4.0	3.6	3.4	3.2	3.4	3.2	3.4	3.4	3.8	3.8	3.6	4.0	3.8
b	4.6	4.4	4.4	4.4	4.0	4.0	4.6	4.2	4.4	4.0	3.6	4.2	3.8	4.0	3.8	4.2	4.2	4.2	4.2	4.2	4.6	4.2
c	4.0	4.0	4.8	4.4	4.0	4.8	4.4	4.2	3.4	4.2	3.4	4.0	4.2	3.6	3.8	3.6	4.2	4.0	4.0	3.8	4.4	3.6
Bank	MA3	MA4	RD1	RD2	RD3	RD4	IL1	IL2	IL3	IL4	MP1	MP2	MP3	MP4	MK1	MK2	MK3	MK4	MT1	MT2	MT3	MT4
a	3.6	3.8	3.6	3.8	3.6	3.6	4.0	3.4	3.6	3.2	4.2	3.4	3.8	3.8	4.6	3.8	3.8	4.6	4.4	3.6	3.8	3.4
b	4.2	4.4	4.4	4.0	4.4	4.2	4.0	4.0	4.2	4.0	4.4	4.2	4.2	4.0	4.0	4.2	4.0	4.0	4.2	4.2	4.4	4.2
c	3.8	4.2	4.0	3.8	3.6	3.6	4.2	4.2	4.2	4.0	4.4	4.4	4.0	4.2	4.2	4.2	4.0	3.8	3.8	3.8	3.8	4.2

The IC evaluation for the three banks is composed of two levels of aggregations as shown in Fig. 1. In the lower level aggregation, the 4 sub-IMPs associated with each IMP at each bank are aggregated. Eq. (2) with the values of Table 3 gives the average scores of the 11 IMPs for the three banks in the sample.

To aggregate the 11 IMPs in the upper level, we first need to determine the optimal weights of the 11 IMPs for each of the three banks by solving model (3) under the constraints (4) and (5). ϵ in the constraints (5) was run with the initial value of 0 and the increased step size of 0.05. Figure 2 shows different values of ϵ and corresponding standard deviations of weight values. In this study, we chose $\epsilon = 0.85$ for Bank a, $\epsilon = 0.65$ for Bank b, and $\epsilon = 0.70$ for Bank c so that the corresponding standard deviations of weight values are in the middle area of its possible range. Table 4 displays the optimal set of weights for each bank at the chosen ϵ. As a final result, the $CICI$ values of Bank a, Bank b, and Bank c were determined to be 4.15, 4.35, and 4.30, respectively using each bank's optimal sets of weights. According to that, Bank b is the most innovative bank among the three evaluated bank. This results were verified by comparing with the ranking of the same three banks based on subjective models in [23].

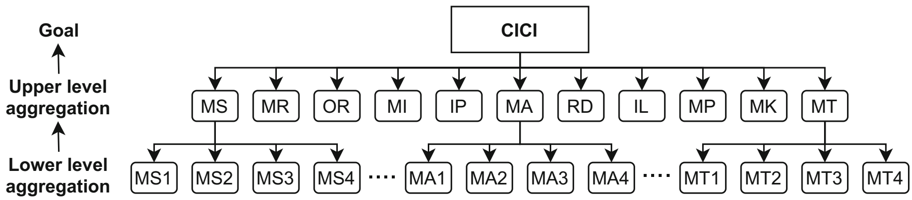

Fig. 1. Hierarchical structure of IMPs and sub-IMPs for evaluating IC in banking

Table 3. Average scores of 11 IMPs for three banks in Vietnam

	MS	MR	OR	MI	IP	MA	RD	IL	MP	MK	MT
Bank a	4.10	3.75	3.70	3.30	3.65	3.80	3.65	3.55	3.80	4.20	3.80
Bank b	4.45	4.20	4.05	3.95	4.20	4.35	4.25	4.05	4.20	4.05	4.25
Bank c	4.30	4.35	3.75	3.80	4.00	4.00	3.75	4.15	4.25	4.05	3.90

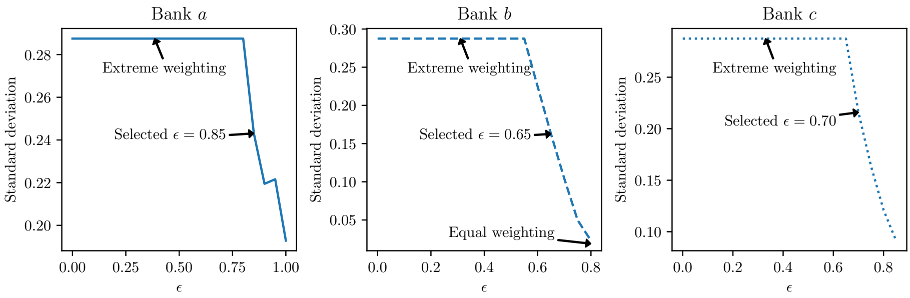

Fig. 2. Different ϵ values and corresponding standard deviations of weight values

Table 4. Optimal weights and $CICI$ for each bank

	w_{MS}	w_{MR}	w_{OR}	w_{MI}	w_{IP}	w_{MA}	w_{RD}	w_{IL}	w_{MP}	w_{MK}	w_{MT}	$CICI$
$W^{(a)}(\epsilon = 0.85)$	0.051	0.009	0.011	0.006	0.008	0.013	0.009	0.007	0.013	0.859	0.014	$CICI^{(a)} = 4.15$
$W^{(b)}(\epsilon = 0.65)$	0.603	0.036	0.029	0.022	0.043	0.073	0.055	0.024	0.038	0.024	0.052	$CICI^{(b)} = 4.35$
$W^{(c)}(\epsilon = 0.70)$	0.072	0.771	0.008	0.011	0.016	0.014	0.007	0.028	0.042	0.02	0.011	$CICI^{(c)} = 4.30$

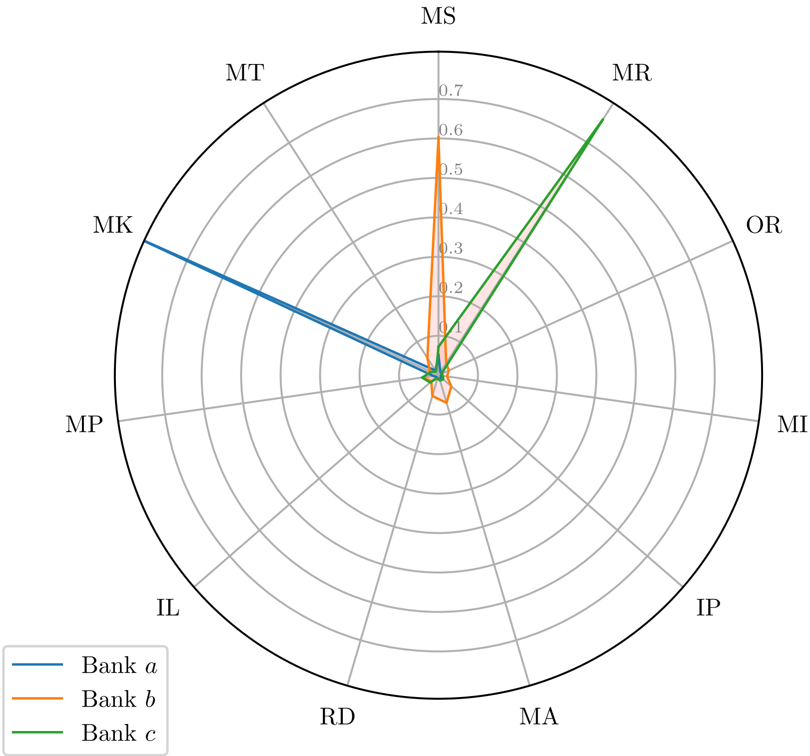

Fig. 3. Weights of IMPs in three banks in Vietnam

5 Conclusion

This study proposes a data-driven weighting method based on DEA to solve a multi-criteria problem that is then applied in evaluating the IC of the three banks in Vietnam. The proposed method can determine the optimal set of weights for maximizing each bank's IC. This way contributes an objective evaluation or ranking approach on IC without bias toward any banks. Based on the optimal set of weights of each bank, we can point out which IMPs each bank is focusing on (strengths) or ignoring (weaknesses). Particularly, by applying the proposed method in the case of the three banks in Vietnam, we found distinctive IMPs of each bank as follows:

- Bank *a*: This bank was found to pay attention to only two IMPs (MK "managing knowledge" and MS "managing strategies") while almost neglecting the rest of IMPs. It must be noted that most IMPs in Bank *a* have the least implemented levels among the three banks, except for MK. Generally, the IC level of Bank *a* is lower than the other two banks.
- Bank *b*: Except for MI "managing ideas" where its score is a bit lower than other IMPs, Bank *b* widely develops other IMPs, especially focuses on managing strategies, marketing, R&D, managing technologies, and improving processes. Most IMPs have the implemented levels generally higher than the other banks. Globally, this bank may be considered as being most seriously pursuing innovation activities.
- Bank *c*: This bank puts more efforts into managing resources, managing strategies, and managing portfolio while keeping good levels on improving processes, marketing, interactive learning, and managing knowledge. It is at low levels in organizing, managing ideas, R&D, and managing technologies.
- It can also be noticed that all of the three banks, specially the most innovative bank (Bank *b*) give prominence to managing strategies in innovation management, which proves that strategies management is an important practice in innovation management in Vietnamese banks. The above-mentioned points are graphically described in Fig. 3.

The research results also reveal the ranking of the three banks based on their IC. In details, Bank *b* is the most innovative bank among the three banks, the next is Bank *c*, and Bank *a* was ranked last. The findings provide a basis for bank managers to improve their innovation management policies to upgrade their IC. Specifically, to increase the IC level, a bank can strengthen its IC by prioritizing to allocate more resources into the most important IMPs that have the strongest weights such as strategies management, marketing, and R&D as the most innovative bank (Bank *b*) does.

This study is limited by the a small sample size with only three banks in Vietnam. The future study should use a bigger sample size to establish a greater degree of applicability and validity of the proposed method. In addition, the discriminating power among the evaluated banks is still low (in case of comparing the IC levels between Bank *b* and Bank *c*). Considerably more work will need to be done to develop other methods that can create a more distinguishable ranking, for example using multi-objective approach.

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