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JAPAN ADVANCED INSTITUTE OF SCIENCE AND TECHNOLOGY

Japan Advanced Institute of Science and Technology

Doctoral Dissertation

A Methodology for Evaluation of Innovation Capability in Banking

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Abstract

Nowadays, innovation is considered as a major source to create competitive advantages of organizations across sectors. Especially, the evolution of a bunch of modern technologies such as internet of things, artificial intelligence, and blockchain that results in the higher customers' expectations of new values in their daily consumed products or services. That has forced organizations to increasingly apply advanced technologies into their production of new or improved products or services to better satisfy market needs, increase customer satisfaction, and ultimately achieve higher business performance. In this context, banks have also been placed innovation as a top priority in their strategies by taking advantages of new technologies to innovate their services.

In the era of innovation, the innovation capability (IC) evaluation becomes necessary to banking organizations since it helps banks broadly review their innovation management process and then be able to modify their innovation strategies. IC is typically a multi-criteria concept according to that banks have to take into account a variety of innovation management practices (IMPs) related to strategies, resources, technologies, knowledge, etc. to comprehensively develop their IC. Under the limited resources, banks should intelligently invest into the more significant IMPs first. Therefore, an IC evaluation method is required to clarify the different importance of IMPs in banking innovation, the maturity degrees of IMPs at banks to be evaluated, as well as the current status of IC of banks which will be a useful basis for proposing effective innovation strategies.

This research develops a four-stage methodology for evaluating IC in banking under uncertainty using multi-criteria decision making approaches. In particular, the first stage is to extract a list of vital IMPs (VIMPs) from the prior studies based on Pareto analysis. The measurement indicators for these VIMPs (sub-VIMPs) are also adapted from the literature. In the second stage, the Analytic Hierarchy Process (AHP) is applied to determine the relative importance weights of VIMPs and their corresponding sub-VIMPs relying on the opinions of experts who works in banking-related fields. In the third stage, measurement for sub-VIMPs at the evaluated banks is conducted using a questionnaire sent to experts who work independently from the evaluated banks. The data is then formulated in both numeric and linguistic forms. In the final stage, the numeric data is aggregated to derive the overall IC evaluation using weighted sum and the linguistic data with uncertainty is aggregated using the Evidential Reasoning (ER) approach in terms of the Dempster–Shafer theory of evidence. Finally, the aggregated evaluations of IC of banks are used for ranking.

To demonstrate the feasibility of the proposed methodology, it was applied into a case study of three bank in Vietnam. In addition, we also develop alternative approaches to fully understanding the IC of banks by using a data-driven IC evaluation method based on the Data Envelopment Analysis (DEA) model and a customer-driven service innovation evaluation.

This research contributes to the literature by conducting a comprehensive literature review on IMPs and proposing a new integrated methodology based on combining the AHP and the ER approach in terms of Dempster-Shafer theory of evidence for IC evaluation in banking under uncertainty. As for practical implications, the research findings could be the guidance for banks to adjust their innovation strategies toward focusing on the more important VIMPs in order to more efficiently upgrade their IC.

Keywords: innovation capability, evaluation, banking, uncertainty, Analytic Hierarchy Process (AHP), Evidential Reasoning (ER) approach.

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List of Abbreviations

AHP	Analytic Hierarchy Process
CI	Consistency Index
COO	Cooperative learning
CR	Consistency Ratio
D-S	Dempster–Shafer
DEA	Data Envelopment Analysis
ER	Evidential Reasoning
IC	Innovation Capability
ICI	Innovation Capability Index
IDE	Idea management
IMP	Innovation Management Practice
KNO	Knowledge management
MAR	Marketing management
MCDM	Multi-Criteria Decision Making
ORG	Organization management
POR	Portfolio management
PRO	Process improvement
RAD	R&D
RES	Resource management
RI	Random Index
SI	Service Innovation
STR	Strategic management
TEC	Technology management
VIMP	Vital Innovation Management Practice

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Chapter 1

Introduction

We first introduce the research context based on which the research problem is formulated in section 1.1. Section 1.2 presents the motivations to conduct this research. That is followed by research objectives in section 1.3, scope of this research in section 1.4, and research process in section 1.5. Next, we summarize the key contributions of this research to theory, practice, and knowledge science in section 1.6. Finally, the dissertation's structure is illustrated in section 1.7.

1.1 Problem statement

Today, we are living in the era of the industrial revolution 4.0 that has changed every aspect of the economy and society. The development and spreading of a series of advanced technologies such as Internet of Things, Artificial Intelligence, big data analysis, blockchain, biometric technologies, and robotics has leveraged innovation speed across sectors including manufacturing sectors and service sectors. In addition, customers today have more diverse and dynamic needs and are more proficient in using technology devices in their daily life. Along with that, globalization facilitates favorable conditions for foreign organizations to spread their networks to different countries, which leads to fierce competition on a global scale. All of these have prompted organizations to drastically innovate processes, organizations, technologies, etc. to develop new products or services or improve existing products or services in order to create new values for better satisfying customer demands, maintaining customer loyalty, increasing competitiveness, and thereby achieving sustainable growth. There have been a number of evidences suggesting that innovation is a pivotal source to achieve sustainable competitive advantages in the markets [1–3]. Because of the importance role of innovation in today's era, banks are not left out of this innovation trend. Since banks almost offer similar core services such as deposits, loans, money transfers, international payment, and electronic banking; therefore, to effectively compete and survive in this dynamic industry, banks strive to innovate their services to produce better and differentiated services compared with competitors to their customers [4]. By increasingly applying advanced technologies in banking operations, banks have been able to improve service quality, speed up service delivery, and provide personalized experiences to their customers. In Ghana's banking industry, innovation was found to significantly improve service delivery processes as well as customer satisfaction toward banking services [4]. Through continuous innovations, banks can boost their profitability and business performance [5, 6]. Service innovation can be considered a sustainable development strategy for today's organizations, aiming to create new values of services in response to customers' varied demands and lead to customer satisfaction [7]. To effectively innovate, firms should continuously upgrade their Innovation Capability (IC) by managing well a set of dynamic capabilities that enable innovation activities [3,8,9]. As a result, the problem of IC evaluation becomes necessary in the innovation management of organizations.

Under this context, the evaluation problem of innovation and IC plays a key role in innovation management and therefore has lately become hot topics gaining considerable interests from researchers. For example, a two-stage model Data Envelopment Analysis (DEA) model was proposed by Wang et al. for evaluating the innovation efficiency in patent-intensive companies [10]. In a study on blockchain technology innovation in banking, Dozier and Montgomery used a grounded theory approach to deeply investigate the evaluation process [11]. Koliouska et al. [12] presented a multi-criteria evaluation model for evaluating and ranking the websites of tourism companies in Chania, Greece that not only makes it possible to find the best practices but also suggests the website features that need to be improved for exploiting the opportunities that the technological innovation brings to the tourist sector. There have been also comprehensive studies that broadly consider multiple aspects for the assessment of IC, but mainly in manufacturing sectors [13–15]. Regardless of the emergence of innovation in banking, studies devoted to innovation management problem in banking remain scarce. Almost existing research in innovation in banking only addresses single aspects; for instance, top management [16], culture and strategies [17], customer knowledge management [18], technology [19], organizational learning [20], and teamwork [21]. A number of important Innovation Management Practices (IMPs) were discussed by Draw in the case of the financial services firms and banks in Canada, including strategic planning, human resources and budgets for innovation, process and product development, organizational and cultural change, R&D, idea creation and transfer, and joint ventures to promote innovation [22]. Under our careful observations, there is no single comprehensive research that adequately addresses the evaluation problem of IC in banking, and the importance roles of different IMPs in this context continue to be debated. An IC evaluation methodology in banking is needed to help banks comprehensively review IMPs, recognize important IMPs in banking innovation, know well their IC levels, based on which they can develop according innovation strategies to improve their IC.

There are several severe difficulties that make the development of a comprehensive IC evaluation in banking a challenge. *First*, IC management is complex requiring organizations to simultaneously consider multiple aspects related to capital, innovation decision, marketing, research and development (R&D), etc. [13]. Among a variety of IMPs, organizations need to know which ones are more important to put more effort into and make reasonable investments. The prior literature has documented a variety of different IMPs across sectors [23–26]. Based on the specific business contexts, managers should carefully adopt suitable IMPs, appropriately allocate resources to significant IMPs, and make a proper roadmap to make sure their organizations are on the right way to be more innovative [27]. *Second*, the IC concept is general and qualitative in nature that is difficult to assess directly. It should be decomposed into smaller qualitative criteria until evaluators can assess. The evaluation for such qualitative criteria is usually attached with high uncertainty and imprecision from subjective human judgments. *Third*, evaluators (experts, managers, customers, etc) with different viewpoints and backgrounds may have different judgments even on the same criteria, which makes the issue of IC evaluation more complicated. The combination of various uncertain evaluations of criteria into an overall IC evaluation is also a challenging task when developing a methodology for evaluating IC under uncertainty.

1.2 Motivation of research

Although the IC evaluation problem under uncertainty is challenging, it is vital to banking organizations since it enables banks to have an overall view of the whole innovation management process in their banks and comprehensively review multiple IMPs arranged in a structured hierarchy. The IC evaluation also aims to find the importance roles of different IMPs in banking innovation; under limited resources, the findings are helpful for banks to effectively utilize their resources for the more significant IMPs in banking innovation that yield more improvement in terms of IC. Based on the uncertain evaluations for IMPs from different evaluators, banks can have more insights into their strengths and weaknesses from different perspectives and then reconsider issues in their innovation management process to make it better. The IC evaluation also shows the IC ranking of banks based on which each bank can know its position in the market and learn useful lessons from competitors for better managing innovation activities. To this end, the comprehensive research on the IC evaluation problem is expected to be the foundation for the prosperous innovation of the banking industry.

1.3 Research objectives

To fill the gap in the literature regarding the IC evaluation in banking, the main objective of this study is to propose a new integrated methodology for the evaluation of IC in banking with uncertainty. The findings could serve as a basis for banks to propose appropriate innovation strategies toward prioritizing the most important IMPs that yield more improvement in the IC levels.

To accomplish the main objectives, the following sub-objectives should be achieved:

- Conducting a review on the related literature on the concepts of innovation, IC, and IC in banking industry, and then determining the most common IMPs from the literature.
- Synthesizing previous evaluation methods on IC and studying the processes of Multi-Criteria Decision Making (MCDM) methods.
- Developing a new integrated methodology for IC evaluation in banking that is capable of representing the uncertainty in subjective assessments on qualitative criteria, finding the importance weights of different criteria, and handling the aggregation of various uncertain subjective evaluations on multiple criteria.
- Applying the proposed methodology in a case study for checking its feasibility.
- Developing alternative approaches to fully understand the IC of banks by using another method and under another perspective.

1.4 Scope of research

Innovation refers to newness and thus IC can be viewed as dynamic capabilities that appears in the form of routinized activities aimed at developing and adapting operating routines [28]. In addition, literature presents three main approaches for IC evaluation: 1) input/resoures used in innovation process such as R&D intensity [29], human resources [30], 2) activities/practices implemented in innovation process such as strategic planning, technological training, knowledge management, etc. [15], and 3) output/results of innovation process such as patents, academic publications, innovation awards, the total percentage of sale volume of new products [15, 31, 32]. Because several simple input and output criteria are insufficient to evaluate a complex problem like IC, this study uses activity-oriented approach for measuring the IC of banks based on multiple IMPs, particularly concentrates on IMPs at the firm level as it is a significant level to evaluate innovation management [15].

The case study in this research includes three joint stock commercial banks in Vietnam because these banks run for profit purposes and face severe pressure to continuously innovate to survive in fierce competition. The fully state-owned banks that operate for social purposes were not chosen for this research because they receive strong support from the central bank, which may reduce their motivation to innovate. These three banks are all famous in Vietnam, have branches in almost all regions in Vietnam, and directly compete with each other.

1.5 Research process

This study aims to propose a new integrated methodology for evaluating the IC of banks under uncertainty by combining the Analytic Hierarchy Process (AHP) and the Evidential Reasoning (ER) approach in terms of the Dempster–Shafer (D-S) theory of evidence [33]. The research process can be summarized as follows:

- A review on a number of prior studies on innovation management-related topics is conducted to investigate broadly different IMPs that are possible to be applied in banking. On the basis of the frequency of occurrences of the IMPs in the literature, Vital Innovation Management Practices (VIMPs) as the most popular IMPs are extracted from the literature based on Pareto analysis. Measurement indicators for these VIMPs (sub-VIMPs) are also adapted from the related works to ensure the reliability and validity.
- The AHP, proposed by Saaty [34], is known as a robust technique in MCDM that is employed in this study to determine the priorities among the VIMPs and their sub-VIMPs in banking innovation.
- The maturity degrees of sub-VIMPs in the banks to be evaluated are rated by experts in banking-related areas individually using a five-point evaluation scale from $1 - \textit{very poor}$ to $5 - \textit{very good}$; however, different experts with different perspectives may have disagreements in judging sub-VIMPs.

- To tackle the above problem, the ER approach in terms of the D-S theory of evidence, proposed by Yang and Singh [35] and Yang and Xu [36], presents a rational method for aggregating multiple attributes under various uncertainties.
- For the purpose of ranking banks, the pignistic transformation and utility function used by Yang and Xu [36], Huynh et al. [37], and Huynh et al. [38] are applied to drive crisp values representing the overall IC levels of banks.
- The feasibility of the proposed methodology is then empirically illustrated through an actual case study of three banks in Vietnam.
- Reconfirmation of the ranking results and further discussions are also provided.

1.6 Contributions of research

This research has made great contributions to theory, practice, and knowledge science that are summarized below:

- Contributions to theory:
  - This research conducts a comprehensive review on a large body of previous research on innovation management-related topics, which forms a firm foundation for researchers in innovation areas.
  - The importance roles of different VIMPs and sub-VIMPs in banking innovation are disclosed, which shines a new light in the problem of innovation management in banking.
  - This research contributes a new integrated methodology to evaluate the IC of banks with uncertainty based on the combination of the AHP and the ER approach. Despite the popularity of the ER approach in evaluating services [38–43], this study marks the first time that the ER approach is applied in conjunction with the AHP for evaluating IC in banking.
  - To gather empirical evidence, data on innovation practices was collected and the corresponding IC was computed in a case study of commercial banks in Vietnam where there is still little research on IC the evaluation problem.
- Contributions to practice:
  - The findings of this research offer a comprehensive framework for banks to extensively inspect their performance on a set of structured VIMPs.

  - The research results provide valuable information on the most important VIMPs that serve as a basis for bank managers to make priority policies in innovation management process to leverage their IC levels.
  - The differences among experts' assessments on sub-VIMPs at a bank represented in the uncertain form by means of so-called mass functions in the D-S theory could help bank managers to detect the problematic sub-VIMPs.
  - The proposed methodology can also be adapted for evaluating the IC of organizations in other service sectors, but probably needs a slight adjustment in the measurements for VIMPs.
- Contributions to knowledge science:
  - Creating new knowledge in how to improve the IC of banks by indicating the most significant areas that banks have to focus more on instead of spreading investment into all areas while resources are limited.
  - Developing different mathematical approaches for the IC evaluation that can extract useful knowledge for innovation management in banking from uncertain data.

1.7 Structure of dissertation

The content of this dissertation is divided into 6 chapters with their brief description as follows:

Chapter 1 introduces the current issues and the gaps in the literature, formulates the research problem, and presents the motivation of this research, research objectives, scope of research, research process, and the main contributions of the dissertation.

Chapter 2 presents a review on the concepts of innovation, IC, IC in banking industry, along with IC evaluation methods in the previous works. In addition, a summary of MCDM methods that are going to be applied in this study are also introduced in this chapter.

Chapter 3 describes our proposed methodology for evaluating the IC of banks under uncertainty in stages.

Chapter 4 displays the empirical results of applying the proposed IC evaluation methodology in the case study of three banks in Vietnam stage by stage. The final results will show the ranking of the three banks in terms of their IC levels.

Chapter 5 presents two alternative approaches to evaluate the IC of banks. The first approach based on another method called DEA-like model and the second approach based on another evaluation perspective using customer survey are employed to see how the rankings of the three banks in Vietnam will change.

Chapter 6 yields the conclusions, discussions, implications for theory and practice, limitations of this study, and suggestions for future works.

Chapter 2

Literature Review

In chapter 2, we first review on the key concepts of this research including innovation and IC in section 2.1 and section 2.2. The studies on IC in banking industry is then presented in section 2.3. Multi-criteria evaluation approaches to IC in the related works was listed in section 2.4. Finally, MCDM methods that are going to be applied in this research will be summarized in section 2.5.

2.1 Innovation

Today, scientific studies and discussions often refer to the notion of "innovation", though experts and researchers have not reached consensus on its meaning. Chan et al. [44] described innovation as purposeful and organized changes in business activities that might bring new opportunities for enhancing economic and social benefits. Comparably, Rogers [45] contended that innovation is an adjustment in business practices to enhance business performance of the firm. Du Plessis [46] argued that innovation is the establishment of novel ideas and knowledge to better business procedures and devise new products or services for creating new business results. Further, Bigliardi [47] stated that innovation is a process of making, spreading, and converting knowledge in creating new or adapted products, services, or processes. In the same line with Du Plessis, Love et al. [48] briefly considered innovation as the commercialization of new knowledge. Similarly, Straub [49] argued that innovation is the successful development of new, improved, or more competitive products or services or organizational structures. In addition, Ferreira et al. [50] claimed that innovation is the designing and launching of new products, processes, and systems to meet the changes in technologies and competing markets. Baregheh et al. [51] undertook a content analysis of various definitions of innovation sourced from various disciplines. They revealed that three words—"change," "new," and "improve"—commonly happen alongside innovation. Generally, innovation can be typically defined as the affirmative changes in business processes of an organization surrounding new ideas that lead to something new or significantly improved such as new products, services, or processes to achieve greater business outcomes.

Innovation comes in a variety of forms, e.g., new products or services, organizational frameworks, processes or methods, management structures, plans or agendas, markets, technologies, and marketing activities [1, 52–57]. The level of newness of an innovation can be categorized as either radical and incremental [58,59]. Radical innovation relates to a major change of absolute novelty that is completely different from the previous practices and results in substantial challenges and opportunities [57, 60]. Meanwhile, incremental innovation is a change that is not highly novel in comparison to current products or services, processes, technologies, and organizations [61]. While a radical innovation can assist a firm to get into a new marketplace, incremental innovations are what keep a firm competitive [9]. Since radical innovations need greater resources and entail more risks as opposed to incremental innovations [62], most innovations are incremental. Here are some examples of:

- Radical innovations in banking:
  - Blockchain technology was considered as a revolutionary technology that can replace the current financial fraud prevention methods [63].
  - Big data analytics, new payment system were radical innovations in banking [64].
- Incremental innovations in banking:
  - In bank branches, self-serve teller kiosks allow customers to help themselves instead of waiting in line to speak with human tellers [63].
  - Initially, the basic services on mobile banking are deposits, loans, and money transfers. Over time, banks continuously add additional functions into mobile banking services that bring about more convenience to customers such as bills payment, insurance buying, tickets booking, security account opening, and much more.

2.2 Innovation Capability (IC)

As IC is a distinct resource of organizations that forms the foundation for their competitive advantages [65], and if organizations have better IC, they can rapidly implement new processes to limit production costs, create new products or services to draw more clients, raise obstacles to counter mimicry by competitors, and as such gain more competitive advantages [66], various studies have been devoted to clarify the definitions of IC. Christensen [67] suggested that an innovation involves the mixture of numerous types of assets, from process innovative assets to product innovative, aesthetic design, and scientific research. Taking a similar approach, Sen and Egelhof [9] claimed that organizations must use a wide variety of their assets, advantages, and competences to apply an innovation effectively. As such, they stated that IC happens over a wide range of latitudes and stages to serve an organization's tactics and reactions to the outside environment's requirements. Szeto [68] stated that IC means the ongoing creation of the absolute competencies and resources within to determine and take advantage from the establishment of novel products to respond to market shifts. Burgelman et al. [69] argued that IC involves all aspects in an organization that assist and encourage the organization's innovation approach. Wang and Ahmed [70] thought of IC as the capabilities to apply strategic direction, technological procedures, and innovative actions to create new products. Chen and Jaw [71] outlined the concept of IC as how a firm can make an innovative process or product founded on processes, organizational frameworks, and approaches. Many elements must be taken into account to enhance a firm's IC, such as management, information sharing, as well as organizational support [72, 73]. Based on the many definitions of IC, IC can be defined as a multi-criteria concept that involves various IMPs linked to strategies, processes, knowledge, resources, technologies, and organization, etc. that help to put into action innovative ideas with regard to new or significantly improved products or services.

Due to the complexity of IC, it is necessary to consider many criteria at the same time when checking a firm's IC. This is needed to completely understand all of a firm's basic abilities to effectively innovate. Authors of prior studies in the literature chiefly used the number of IMPs to determine IC in various industries. For instance, Rejeb et al. [74] created a method for measuring IC that takes into account 13 observable IMPs: creativity, moral support, collective learning, design tasks, knowledge management, integrated strategy, competence management, process improvement, network management, project management, portfolio management, suitable organization definition, and survey tasks. Wang and Chang [75] devised an innovation value diagnosis system comprising five constructs. These are strategy innovation, process innovation, product innovation, organization innovation, and resource innovation. Tidd and Thuriaux-Alemán [26] suggested that sectors' differing degrees of effectiveness can be measured using eight main IMPs: innovative strategies, product portfolio management, competence and resources management, idea management, development and launch, technology portfolio management, external business intelligence, and post-launch.

To evaluate IC in banking, the innovation management processes of various IMPs are also used in this study. We searched keywords related to IC management such as IC, IC evaluation, innovation practices, IMPs, innovation management measurement, new product development practices, and empirical innovation management. From the results, 32 articles most closely linked to the target of this study were selected. From these 32 studies, a number of IMPs were obtained. The relevant IMPs were categorized in terms of their descriptions in the related works. This formed 23 fundamental IMPs to be applied in the banking sector as shown in Table 2.1.

Table 2.1: IMPs documented in the literature

No	IMPs	Sources
1	Strategic management	[13, 15, 22, 24, 26, 74–93]
2	Resource management	[13, 15, 22–24, 26, 32, 74, 75, 77, 79–82, 84, 86–90, 92–95]
3	Organization management	[15, 22–24, 32, 74–76, 78, 79, 82, 83, 86–90, 92–94, 96, 97]
4	Idea management	[15, 22, 26, 74, 76, 79, 80, 84–86, 90, 91, 98]
5	Process improvement	[15, 22, 26, 74, 75, 78, 84, 86, 88, 92, 94, 97, 99]
6	Marketing management	[13, 15, 23, 80, 82, 87, 89, 90, 94, 97, 100]
7	R&D	[13, 15, 22, 23, 32, 80, 82, 87, 89, 93]
8	Technology management	[79, 80, 85, 86, 89, 91, 94, 95, 100]
9	Cooperative learning	[15, 23, 74, 82, 85, 87, 89, 94]
10	Knowledge management	[15, 24, 74, 88–90, 93, 95]
11	Portfolio management	[15, 24, 26, 74, 81, 83, 84]
12	Network management	[15, 74, 77, 83, 89, 95]
13	Product innovation	[22, 75, 86, 91, 94, 97]
14	Project management	[15, 24, 74, 86]
15	Performance measurement	[76, 78, 80, 83]
16	Team management	[85, 89, 96]
17	Moral support	[15, 74]
18	Commercialization management	[24, 86]
19	Business intelligence	[26, 79]
20	Survey task	[15, 74]
21	Risk management	[89, 95]
22	Involvement	[85, 95]
23	Senior management	[96]

2.3 IC in banking industry

Banks are intermediary financial institutions that match up savers and borrowers by collecting funds from those who have spare money (savers) in the form of savings and lending funds to those who need them (borrowers) in the form of credit loans or other forms [101,102]. Besides that, banks also offer other financial services such as domestic and international payments, debit and credit cards, insurance, wealth management, merchant services, treasury services, digital banking, etc. Banks play an important role because they ensure that economic activities take place smoothly and therefore accelerate the overall economic growth of countries.

In a changing business environment, banks should uncover new ways to be innovative so as to obtain long-term results and sustainable outcomes [103]. By investing in innovation and related technologies, banks can bolster themselves against uncertainty and encourage growth [104]. Today, the implementation of high-tech solutions can be used to evaluate the degree of a bank's innovation. Abualloush et al. [105] discovered that, in the Housing Bank in Irbid Governorate, management information systems including executive information systems plus decision support system are beneficial for product innovation and process innovation. New technologies such as blockchain, deep learning, and machine learning assist banks not only serve customers more rapidly and limit the costs of operating but also support security and transparency [11]. New digital banking platforms continue to emerge, enhancing banks' networks in terms of withdrawals, deposits, and other activities. As a result, there are positive results for financial inclusion [106, 107]. Simultaneously, to improve the quality of customer services, banks are gathering and analyzing a very large data set of customers including via credit or debit transactions, social networks, behavioral psychology, telecommunications with using artificial intelligence, big data analytics, as well as working with FinTech companies in order to create customer profiling, promote product cross selling, and much more [108]. The technical associations with FinTech companies tends to bolster organizational IC [9]. Specifically, the harmonization between banks and FinTech companies assists both to maximize their particular assets. While banks are advantaged by their customer base, prediction ability of trends in the banking field, and expertise regarding laws and regulations, FinTech companies can devise disruptive innovations due to their cutting-edge technological platforms that are not restrained by standard systems [109]. Hence, Palmié et al. [110] suggested that FinTech frameworks can shake up the financial service industry to drive significant innovative adjustments in upcoming years.

In addition to the numerous opportunities that the upsurge of new technologies create, banks are facing major issues regarding transforming processes, developing infrastructure, employing high-quality human resources, and dealing with the dangers of the new age of technological development. Harle et al. [111] stated that the ongoing establishment of technology innovations means there is a need for new risk-management strategies to find, deal with, and minimize risks in carrying out banking operations. Azarenko et al. [112] suggested that due to the digital revolution of the economy, workers must be trained to obtain professional digital skills and technology abilities. As such, to innovate effectively, banks should take on a comprehensive innovation management system based on multiple criteria to improve their IC and gain higher-quality innovation performance.

2.4 Related works on evaluation methods for IC

2.4.1 Value test method

Rejeb et al. [74] and Boly et al. [15] used the multiple criteria approach and value test method for an IC measure framework. They took into account several IMPs that are categorized into numerous criteria that can be directly observed. If a criterion is present, its score is 1; on the other hand, its score is 0. The difficulty of testing the IC of companies is fixed by applying two aggregation levels. In the first level of aggregation, the maturity degree of IMP t at a company (a_t) is found by taking the average of the values of the related criteria:

$$a_t = \frac{1}{K_t} \sum_{k=1}^{K_t} s_{tk} \tag{2.1}$$

where K_t is the quantity of criteria linked with IMP t; and s_{tk} is the score of criterion k linked with IMP t, $s_{tk} \in \{0,1\}$. The second level of aggregation is to calculate the Potential Innovation Index (PII) of a company as:

$$\text{PII} = \sum_{t=1}^{T} W_t a_t \text{ with } \sum_{t=1}^{T} W_t = 1 \tag{2.2}$$

where T is the quantity of IMPs; a_t is the maturity degree of IMP t at a company, $a_t \in [0;1]$; and W_t is the weight of IMP t, $W_t \in [0;1]$.

According to PII values, companies will be classified into four innovative classes: proactive, preactive, reactive, or passive. The classification process is shown in Fig. 2.1. The input of this process is the initial classification C_0 and the output is the final classification C_F. The C_0 is achieved by applying the same weights for all IMPs in all of the four classes to determine PII values of companies. If a company has a PII value from 0 to 0.29, it is classified into the passive class. If its PII value is from 0.29 to 0.41, it belongs to the reactive class. When its PII value is between 0.41 and 0.6, it is in the preactive class. If its PII value is over 0.6, it belongs to the proactive class. Then the C_0 serves as the previous classification C_{k-1} of the latter classification C_k. The C_k is obtained using "value test" – a statistical method that is used to re-calculate the characteristic weight vector for each class based on the previous classification. Specifically, the characteristic weight vector of each class in the C_k is calculated based on the data of companies belonging to that class in the C_{k-1}. The classification process is iterative until the latter classification C_k is the same as the previous classification C_{k-1} when the final classification C_F can be determined. Otherwise, the C_k becomes the C_{k-1} that is the input for the next classification process.

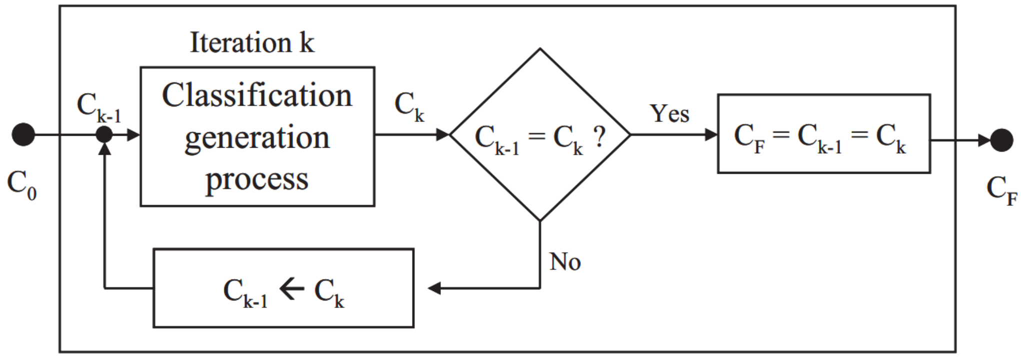


Figure 2.1: Classification process

The value test of an IMP in a class is measured as:

$$v_j(x) = \frac{\bar{x}_j - \bar{x}}{s_j(x)} \quad \text{with} \quad s_j^2(x) = \frac{q - q_j}{q - 1}\frac{s^2(x)}{q_j} \tag{2.3}$$

where $v_j(x)$ signifies the value test of IMP x in class j; $s_j(x)$ and $s(x)$ signify the standard deviation of IMP x in class j and the standard deviation of IMP x in the research sample, respectively; $\bar{x}_j$ and $\bar{x}$ signify the average value of IMP x in class j and the average value of IMP x in the research sample, respectively; and q_j and q signify the quantity of companies in class j and the quantity of companies in the research sample, respectively. The weight of each IMP in each class is then worked out in proportion to the value test of this IMP in each class. After computing the characteristic weight vectors for the four classes, the classification of companies into each class is conducted following four stages:

- *Stage 1:* The PII values of all companies are calculated applying the characteristic weight vector of the proactive class. Next, all companies are ranked in the descending order of PII values and the well-ranked companies are chosen for the new proactive class.

- *Stage 2:* The PII values of the remaining companies are calculated using the characteristic weight vector of the preactive class. Next, these companies are ranked in the descending order of PII values and the well-ranked companies are chosen to form the new preactive class.
- *Stage 3:* The PII values of the remaining companies are calculated using the characteristic weight vector of the reactive class. Next, these companies are ranked in the descending order of PII values and the well-ranked companies are chosen to form the new reactive class.
- *Stage 4:* The PII values of the remaining companies are calculated using the characteristic weight vector of the passive class. Next, these companies are ranked in the descending order of PII values and form the new passive class.

2.4.2 Fuzzy integral method

Wang et al. [13] utilized a non-additive measure and fuzzy integral method to test technological IC founded on a hierarchical analytical system of five aspects comprising a range of qualitative and quantitative criteria. To evaluate the IC degrees of criteria, quantitative criteria are explained by crisp numbers, but qualitative criteria are valued by five linguistic terms from *very poor* to *very good.* The importance degrees of criteria are presented by five linguistic terms from *very low* to *very high.* Those linguistic terms for presenting the IC degrees and the importance degrees of criteria are then converted into triangular fuzzy numbers.

The authors then used the fuzzy arithmetic to three vertices of triangular fuzzy numbers given by all evaluators participating in the evaluation to obtain the aggregated fuzzy evaluation for the IC degree of each criterion (see Eq. (2.4)). In a similar fashion, the importance degree of each criterion based on the all evaluators' assessments is worked out using Eq. (2.5).

$$\bar{x}_{tk} = \left(\frac{1}{E} \sum_{e=1}^{E} L_{x_{tk}^{e}}, \frac{1}{E} \sum_{e=1}^{E} M_{x_{tk}^{e}}, \frac{1}{E} \sum_{e=1}^{E} R_{x_{tk}^{e}} \right) \tag{2.4}$$

$$\bar{g}_{tk} = \left(\frac{1}{E} \sum_{e=1}^{E} L_{g_{tk}^{e}}, \frac{1}{E} \sum_{e=1}^{E} M_{g_{tk}^{E}}, \frac{1}{E} \sum_{e=1}^{E} R_{g_{tk}^{e}} \right) \tag{2.5}$$

where E is the number of evaluators; $\bar{x}_{tk}$ signifies the average assessment over E evaluators for the IC degree of criterion k linked with aspect t; $L_{x_{tk}^{e}}, M_{x_{tk}^{e}}, R_{x_{tk}^{e}}$ are the left, middle, and right loci of the triangular fuzzy number for evaluator e's assessment for the IC degree of criterion k linked with aspect t, $e = 1, ..., E$; $\bar{g}_{tk}$ is the average assessment over E evaluators for the importance degree of criterion k linked with aspect t; $L_{g^e_{tk}}, M_{g^e_{tk}}, R_{g^e_{tk}}$ are the left, middle, and right loci of the triangular fuzzy number for evaluator e's assessment of the importance degree of criterion k linked with aspect t, $e = 1, ..., E$. After that, the fuzzy numbers $\bar{x}_{tk}$, $\bar{g}_{tk}$ are defuzzified into crisp numbers as per the method in [113].

Since all criteria are supposed not to be completely independent, the Choquet integral, which is thought of as a non-additive fuzzy integral, is used to figure out the aggregated assessment for each aspect plus to create the overall evaluation of the technological IC for each company applying the same manner. The Choquet integral of p regarding g is found by:

$$(C)\int p\mathrm{d}g = p(x_1).g(\mathcal{B}_1) + p(x_2).[g(\mathcal{B}_2) - g(\mathcal{B}_1)] + \dots + p(x_K).[g(\mathcal{B}_K) - g(\mathcal{B}_{K-1})] \tag{2.6}$$

where $p(.)$ signifies the IC degree of a criterion linked to an aspect, satisfying $p(x_1) \geq p(x_2) \geq ... \geq p(x_K)$; $g(.)$ is the subjective importance degree of a finite set of criteria: $\mathcal{B}_1 = \{x_1\}, \mathcal{B}_2 = \{x_1, x_2\}, ..., \mathcal{B}_K = \{x_1, x_2, ..., x_K\}$. The computation of $g(\mathcal{B}_k)$ with $k = 1, ..., K$ is as follows:

$$g(\mathcal{B}_k) = g_\lambda(x_1, x_2, ..., x_k) = \frac{1}{\lambda}\left|\prod_{z=1}^{k}(1 + \lambda \,.\, g_z) - 1\right| \tag{2.7}$$

where the parameter λ of a λ-fuzzy measure [114] is found using the following equation: $\lambda + 1 = \prod_{z=1}^{K}(1 + \lambda.g_z)$; g_z is the importance degree of each criterion.

More details may be referred in Wang et al. [13].

2.4.3 Technique of Order Preference Similarity to the Ideal Solution (TOPSIS)

Cheng and Lin [14] came up with a fuzzy expansion of TOPSIS to calculate the performance of technological IC with uncertainty based on seven criteria: information and communication, planning and commitment of the management, knowledge and skills, marketing, operation, R&D, and external environment. As with Wang et al. [13], fuzzy set theory was used to reflect the evaluators' subjective judgments' ambiguity regarding the technological IC performance and the importance of qualitative criteria mathematically, employing trapezoidal fuzzy numbers. The idea of the TOPSIS method established by Hwang and Yoon [115] aims to choose the best option that is closest to the positive ideal solution (PIS) consisting of all of the optimal values for criteria and at the most distance from the negative ideal solution (NIS) comprising all of the worth values for criteria. In detail, the technological IC evaluation process using fuzzy TOPSIS in Cheng and Lin [14] is as follows:

- *Stage 1:* The fuzzy weight of a criterion is computed using the arithmetic mean of all evaluators' assessments concerning the importance of this criterion. The best non-fuzzy performance (BNP) values are then utilized to defuzzy the fuzzy weights of criteria into crisp numbers.
- *Stage 2:* The fuzzy decision matrix for I alternatives, T criteria, is created. The ratings of each alternative with respect to each criterion by all evaluators are aggregated using geometric means.
- *Stage 3:* The normalized fuzzy decision matrix is calculated.
- *Stage 4:* The weighted normalized fuzzy decision matrix is calculated by multiplying the importance weights of criteria and the normalized fuzzy decision matrix.
- *Stage 5:* (1,1,1,1) represents the fuzzy PIS and (0,0,0,0) describes the fuzzy NIS. The distances of each alternative to the fuzzy PIS (d_i^+) and the fuzzy NIS (d_i^-) with $i = 1, ..., I$ are computed using the Minkowski distance.
- *Stage 6:* The closeness coefficient of alternative i (CC_i) is determined by Eq. (2.8). The alternative with the highest CC_i is the most optimal alternative.

$$\mathrm{CC}_i = \frac{d_i^-}{d_i^+ + d_i^-}, \quad i = 1, ..., I \tag{2.8}$$

2.5 Multi-Criteria Decision Making (MCDM) methods

2.5.1 Analytic Hierarchy Process (AHP)

The AHP, suggested by Saaty [34], is a useful and powerful tool for solving multi-criteria decision making problem. According to this method, factors that are important for the decision will be structurized into successive levels of a hierarchy: the highest level represents the overall goal, the intermediate levels show criteria and sub-criteria (if any) of decision making, and the lowest level includes alternatives associated with the problem. For simplicity, let us

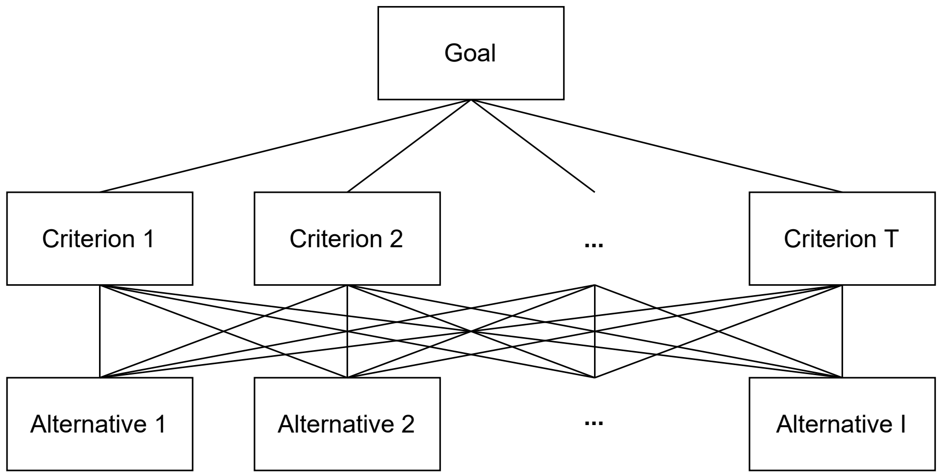


Figure 2.2: Three-level AHP hierarchy

assume a three-level hierarchy where there are T criteria taken into account for assessing I alternatives as shown in Figure 2.2.

By the above presentation, the AHP can help to decompose a complex problem into smaller problems using a hierarchical structure, which provides an thoroughly overall view of the complicated relationships that inherently exist in the real situation. This method then provides an effective solution for the task of computing priorities of criteria, sub-criteria (if any), and alternatives.

The AHP first adopts the Saaty scale as shown in Table 2.2 [116] to make pairwise comparisons on the relative importance of decision elements in a lower stage in terms of those belonging in a higher-stage element. In details, evaluators will take a pair of elements in a lower level and compare the relative importance of the two element with respect to a general element in a higher level that includes the two elements being compared.

Table 2.2: Saaty scale of relative importance

Intensity of relative importance	Definition
1	Equally important
3	Moderately more important
5	Strongly more important
7	Very strongly more important
9	Extremely more important
2, 4, 6, 8	For compromises between the above terms

Given T elements to be compared, $A_1, A_2, ..., A_T$, a $T \times T$ pairwise comparison matrix presenting the relationships between the unknown weights of elements is then formed as follows:

Table 2.3: Pairwise comparison matrix

	A_1	A_2	...	A_T
A_1	1	a_{12}	...	a_{1T}
A_2	a_{21}	1		a_{2T}
...	...	...	...	...
A_T	a_{T1}	a_{T2}	...	1

where a_{rh} show how much element r is more important than element h. Note that all the values in the pairwise comparison matrix are positive and satisfy the reciprocal axiom: $a_{rh} = 1/a_{hr}$. For example, in comparing elements r and h, if element r is 5 compared to element h, then element h is 1/5 compared to element r. In addition, we should ensure the consistence of opinions in pairwise comparison matrix based on the condition that if element r is more important than element h and element h is more important than element z, then element r is more important than element z.

The pairwise comparison matrix is then normalized by dividing the value of each element in the matrix by the sum of its column. To get the weights of elements, we will average the values of each row in the normalized pairwise comparison matrix. Finally, we have to compute Consistency Ratio (CR) to confirm if the opinions of pairwise comparisons above are close to completely random opinions. The CR is determined by Eq. (2.9):

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{2.9}$$

where Consistency Index (CI), calculated by Eq. (2.10), displays the consistency of opinions in a pairwise comparison matrix; Random Index (RI), displayed in Table 2.4, is the average CI of random pairwise comparison matrices. Carefully, a small CR of less than or equal to 0.1 implies that the pairwise comparison matrix is consistent and the estimates of weights are acceptable. Otherwise, we should repeat the procedure of pairwise comparisons to improve the consistency.

$$\mathrm{CI} = \frac{\lambda_{max} - T}{T - 1} \tag{2.10}$$

where T denotes the number of elements to be compared pairwise, λ_{max} denotes the highest eigenvalue of the pairwise comparison matrix, λ_{max} is computed by:

$$CW = \lambda_{max} W \tag{2.11}$$

where C is a pairwise comparison matrix; W, a vector of weights of elements, is called as eigenvector; $\lambda_{max} \geq T$ with T is the number of the elements compared. In case the pairwise comparison matrix is ideally absolutely consistent, $\lambda_{max} = T$, then $CI = 0$, $CR = 0$. Otherwise, the value of λ_{max} to be applied in Eq. (2.10) is the average of the values of λ_{max} calculated from Eq. (2.11).

Table 2.4: Values of the Random Index (RI)

T	1	2	3	4	5	6	7	8	9	10	11	12
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.58

2.5.2 Evidential Reasoning (ER) approach

Yang and Singh [35] proposed an ER based approach to solve MCDM problems with both quantitative and qualitative attributes under uncertainty. Since this study deals with only qualitative attributes, we focus on summarizing their proposed procedure to combine uncertain subjective evaluations on qualitative attributes based on an evaluation analysis model and the evidence combination rule of the D-S theory.

2.5.2.1 Evaluation analysis model for MCDM problems with uncertainty

The MCDM problem considered is to evaluate a set of alternatives $B = \{b_i, i = 1, ..., I\}$ based on their performance on a set of qualitative attributes $A = \{a_t, t = 1, ..., T\}$. Qualitative attributes are usually general concepts that are difficult to directly evaluate; therefore, they are decomposed into a set of detailed sub-attributes that can be probably directly evaluated. Assume each attribute $t,\ t = 1, ..., T$ is measured by a set of sub-attributes $S_t = \{s_{tk}, k = 1, .., K_t\}$ with K_t is the number of sub-attributes associated with attribute t. This MCDM problem can be graphically described by a three-level evaluation hierarchy in Fig. 2.3.

A set of distinct evaluation grades $\mathcal{G}$ used for subjectively evaluating qualitative sub-attributes is defined as follows:

$$\mathcal{G} = \{G_1, ..., G_n, ..., G_N\} \quad (2.12)$$

where $G_n,\ n = 1, ..., N$ is a linguistic evaluation grade to which a sub-attribute of an attribute may be assessed; N is the number of evaluation grades; G_{n+1} is assumed to be a higher grade than G_n.

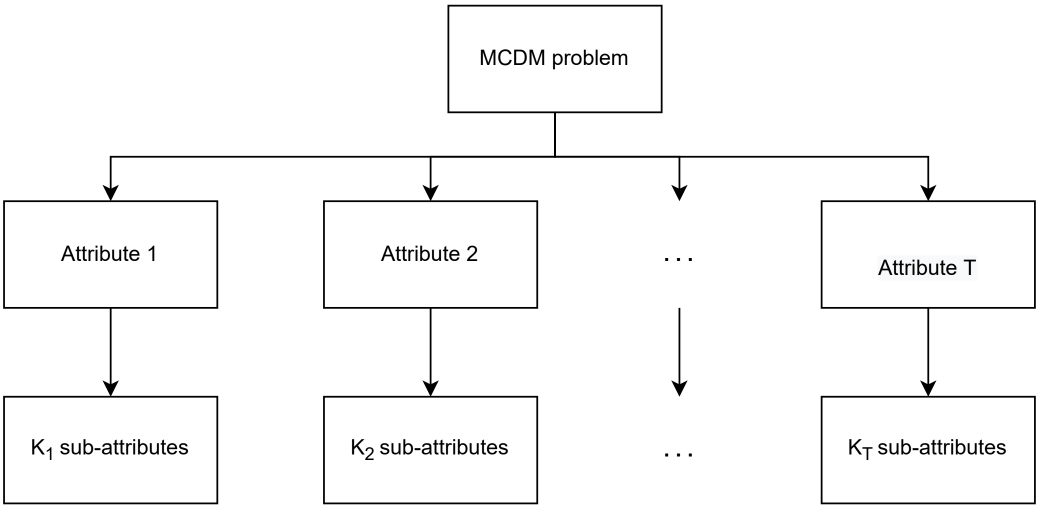


Figure 2.3: Three-level evaluation hierarchy

Because qualitative attributes are usually uncertain in nature; therefore, they could be subjectively evaluated by using different evaluation grades with different confidence degree. For example, evaluators can make the following statement on sub-attributes based on a set of five evaluation grades $\mathcal{G} = \{G_1(very\,poor), G_2(poor), G_3(average), G_4(good), G_5(very\,good)\}$

Statement 1: Sub-attribute 1 of an attribute is evaluated to be *average* with a confidence degree of 0.2 and to be *good* with the confidence degree of 0.4.

Statement 2: Sub-attribute 2 of an attribute is evaluated to be *good* with a confidence degree of 1.

Note that the total confidence degree may be smaller than 1 as in *Statement 1* of a subjective uncertain statement, not necessary to always be 1. In the case of *Statement 1*, the remaining confidence degree is assigned to unknown uncertainty. Other sub-attributes may also be evaluated in the same manner.

The uncertain subjective evaluations of associated sub-attributes of an attribute then need to be combined to derive an aggregated uncertain evaluation for this attribute. The evaluations for attributes of an alternative are eventually combined in a similar fashion to generate an aggregated evaluation for this alternative.

For the sake of simplicity to present aggregation scheme in the next subsubsection, let us denote a two-level evaluation hierarchy with the top level being general attribute a and the bottom level being a set of its associated sub-attributes $\{s_k, k = 1, ..., K\}$ (as shown in Fig. 2.4). We now

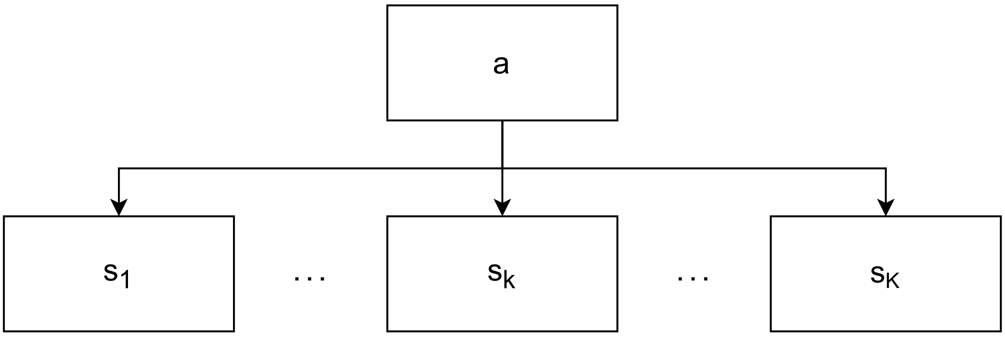


Figure 2.4: Two-level evaluation hierarchy

introduce the aggregation scheme for combining associated sub-attributes of a general attribute.

Using the set of evaluation grades $\mathcal{G}$ as defined in (2.12), the subjective uncertain judgments on sub-attributes at an alternative are then mathematically expressed by means of the following distribution:

$$\{(G_n, \alpha_{n,k})|n = 1, ..., N\} \cup \{\mathcal{G}, \alpha_{\mathcal{G},k})\}, \quad \text{for } k = 1, ..., K. \tag{2.13}$$

where $\alpha_{n,k}$ is the confidence degree that sub-attribute k is assessed by the evaluation grade G_n, such that $\alpha_{n,k} \geq 0$, $\sum_{n=1}^{N} \alpha_{n,k} \leq 1$, and $\alpha_{\mathcal{G},k} = 1 - \sum_{n=1}^{N} \alpha_{n,k}$.

We now can represent the two examples of statements on evaluating sub-attributes 1 and 2 of an attribute in the form of distributions (2.13) below:
For *Statement 1*: $\{(G_3, 0.2), (G_4, 0.4)\} \cup \{\mathcal{G}, 0.4)\}$
For *Statement 2*: $\{(G_3, 1)\}$

With the above formulation, the uncertainty in subjective judgments for qualitative sub-attributes is represented by means of so-called mass functions in the D-S theory of evidence [117]. The next subsubsection will show a rational method applying Dempster's rule of combination to combine these mass functions to get aggregated evaluations of attributes based on their associated sub-attributes' evaluations.

2.5.2.2 ER approach in terms of Dempster-Shafer theory of evidence

Let us define α_n as the confidence degree according to which general attribute a is evaluated to the evaluation grade G_n, $n = 1, ..., N$. We are now summarizing the ER approach to obtain an aggregated evaluation for attribute a denoted by α_n based on aggregating all evaluations on its associated sub-attributes $\{s_k, k = 1, ..., K\}$ as defined by Eq. (2.13).

Suppose $w_k, k = 1, ..., K$ are the respective relative weights of sub-attributes $s_k, k = 1, ..., K$ with $0 \leq w_k \leq 1$ and $\sum_{k=1}^{K} w_k = 1$. The aggregated evaluation on the attribute is then represented by a mass function of $\{(G_n, \alpha_n)|n = 1, ..., N\} \cup \{(\mathcal{G}, \alpha_{\mathcal{G}})\}$. In the ER approach, the aggregated evaluation is obtained by means of the weighted confidence degree operation and Dempster's rule of combination.

First, let $m_{n,k}$ be a basic probability mass to which sub-attribute $s_k, k = 1, ..., K$ supports the hypothesis that attribute a at an alternative is evaluated by the grade of G_n. $m_{\mathcal{G},k}$ signifies the left-over probability mass that is unassigned to any grades after all N grades in the set $\mathcal{G}$ have been confirmed in evaluating attribute a. These basic probability masses may be computed by means of the weighted confidence degree operation:

$$m_{n,k} = w_k \alpha_{n,k}, \quad \text{for } n = 1, ..., N \tag{2.14}$$

$$m_{\mathcal{G},k} = 1 - \sum_{n=1}^{N} m_{n,k} = 1 - w_k \sum_{n=1}^{N} \alpha_{n,k} \tag{2.15}$$

Suppose $S(k)$ is the subset of the first k sub-attributes of attribute a. $m_{n,S(k)}$ denotes a probability mass representing the confidence degree to which all sub-attributes in $S(k)$ support the hypothesis that attribute a is confirmed to the grade G_n. $m_{\mathcal{G},S(k)}$ is the remaining probability mass which is unassigned to any evaluation grades after all sub-attributes in $S(k)$ have been evaluated. The probability masses $m_{n,S(k)}$ and $m_{\mathcal{G},S(k)}$ are obtained by combining the basic probability masses $m_{n,f}$ and $m_{\mathcal{G},f}$, for all $n = 1, ..., N$ and $f = 1, ..., k$.

The key step in the ER approach is based on the Dempster's rule of combination to inductively calculate $m_{n,S(k+1)}$ and $m_{\mathcal{G},S(k+1)}$ (see Eq. (2.16) and Eq. (2.17)) and finally generate an aggregated mass for evaluating attribute a.

$$\begin{aligned} m_{n,S(k+1)} = \ & M_{S(k+1)}(m_{n,S(k)}m_{n,k+1} + \\ & m_{n,S(k)}m_{\mathcal{G},k+1} + m_{\mathcal{G},S(k)}m_{n,k+1)}) \end{aligned} \tag{2.16}$$

$$m_{\mathcal{G},S(k+1)} = M_{S(k+1)}(m_{\mathcal{G},S(k)}m_{\mathcal{G},k+1}) \tag{2.17}$$

for $n = 1, ..., N$, $k = 1, ..., K-1$, and $M_{S(k+1)}$ denotes a normalizing factor that can be computed by Eq. (2.18):

$$M_{S(k+1)} = \left[1 - \sum_{m=1}^{N} \sum_{l=1, m \neq l}^{N} m_{m,S(k)} m_{l,k+1)} \right]^{-1} \tag{2.18}$$

Let us illustrate the computation for combining the evaluations of the first two sub-attributes s_1 and s_2 of attribute a that have been confirmed to the evaluation grades G_n and/or G_{n+1} as follows:

$\{G_n\} : m_{n,S(2)} = M_{S(2)}(m_{n,1}m_{n,2} + m_{n,1}m_{\mathcal{G},2} + m_{\mathcal{G},1}m_{n,2)})$

$\{G_{n+1}\} : m_{n+1,S(2)} = M_{S(2)}(m_{n+1,1}m_{n+1,2} + m_{n+1,1}m_{\mathcal{G},2} + m_{\mathcal{G},1}m_{n+1,2)})$

$\{\mathcal{G}\}$: $m_{\mathcal{G},S(2)} = M_{S(2)}(m_{\mathcal{G},1}m_{\mathcal{G},2})$

where $M_{S(2)} = [1 - (m_{n,1}m_{n+1,2} + m_{n+1,1}m_{n,2}]^{-1}$

In the same manner, the remaining sub-attributes can be combined and consequently, we have:

$$\begin{aligned} \alpha_n &= m_{n,S(K)}, \quad \text{for } n = 1, ..., N \\ \alpha_{\mathcal{G}} &= m_{\mathcal{G},S(K)} = 1 - \textstyle\sum_{n=1}^{N} \alpha_n \end{aligned} \tag{2.19}$$

2.5.3 Data Envelopment Analysis (DEA)

Charnes et al. proposed a DEA model to objectively evaluate the efficiency of decision-making units regarding public programs [118] by choosing optimal weights of multiple inputs and outputs in those programs for each unit based on observational data of those outputs and inputs at each unit. The optimal weights are chosen to satisfy the condition that the efficiency of each unit is maximized. The efficiency of each unit is determined as the maximum of a ratio of a weighted sum of outputs divided by a weighted sum of inputs.

Given a set of units B, the efficiency of unit b is measured by:

$$\text{Maximize: } e_b = \frac{\sum_{o=1}^{n} w_{ob}\mathrm{y}_{ob}}{\sum_{i=1}^{m} u_{ib}\mathrm{x}_{ib}} \tag{2.20}$$

subject to the following constraints:

$$e_{b'} = \frac{\sum_{o=1}^{n} w_{ob}\mathrm{y}_{ob'}}{\sum_{i=1}^{m} u_{ib}\mathrm{x}_{ib'}} \leq 1; \quad \forall b' \in B \tag{2.21}$$

$$w_{ob}, u_{ib} \geq 0; \quad o = 1, ..., n; \quad i = 1, ..., m \tag{2.22}$$

where e_b and $e_{b'}$ denote the efficiency of unit b and unit b', respectively (b and $b' \in B$); n and m are the output and input quantity, respectively; w_{ob} and u_{ib} are defined as the optimal weights of output o ($o = 1, ..., n$) and input i ($i = 1, ..., m$), respectively for unit b ; y_{ob} and $\mathrm{y}_{ob'}$ are the observational values of output o of unit b and unit b', respectively; x_{ib} and $\mathrm{x}_{ib'}$ are the observational values of input i of unit b and b', respectively. The maximization (Eq. (2.20)) will accord each unit the most optimal weights of outputs and inputs for maximizing its efficiency while the constraints in Eq. (2.21) and Eq. (2.22) allow. The efficiency of other units can be similarly computed by changing what to maximize in Eq. (2.20) while still satisfying the constraints in Eq. (2.21) and Eq. (2.22).

DEA has become one of the most popular MCDM methods because of its advantages in reducing the subjectivity in producing composite evaluation indicators. By endogenously deriving the different optimal weights for each unit, the evaluation result of the efficiency of units is more objective. This explains the reason why many research in MCDM problems have applied DEA to effectively and efficiently tackle weighting tasks without any subjectivity. However, we sometimes face difficulties in applying the original DEA model. According to the original DEA model as shown in Eq. (2.20), outputs and inputs must be defined. There exists many situations where there is no input specified in the MCDM problems. To solve with those cases, the latter authors have developed DEA-like models without inputs.

The best practice model proposed by Zhou et al. [119] is among the examples of DEA-like models without input. They considered B units whose composite indices are evaluated based on T attributes. The most favorable composite index for unit b (CI_b, $b \in \{1, ..., B\}$) is determined by solving the following optimization problem:

$$\text{Maximize: } CI_b = \sum_{t=1}^{T} w_{bt} \mathrm{a}_{bt} \tag{2.23}$$

subject to the following constraints:

$$CI_{b'} = \sum_{t=1}^{T} w_{bt} \mathrm{a}_{b't} \leq 1; \quad b' = 1, ..., B; \quad t = 1, ..., T; \tag{2.24}$$

$$w_{bt} \geq \epsilon; \quad t = 1, ..., T; \tag{2.25}$$

where a_{bt} is the value of attribute t at unit b, $t = 1, ..., T$; $a_{b't}$ is the value of attribute t at unit b', $b' = 1, ..., B$, $t = 1, ..., T$; w_{bt} is the optimal weights of attribute t, $t = 1, ..., T$ for unit b; ϵ is a non-Archimedean innitesimal value. Although this approach can provide objective evaluations among different units by solving model (2.23) to pick up the most optimal weights for maximizing the CI of each unit, it still has some limitations that extreme weighting of attributes may occur and therefore the discriminating power among units is poor.

To improve discriminating power among units, Hatefi and Torabi developed an improved version of the above model (2.23) for selecting common weights (the same weights) to be applied in calculating CIs of all units [120]. The common weights are determined based on solving a linear optimization model to minimize the largest deviation among the deviations of CIs from 1, which implies that the selected weights will maximize the lowest CI. Hence, this approach still has a shortcoming that the common weights are controlled by the worst performing unit.

Chapter 3

Proposed Methodology

IC is an abstract concept that can be measured by multiple qualitative criteria; therefore, an IC evaluation is needed to manage multiple pieces of qualitative information. This research considers subjective assessments for banks' IC from a range of angles by experts in various banking-related fields who possess applicable expertise and long-term experience about banking innovation. In studies of group decision-making, at least five to seven experts should be involved to achieve good results [121]. Because each expert has its own belief that could possibly differ from others, there may be differences in experts' assessments on even the same IC criteria at a bank. To deal with such discrepancies, we propose a methodology for evaluating IC in an uncertain scenario. The proposed research process for assessing IC in banking involves four stages, as presented in Fig. 3.1.

- In *Stage 1*, Pareto analysis is employed to identify vital IMPs (VIMPs) from the literature that can be implemented in banking. Next, measurement indicators (sub-VIMPs) for the VIMPs are gathered from the linked research.
- In *Stage 2*, the Analytic Hierarchy Process (AHP) is used to determine the importance weights of the VIMPs and the sub-VIMPs in innovation in the banking context.
- In *Stage 3*, data on the maturity degrees of the sub-VIMPs at banks to be evaluated is accumulated through a questionnaire that is disseminated to various experts in the banking-related areas. The gathered data is next formulated in the forms of both linguistic and numeric responses.
- In *Stage 4*, an overall evaluation of each bank's IC is calculated and then all banks are ranked in terms of their IC levels.

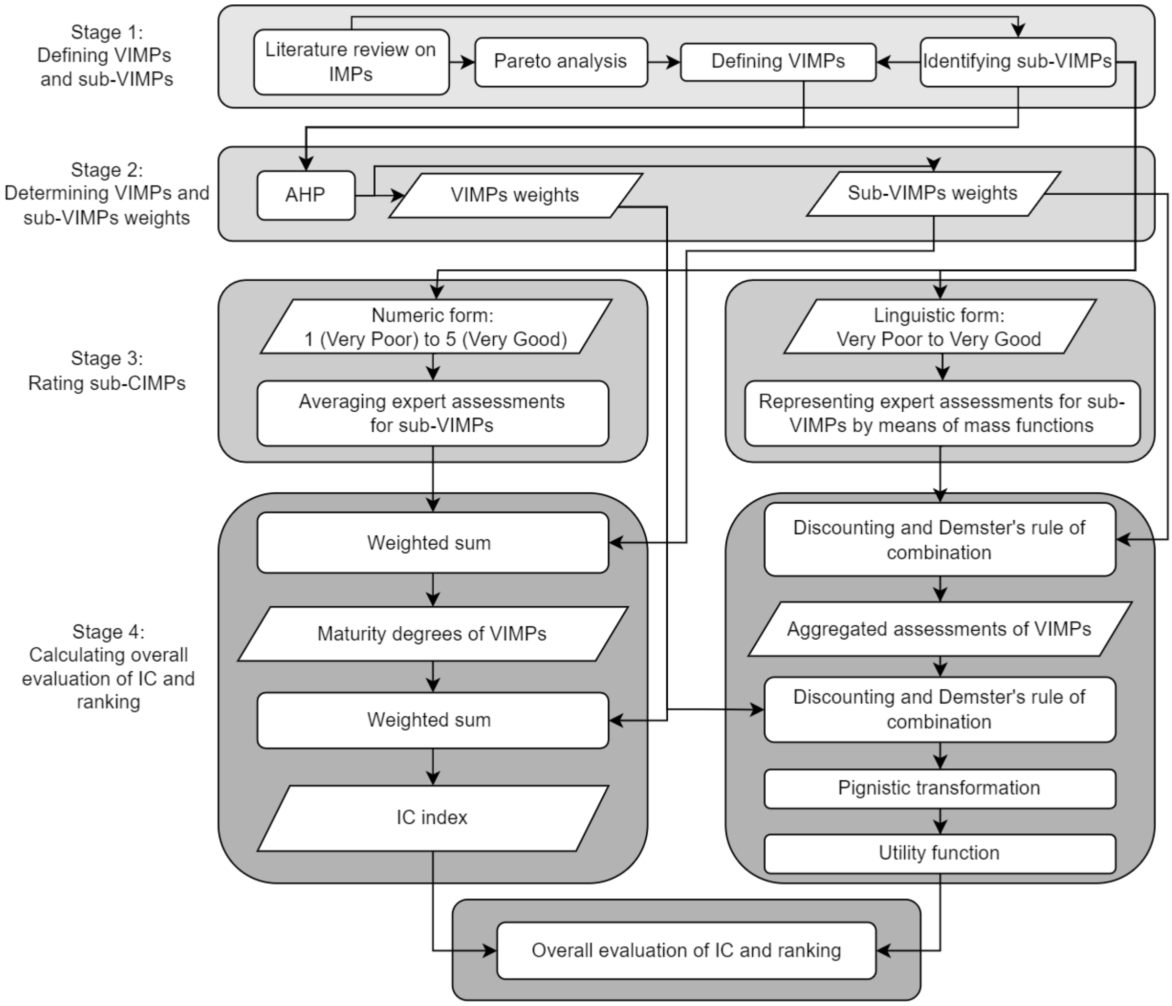


Figure 3.1: Proposed process for IC evaluation in banking

3.1 Defining VIMPs and sub-VIMPs

VIMPs are defined as important constructs that management should put more efforts and resources into. When these constructs are achieved, they assist the realization of successful innovation, improve business performance, and heighten competitive advantages. For solving the task of determining VIMPs, we apply Pareto analysis that can help to choose a limited number of practices that yield a significant influence [122]. This statistical approach helps to differentiate between the “vital few” and the “trivial many” practices. When management are making decisions about which problems to prioritize, such statistics are of great use. The first step of the Pareto analysis commences with a comprehensive review on an extensive body of linked studies to determine all IMPs by looking for related keywords: IC, IC evaluation, innovation practices, IMPs, innovation management measurement, new product development practices, and empirical innovation management (see Table 2.1). The next step is to total the frequencies with which the IMPs show up in the literature and then sort them accordingly, from highest to lowest. Next, the percentage of occurrences for each IMP and the cumulative percentage of occurrences are computed. As per the Pareto principle (80-20 rule), the "vital few" practices—in this research, the VIMPs—will consist of most (80 percent) of the cumulative percentage of occurrences. Meanwhile, the "trivial many" practices will comprise the remaining 20 percent. The Pareto analysis outcomes are usually presented in a table that shows, in order, the IMPs, occurrences (from highest to lowest), occurrences percentages, and cumulative occurrences percentages. In order to find out to what degrees the VIMPs have been matured in the evaluated banks, the relevant sub-VIMPs were also extracted from the existing literature to ensure for the reliability and legitimacy of the measurement scales.

Let us assume that after implementing Stage 1, we have T VIMPs that are measured by the corresponding K_t sub-VIMPs with $t = 1, ..., T$ to be considered in the IC evaluation in banking.

3.2 Determining the VIMPs and the sub-VIMPs weights

Our aim is to find the most innovative bank among banks to be evaluated in terms of their ICs as measured by the VIMPs and the sub-VIMPs described in Stage 1. To be able to aggregate these VIMPs and sub-VIMPs, we first need to identify the weights of those in banking innovation. As such, the AHP methodology is adopted to answer this problem. The hierarchy of the IC evaluation problem in banking consists of four stages (see Fig. 3.2). The first stage is the goal to select the bank that shows the best IC or to rank the banks according to their ICs. The decision criteria (VIMPs) and sub-criteria (sub-VIMPs) make up the intermediate stages. The alternatives that are banks to be evaluated in this study forms the lowest stage.

As description in details about the AHP process in subsection 2.5.1, we first use pairwise comparisons to research the relative importance of sub-VIMPs in a lower intermediate stage with regard to their associated VIMPs in a higher intermediate stage and the relative importance of VIMPs with regard to the goal as per the Saaty scale of relative importance from *1* –

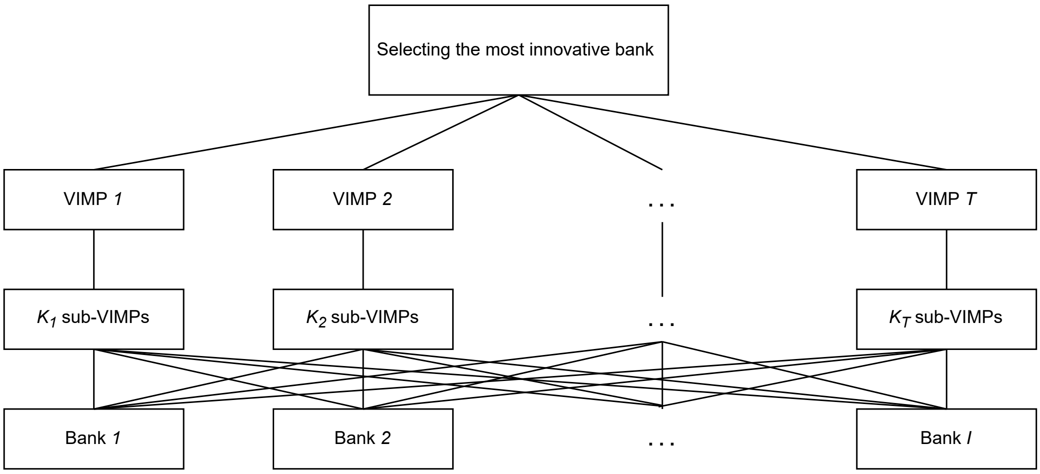


Figure 3.2: AHP hierarchy for IC evaluation in banking

equally important to *9 – extremely more important*, as presented in Table 2.2 [116]. A group of various experts in banking-related fields is chosen to conduct the assessment process, including bank managers, lecturers of banking and finance, auditors in banking, experienced researchers in banking innovation fields, etc. These people were deemed to be able to offer credible views regarding banking innovation; therefore, we consider the same belief in their assessments. The views of all experts are then averaged for the comparison of each pair. These averages are the basis of the formation of the pairwise comparison matrix, which is then normalized using each column's sum. Averaging the values of each row allows us to gather a set of weights of elements in a lower stage with regard to their belonging in a higher stage. Finally, we calculate the Consistency Ratio (CR) by applying Eq. (3.1) to judge the consistency in experts' opinions.

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{3.1}$$

where CI (Consistency Index), calculated by Eq. (2.10), displays the consistency of experts' opinions in a pairwise comparison matrix; RI (Random Index), shown in Table 2.4, is the average CI of pairwise comparison matrices that are made randomly. Essentially, we can trust experts' judgments when a CR is less than or equal to 0.1.

The above-described AHP process is applied to determine the weights of sub-VIMPs with respect to each VIMP as well as the weights of VIMPs with respect to IC in banking. The weighting results will be used in section 3.4 to derive the maturity degrees of VIMPs and the IC level of each bank.

3.3 Rating the sub-VIMPs

Ladhari [123] and Huynh et al. [37] claimed that decision makers may face less difficulty in evaluating the basic attributes of alternatives using a five- or seven-point evaluation scale, in a real-life scenario, that will likely involve uncertainty and inaccuracy. The data of sub-VIMPs is collected via a questionnaire distributed to experts in banking-related areas who have a comprehensive knowledge of all banks being studied and not work in them to ensure fairness of their evaluations. An in-person meeting for a group of all experts to together discuss the questionnaire is not always possible because each expert has a different workplace and available time. Hence, we complete the questionnaire with each expert separately. We ask experts to offer their views and opinions about the progress of each sub-VIMP for each bank using five evaluation grades: *very poor (VP), poor (P), average (A), good (G), very good (VG).*

To allow for comparison, the two methods for formulation of the collected data on sub-VIMPs at the evaluated banks will be proposed as follows.

3.3.1 Data formulation 1

The set of five evaluation grades is communicated numerically via a five-point numeric scale from *1 (VP)* to *5 (VG).* The numeric assessments of all experts on each sub-VIMP are averaged with Eq. (3.2) to obtain its score:

$$s_{tk} = \frac{1}{E}\sum_{e=1}^{E} s_{tk}^{e} \tag{3.2}$$

where s_{tk} is the score of sub-VIMP k associated with VIMP t of a bank, $s_{tk} \in [1,5]$; E is the quantity of experts involved in the assessment process; and s_{tk}^{e} is the score that expert e judges sub-VIMP k tied to VIMP t of a bank, $s_{tk}^{e} \in \{1,2,3,4,5\}$, $e = 1,2,...,E$.

This computation results produce the numeric scores of sub-VIMPs of the evaluated banks that will be used in subsection 3.4.1 to derive the overall IC evaluation of those banks in the numeric form.

3.3.2 Data formulation 2

IC with qualitative nature could be subjectively assessed in linguistic terms with ambiguity and indistinctness. Therefore, the following set of linguistic evaluation grades is applied to evaluate the sub-VIMPs of a bank:

$$\mathcal{G} = \{G_1, ..., G_n, ..., G_N\}$$

where G_n with $n = 1, 2, ..., N$, is a linguistic evaluation grade. In this study, a five-point linguistic scale ($N = 5$) is applied as an assessment tool for sub-VIMPs, i.e.

$$\mathcal{G} = \{G_1(VP), G_2(P), G_3(A), G_4(G), G_5(VG)\}$$

In this study, the IC evaluation via the questionnaire is conducted by E experts individually, which may lead to variation in independent judgments between them. The various judgments of E experts for sub-VIMP k of VIMP t of a bank can then be signified using this distribution:

$$\{(G_n, \alpha_{n,tk}) | n = 1, 2, ..., N\} \cup \{(\mathcal{G}, \alpha_{\mathcal{G},tk})\} \tag{3.3}$$

fulfilling

$$\alpha_{n,tk} \geq 0,$$

$$\sum_{n=1}^{N} \alpha_{n,tk} \leq 1,$$

and

$$\alpha_{\mathcal{G},tk} = 1 - \sum_{n=1}^{N} \alpha_{n,tk}$$

where $\alpha_{n,tk}$ refers to the likelihood that sub-VIMP k linked with VIMP t at a bank is judged in terms of the grade G_n over E assessments. Essentially, this way of expressing data can mirror an uncertain evaluation of sub-VIMPs at a bank with regard to the evaluation grades in the set $\mathcal{G}$. Using the distributed judgment on each sub-VIMP, we can identify each bank's strengths and weaknesses.

This way of data formulation allows the IC evaluation problem to be considered as a multi-attribute evaluation problem with uncertainty and imprecision. Specifically, the uncertainty is being presented through so-called mass functions in the D-S theory of evidence to describe the evaluations for sub-VIMPs [117]. Next, we will use the ER approach with regard to the D-S theory of evidence to combine these mass functions to determine the aggregated evaluations of each bank's VIMPs and IC that will then be considered to rank the banks in subsection 3.4.2. The ER approach established by Yang and Singh [35] and Yang and Xu [36] (see also, Huynh et al. [37]) offers a rational method incorporating Dempster's rule of combination to find an overall evaluation founded on uncertain evaluations involving multiple attributes.

3.4 Calculating the overall evaluation of IC and ranking

3.4.1 Based on data formulation 1

Based on the identified weights and scores of all sub-VIMPs, the maturity degree of a VIMP at a bank is calculated using weighted sum technique with Eq. (3.4):

$$a_t = \sum_{k=1}^{K_t} w_{tk} s_{tk} \text{ with } \sum_{k=1}^{K_t} w_{tk} = 1 \quad (3.4)$$

where a_t is the maturity degree of VIMP t at a bank, $a_t \in [1,5]$; K_t is the number of sub-VIMPs linked with VIMP t; s_{tk} is the score of sub-VIMP k linked with VIMP t at a bank, $s_{tk} \in [1,5]$, $k = 1, ..., K_t$; and w_{tk} is the weight of sub-VIMP k linked with VIMP t, $w_{tk} \in [0,1]$.

To ascertain which banks are best and worst with regard to their ICs, a list of T VIMPs are taken into account to create the overall IC evaluation. The IC of a bank is communicated via an composite index called the Innovation Capability Index (ICI) as

$$ICI = \sum_{t=1}^{T} W_t a_t \text{ with } \sum_{t=1}^{T} W_t = 1 \quad (3.5)$$

where ICI is the innovation capability index of a bank, $ICI \in [1,5]$; T is the number of VIMPs; a_t is the maturity degree of VIMP t at a bank, $a_t \in [1,5]$, $t = 1, ..., T$; and W_t is the importance weight of VIMP t in terms of IC, $W_t \in [0;1]$.

We can then use the ICI values of banks within a sample to specify their ranking. The highest-ranked bank has the highest ICI and is therefore the most innovative bank; meanwhile, the bank that has the lowest ICI is the least innovative bank.

3.4.2 Based on data formulation 2

With the evaluations of K_t sub-VIMPs linked with VIMP t, there are K_t mass functions based on the definition in Eq. (3.3), for $k = 1, ..., K_t$. By joining these mass functions, we can obtain an aggregated evaluation of each VIMP t, for $t = 1, ..., T$, signified by a mass function of $\{(G_n, \alpha_{n,t})|n = 1, ..., N\} \cup \{(\mathcal{G}, \alpha_{\mathcal{G},t})\}$. The evaluations of T VIMPs are next combined to create an overall evaluation of each bank's IC as signified by a mass function $\{(G_n, \alpha_n)|n = 1, ..., N\} \cup \{(\mathcal{G}, \alpha_{\mathcal{G}})\}$. In the ER approach as described in subsection 2.5.2, these aggregated evaluations can be calculated using the weighted probability operation and Dempster's rule of combination.

The weighted probability operation based on the principle demonstrated in Eq. (2.14) and Eq. (2.15) is first used for K_t mass functions: $\{(G_n, \alpha_{n,tk})|n = 1, ..., N\} \cup \{(\mathcal{G}, \alpha_{\mathcal{G},tk})\}$, for $k = 1, ..., K_t$. $m_{n,tk}$ refers to a basic probability mass demonstrating the chance that sub-VIMP k of VIMP t fulfils the hypothesis that VIMP t is judged to the grade G_n. $m_{\mathcal{G},tk}$ refers to the left-over probability mass unassigned to any grades once all N grades in the set $\mathcal{G}$ have been considered for assessing VIMP t. $m_{n,tk}$ and $m_{\mathcal{G},tk}$, for $k = 1, ..., K_t$ are calculated by Eq. (3.6) and (3.7):

$$m_{n,tk} = w_{tk}\alpha_{n,tk}, \quad \text{for } n = 1, ..., N \tag{3.6}$$

$$m_{\mathcal{G},tk} = 1 - \sum_{n=1}^{N} m_{n,tk} = 1 - w_{tk} \sum_{n=1}^{N} \alpha_{n,tk} \tag{3.7}$$

where $\alpha_{n,tk}$ is the likelihood that sub-VIMP k linked with VIMP t at a bank is judged in terms of the grade G_n over all experts' assessments; and w_{tk} is the weight of sub-VIMP k linked with VIMP t, $w_{tk} \in [0, 1]$.

$S(k)$ refers to the subset of the first k sub-VIMPs of VIMP t. $m_{n,S(k)}$ is a probability mass indicating the chance that all of the sub-VIMPs in $S(k)$ fulfill the hypothesis that VIMP t is assessed to the grade G_n. $m_{\mathcal{G},S(k)}$ is the leftover probability mass unassigned to any grades once all of the sub-VIMPs in $S(k)$ have been evaluated. When bringing together the probability masses $m_{n,tf}$ and $m_{\mathcal{G},tf}$, for all $n = 1, ..., N$ and $f = 1, ..., k$, we get $m_{n,S(k)}$ and $m_{\mathcal{G},S(k)}$.

Next, the principle of Dempster's rule of combination, as outlined in Eq. (2.16), Eq. (2.17), and Eq. (2.18), is implemented to create an aggregated mass for judging VIMP t. In the ER approach, $m_{n,S(k+1)}$ and $m_{\mathcal{G},S(k+1)}$ is inductively calculated as follows:

$$\begin{aligned} m_{n,S(k+1)} = \; & M_{S(k+1)}(m_{n,S(k)}m_{n,t(k+1)}+ \\ & m_{n,S(k)}m_{\mathcal{G},t(k+1)} + m_{\mathcal{G},S(k)}m_{n,t(k+1)}) \end{aligned} \tag{3.8}$$

$$m_{\mathcal{G},S(k+1)} = M_{S(k+1)}(m_{\mathcal{G},S(k)} m_{\mathcal{G},t(k+1)}) \tag{3.9}$$

for $n = 1, ..., N$, $k = 1, ..., K_t - 1$, and $M_{S(k+1)}$ is a normalizing factor determined by Eq. (3.10):

$$M_{S(k+1)} = \left[1 - \sum_{m=1}^{N} \sum_{l=1, m \neq l}^{N} m_{m,S(k)} m_{l,t(k+1)}\right]^{-1} \tag{3.10}$$

As a final outcome, we get:

$$\begin{aligned} \alpha_{n,t} &= m_{n,S(K_t)}, \quad \text{for } n = 1, ..., N \\ \alpha_{\mathcal{G},t} &= m_{\mathcal{G},S(K_t)} = 1 - \textstyle\sum_{n=1}^{N} \alpha_{n,t} \end{aligned} \tag{3.11}$$

Similarly, the weighted probability operation is implemented for the evaluations for each bank's T VIMPs with their corresponding weights of W_t, for $t = 1, \ldots, T$. These weighted evaluations are then joined using Dempster's rule of combination to obtain the overall evaluation of each bank's IC (α_n, for $n = 1, ..., N$ and $\alpha_{\mathcal{G}}$).

Lastly, we apply pignistic transformation, defined by Smets and Kennes [124], to obtain the approximate distribution of the overall evaluation of each bank's IC. Specifically:

$$p_n = \alpha_n + \frac{1}{N}\alpha_{\mathcal{G}}, \quad \text{for } n = 1, ..., N \tag{3.12}$$

To make a ranking among the banks in terms of their ICs to see which is the most innovative bank, we have to create a number from the distribution of the overall IC evaluation of each bank. This figure can be expressed with regard to an expected utility function $u : \mathcal{G} \to [0, 1]$ established by Yang and Xu [36], also used in Huynh et al. [37] and Huynh et al. [38]:

$$\begin{aligned} &u(VP) = 0, \\ &u(P) = 0.35, \\ &u(A) = 0.55, \\ &u(G) = 0.85, \\ &u(VG) = 1 \end{aligned}$$

A bank's expected performance in terms of IC is finally found by:

$$u(IC) = \sum_{n=1}^{N} p_n u(G_n) = \sum_{n=1}^{N} (\alpha_n + \frac{1}{N}\alpha_{\mathcal{G}}) u(G_n) \tag{3.13}$$

Chapter 4

Empirical Results

In this chapter, we present the empirical results from applying the proposed methodology into a case study of three banks in Vietnam, which are anonymized as Bank b_1, Bank b_2, and Bank b_3. We will present the results stage by stage presented in Chapter 3. Section 4.1 discloses the results of defining VIMPs and sub-VIMPs based on literature review. Section 4.2 represents the results of applying the AHP in determining the importance weights of the VIMPs and the sub-VIMPs. Section 4.3 shows the maturity degrees of sub-VIMPs at the three banks in numeric form and the distributed assessments on these sub-VIMPs in linguistic form. Section 4.4 reveals the overall evaluations and the ranking of the three banks in terms of IC.

4.1 Defining VIMPs and sub-VIMPs

Table 4.1 displays the results from applying the Pareto analysis. In the first step in the Pareto analysis, 23 fundamental IMPs extracted from 32 relevant articles (as shown in Table 2.1) were arranged from highest to lowest based on how frequently they occurred in the selected studies. The percentage of occurrences for each IMP was next determined as well as the cumulative percentage of occurrences. In alignment with the Pareto principle of 80-20, the "vital few" practices (VIMPs in this study) take most (80 percent) of the cumulative percentage of occurrences whereas the"trivial many" practices make up the remaining 20 percent. Therefore, the first 11 IMPs in Table 4.1) were chosen as the VIMPs because they comprise 80.645 percent of the cumulative percentage of occurrences. They are: strategic management (STR), resource management (RES), organization management (ORG), idea management (IDE), process improvement (PRO), marketing management (MAR), R&D (RAD), technology management (TEC), cooperative learning (COO), knowledge management (KNO), and portfolio management (POR). Table 4.2 displays 44 measurement indicators (sub-VIMPs) based on the prior studies to evaluate the 11 VIMPs.

Table 4.1: Pareto analysis for 23 IMPs in the literature

No	IMPs	Occurrences	Occurrences percentage (%)	Cumulative occurrences percentage(%)
1	Strategic management (STR)	25	13.441	13.441
2	Resource management (RES)	24	12.903	26.344
3	Organization management (ORG)	22	11.828	38.172
4	Idea management (IDE)	13	6.989	45.161
5	Process improvement (PRO)	13	6.989	52.151
6	Marketing management (MAR)	11	5.914	58.065
7	R&D (RAD)	10	5.376	63.441
8	Technology management (TEC)	9	4.839	68.280
9	Cooperative learning (COO)	8	4.301	72.581
10	Knowledge management (KNO)	8	4.301	76.882
11	Portfolio management (POR)	7	3.763	80.645
12	Network management	6	3.226	83.871
13	Product innovation	6	3.226	87.097
14	Performance measurement	4	2.151	89.247
15	Project management	4	2.151	91.398
16	Team management	3	1.613	93.011
17	Moral support	2	1.075	94.086
18	Commercialization management	2	1.075	95.161
19	Business intelligence	2	1.075	96.237
20	Survey task	2	1.075	97.312
21	Risk management	2	1.075	98.387
22	Involvement	2	1.075	99.462
23	Senior management	1	0.538	100
Total		186	100	

The relationships between the 11 VIMPs and IC are explained below:

- *The relationship between STR and IC:* Strategies are considered as strategic orientations, overall objectives, and practical guidance for innovation activities in an organization. Planning strategies is a first step in the innovation process [125] and top managers are the leaders in the process of discovering and exploiting opportunities for developing new products or processes [126].
- *The relationship between RES and IC:* Resource management in this

study deals mainly with financial and human issues. Finance and human can be considered as two indispensable resources for implementing innovation process. Resource management helps develop and distribute sufficient and suitable resources for conducting innovation activities.

- *The relationship between ORG and IC:* Companies' innovative cultures reflect their willingness to adopt innovations without fearing risks, which create a favorable environment supporting creativity and reinforcing the motivation of employees to contribute to innovation and therefore helps companies adapt to changing market conditions and competitive environments [127–129].
- *The relationship between IDE and IC:* Idea management is a critical phase in the innovation process because innovations are based on new ideas that are actually applied in different manners to create new or additional values [130]. One of major challenges in managing innovation is to collect the large volume of ideas from different sources for screening and evaluating [131].
- *The relationship between PRO and IC:* Defining a formal process for developing new products or services was usually observed in the firms with high performance in innovation [132, 133]. In addition, the use of facilitators and the review of top management during the processes of carrying out innovation tasks will ensure innovation processes to take place smoothly, attach with defined strategies, and be adjusted timely.
- *The relationship between MAR and IC:* In marketing management, interactions with customers can help companies to better understand customer demands and preferences, advertise sales promotions, introduce new products or services, as well as cultivate customer feedback that are useful for developing new products or services. As stated by Huang and Lin [134], it is important to have a good customer relationship management strategy to enhance their loyalty and thus increase sales that generate more resources for developing innovations in future.
- *The relationship between RAD and IC:* The purpose of R&D activities is to produce new knowledge and to promote new product or service development based on new ideas [135], and thus R&D capability is directly related with IC. It was confirmed that there are the relationships between R&D spending and patent [136, 137], trademark [136], and innovation on medium-high technology exports [136].
- *The relationship between TEC and IC:* The use of new technologies can help innovation process undertake more efficiently because they assists in integrating internal and external resources in innovation, building effective communications between different departments within com-

panies for sharing knowledge, and receiving immediate feedback from customers and business parties [138]. The application of new technologies into new product development can contribute new approaches and improve the quality of products [139].

- *The relationship between COO and IC:* Through organizing interactive learning, companies can tap into new issues based on discussions among employees between departments that serves as the sources for innovations. At the same time, employees can improve their competence by exchanging ideas and learning knowledge, experiences, and new approaches from each other [140].
- *The relationship between KNO and IC:* Knowledge management enables the development and spreading experiences, knowledge, and expertise throughout organizations that produce new capabilities and stimulate innovation [141]. Knowledge, especially tacit knowledge, is a critical resource for organizations' IC [142].
- *The relationship between POR and IC:* Under limited resources, companies need to consider the allocation of resources into an appropriate portfolio of innovation projects to balance returns and investment risks and ensure the achievements of organizational strategic objectives on innovations [3, 143].

Table 4.2: VIMPs and sub-VIMPs

VIMPs	Sub-VIMPs	Sources
STR	STR1: Determine apparently innovation objectives in strategic plans STR2: Innovation strategies are commonly understood in the bank STR3: Top management is dedicated to encouragement of innovation practices STR4: Adopt decision aid techniques such as SWOT to devise the bank strategies	[15, 81] [76, 84] [74, 75]
RES	RES1: Offer appropriate innovation resources RES2: Have adaptable and varied capital sources RES3: Focus on hiring capable staffs RES4: Plan regular training courses for comprehension needed for future product creation	[15, 23] [75, 144] [87]
ORG	ORG1: Organizational culture and ambiance support innovation ORG2: Incentivize staffs for innovation ORG3: Allow for failures in innovation ORG4: Adopt an accessible communication system in the bank	[15, 96] [74, 84] [75]
IDE	IDE1: Gather ideas from the bank's different divisions using a validated process IDE2: Develop ideas in collaboration with outside organizations IDE3: Develop a quick method for evaluating new ideas IDE4: Test market reaction prior to initiating new services	[15, 76] [84]
PRO	PRO1: Use a planned innovation procedure PRO2: Involve facilitators in innovation procedure PRO3: Hold meetings to examine innovation undertakings PRO4: Top management frequently appraises progress of innovation projects	[15, 78] [74]
MAR	MAR1: Maintain good relationships with customers MAR2: Have proficient sales personnel MAR3: Measure degree of customer satisfaction after using banking services MAR4: Uphold a strong brand image in customers' minds	[15, 82] [87]
RAD	RAD1: Have a structured R&D program RAD2: Enhance budget for R&D activities on an ongoing basis RAD3: Use teamwork and collaboration across functions RAD4: Organize regularly sessions to program research topics	[15, 26]
COO	COO1: Adopt cooperative learning practices such as inter-service gatherings COO2: Some managers are accountable for cooperative learning activities COO3: Organize evaluation meetings at the conclusion of projects COO4: Communicate lessons acquired from past experiences throughout the bank	[15, 23] [93]
POR	POR1: Make the bank strategies align with investment portfolios POR2: Utilize multi-criteria analysis to manage all continuing projects POR3: Have routine reports about resource distribution into multi-projects POR4: Weigh up long- and short-term, high- and low-risk, etc. projects	[15, 81] [26]
KNO	KNO1: Detect and develop the knowledge of employees to match job requirements KNO2: Foster knowledge sharing and exchange KNO3: Categorize and keep knowledge accessible for staffs KNO4: Use knowledge distribution methods	[15, 93]
TEC	TEC1: Consider technology development and application as a crucial success factor TEC2: Have practices such as scenario planning to forecast precisely new technology trends TEC3: Know the key technological capability of competitors TEC4: Third party technology acquisition matches the bank's infrastructure systems and operations	[23, 85] [89]

4.2 Determining the VIMPs and the sub-VIMPs weights

Our IC assessment problem can be separated into a four-level hierarchical tree, as presented in Fig. 4.1. The first stage demonstrates the goal of selecting, from the three banks in Vietnam in our case study, the most innovative one. The IC level is assessed by multiple criteria and sub-criteria. The two intermediate stages comprise 11 criteria/VIMPs plus 44 sub-criteria/sub-VIMPs. The lowest level includes the three bank alternatives (Bank b_1, Bank b_2, and Bank b_3).

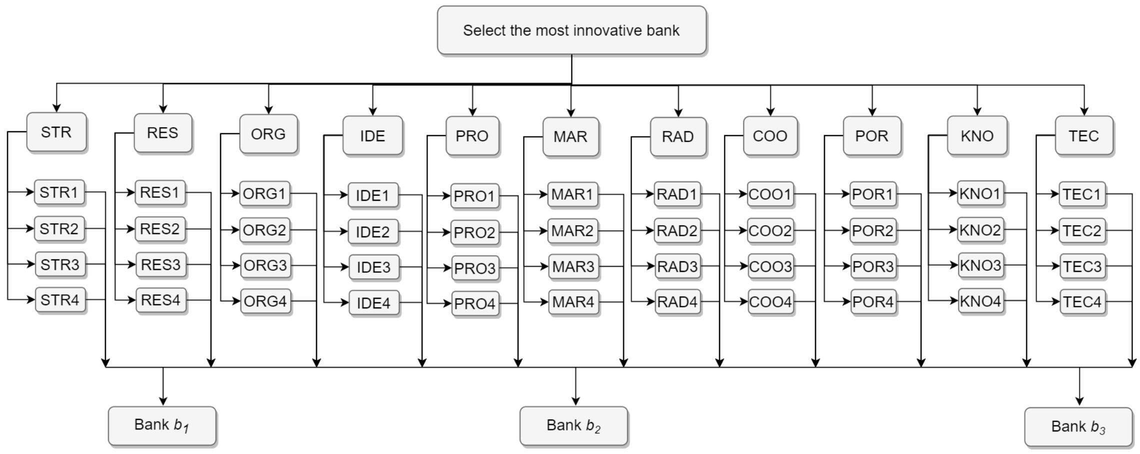


Figure 4.1: Hierarchical tree for problem of IC evaluation

Each IMP has a particular function in innovation in banking; as such, the AHP was implemented to find the importance weights of the 11 VIMPs plus the 44 sub-VIMPs in terms of pairwise comparisons as per the Saaty scale (Table 2.2). The pairwise comparison process was undertaken by five experts who works in banking-related areas and have a comprehensive knowledge of the banking system and banking innovation in Vietnam. Specifically, we invited two vice directors of banks, two lecturers with more than 10 years of working at the Banking University of Hochiminh City, and one banking auditor who works in the central bank of Vietnam. Based on the AHP process as presented in section 3.2, the importance weights of the 11 VIMPs (STR, RES, ORG, IDE, PRO, MAR, RAD, COO, POR, KNO, and TEC) with regard to IC were then found to be 0.28, 0.19, 0.05, 0.05, 0.02, 0.06, 0.08, 0.05, 0.02, 0.09, and 0.10, respectively, as displayed in Table 4.3. As the CR value for the pairwise comparisons of 11 VIMPs is 0.06 less than 0.1, the experts' evaluations are trustworthy. As such, the IC evaluation of banking innovation reveals importance rankings as follows: strategic management (STR), resource management (RES), technology management (TEC), knowledge management (KNO), R&D (RAD), marketing management (MAR), organization management (ORG) and idea management (IDE) and cooperative learning (COO) with the same importance, and process improvement (PRO) and portfolio management (POR) with the same importance. The importance weights of the sub-VIMPs with respect to each VIMP were also found using the AHP process. The results of the weights of sub-VIMPs linked with each VIMP are shown in Table 4.4. Because all of the CR values were less than 0.1, the experts' evaluations in this stage are thought to be reliable.

Table 4.3: Pairwise comparisons of 11 VIMPs in terms of IC

VIMPs	STR	RES	ORG	IDE	PRO	MAR	RAD	COO	POR	KNO	TEC	Weight
STR	1	3	5	5	7	5	5	5	7	5	4	0.28
RES	1/3	1	5	4	6	3	4	4	5	4	4	0.19
ORG	1/5	1/5	1	2	3	1/3	1/2	1/2	4	1/3	1/4	0.05
IDE	1/5	1/4	1/2	1	4	1	1/2	1	4	1/2	1	0.05
PRO	1/7	1/6	1/3	1/4	1	1/4	1/4	1/3	2	1/4	1/5	0.02
MAR	1/5	1/3	3	1	4	1	1/2	2	4	1/3	1/2	0.06
RAD	1/5	1/4	2	2	4	2	1	3	5	1	1/2	0.08
COO	1/5	1/4	2	1	3	1/2	1/3	1	3	1/2	1/2	0.05
POR	1/7	1/5	1/4	1/4	1/2	1/4	1/5	1/3	1	1/6	1/6	0.02
KNO	1/5	1/4	3	2	4	3	1	2	6	1	1/2	0.09
TEC	1/4	1/4	4	1	5	2	2	2	6	2	1	0.10

Table 4.4: Weights of sub-VIMPs of 11 VIMPs

sub-VIMPs	Weights	CR
STR1, STR2, STR3, STR4	0.45, 0.09, 0.14, 0.32	0.03
RES1, RES2, RES3, RES4	0.36, 0.09, 0.34, 0.20	0.02
ORG1, ORG2, ORG3, ORG4	0.35, 0.32, 0.11, 0.22	0.04
IDE1, IDE2, IDE3, IDE4	0.43, 0.15, 0.07, 0.35	0.08
PRO1, PRO2, PRO3, PRO4	0.44, 0.29, 0.12, 0.16	0.05
MAR1, MAR2, MAR3, MAR4	0.17, 0.39, 0.24, 0.21	0.07
RAD1, RAD2, RAD3, RAD4	0.39, 0.10, 0.37, 0.15	0.02
COO1, COO2, COO3, COO4	0.11, 0.40, 0.17, 0.32	0.05
POR1, POR2, POR3, POR4	0.12, 0.45, 0.26, 0.17	0.03
KNO1, KNO2, KNO3, KNO4	0.35, 0.32, 0.11, 0.22	0.04
TEC1, TEC2, TEC3, TEC4	0.08, 0.50, 0.27, 0.14	0.09

4.3 Rating the sub-VIMPs

4.3.1 Data formulation 1

The five experts involved in Stage 2 also work independently from the three banks being evaluated; therefore, they were sent a questionnaire regarding innovation management practice assessment for the three banks. The questionnaire is made up of 44 questions about rating the 44 sub-VIMPs based on a five-point scale from 1 (VP) to 5 (VG). Because each expert completed the questionnaire separately, we then calculated the average of their assessment scores to find the score for each sub-VIMP at each bank, applying Eq. (3.2). Table 4.5 reveals the three banks' average scores for the 44 sub-VIMPs.

Table 4.5: Average scores of sub-VIMPs at three banks in Vietnam

Sub-VIMPs	Bank b_1	Bank b_2	Bank b_3	Sub-VIMPs	Bank b_1	Bank b_2	Bank b_3
STR1	4.4	4.6	4.0	MAR3	3.6	4.2	3.8
STR2	4.2	4.4	4.0	MAR4	3.8	4.4	4.2
STR3	3.8	4.4	4.8	RAD1	3.6	4.4	4.0
STR4	4.0	4.4	4.4	RAD2	3.8	4.0	3.8
RES1	3.4	4.0	4.0	RAD3	3.6	4.4	3.6
RES2	4.2	4.0	4.8	RAD4	3.6	4.2	3.6
RES3	4.0	4.6	4.4	COO1	4.0	4.0	4.2
RES4	3.4	4.2	4.2	COO2	3.4	4.0	4.2
ORG1	3.8	4.4	3.4	COO3	3.6	4.2	4.2
ORG2	4.0	4.0	4.2	COO4	3.2	4.0	4.0
ORG3	3.6	3.6	3.4	POR1	4.2	4.4	4.4
ORG4	3.4	4.2	4.0	POR2	3.4	4.2	4.4
IDE1	3.2	3.8	4.2	POR3	3.8	4.2	4.0
IDE2	3.4	4.0	3.6	POR4	3.8	4.0	4.2
IDE3	3.2	3.8	3.8	KNO1	4.6	4.0	4.2
IDE4	3.4	4.2	3.6	KNO2	3.8	4.2	4.2
PRO1	3.4	4.2	4.2	KNO3	3.8	4.0	4.0
PRO2	3.8	4.2	4.0	KNO4	4.6	4.0	3.8
PRO3	3.8	4.2	4.0	TEC1	4.4	4.2	3.8
PRO4	3.6	4.2	3.8	TEC2	3.6	4.2	3.8
MAR1	4.0	4.6	4.4	TEC3	3.8	4.4	3.8
MAR2	3.8	4.2	3.6	TEC4	3.4	4.2	4.2

4.3.2 Data formulation 2

The assessments for the sub-VIMPs of the three banks in our case study are presented using five linguistic evaluation grades:

$$\mathcal{G} = \{G_1(VP), G_2(P), G_3(A), G_4(G), G_5(VG)\}$$

The questionnaire data shows the five experts' differing judgments regarding each bank's sub-VIMPs. As such, the data revealed via the distribution defined by Eq. (3.3) seems to be an useful means to resolve the experts' conflicting opinions. Table 4.6 displays the distributions for the five experts' assessments regarding the three banks' sub-VIMPs.

Table 4.6: Evaluation matrix of sub-VIMPs at three banks in Vietnam

VIMPs		Sub-VIMPs	Banks		
			Bank b_1	Bank b_2	Bank b_3
Goal	STR (0.28)	STR1 (0.45)	{(A,0.2),(G,0.2),(VG,0.6)}	{(G,0.4),(VG,0.6)}	{(A,0.2),(G,0.6),(VG,0.2)}
		STR2 (0.09)	{(A,0.2),(G,0.4),(VG,0.4)}	{(G,0.6),(VG,0.4)}	{(A,0.2),(G,0.6),(VG,0.2)}
		STR3 (0.14)	{(A,0.2),(G,0.8)}	{(G,0.6),(VG,0.4)}	{(G,0.2),(VG,0.8)}
		STR4 (0.32)	{(A,0.4),(G,0.2),(VG,0.4)}	{(G,0.6),(VG,0.4)}	{(G,0.6),(VG,0.4)}
	RES (0.19)	RES1 (0.36)	{(A,0.6),(G,0.4)}	{(G,1.0)}	{(G,1.0)}
		RES2 (0.09)	{(A,0.2),(G,0.4),(VG,0.4)}	{(A,0.2),(G,0.6),(VG,0.2)}	{(G,0.2),(VG,0.8)}
		RES3 (0.34)	{(A,0.4),(G,0.2),(VG,0.4)}	{(G,0.4),(VG,0.6)}	{(A,0.2),(G,0.2),(VG,0.6)}
		RES4 (0.20)	{(P,0.4),(G,0.4),(VG,0.2)}	{(A,0.2),(G,0.4),(VG,0.4)}	{(G,0.8),(VG,0.2)}
	ORG (0.05)	ORG1 (0.35)	{(A,0.4),(G,0.4),(VG,0.2)}	{(G,0.6),(VG,0.4)}	{(A,0.6),(G,0.4)}
		ORG2 (0.32)	{(A,0.4),(G,0.2),(VG,0.4)}	{(G,1.0)}	{(G,0.8),(VG,0.2)}
		ORG3 (0.11)	{(A,0.4),(G,0.6)}	{(A,0.4),(G,0.6)}	{(A,0.8),(VG,0.2)}
		ORG4 (0.22)	{(A,0.8),(VG,0.2)}	{(G,0.8),(VG,0.2)}	{(A,0.2),(G,0.6),(VG,0.2)}
	IDE (0.05)	IDE1 (0.43)	{(A,0.8),(G,0.2)}	{(A,0.4),(G,0.4),(VG,0.2)}	{(A,0.2),(G,0.4),(VG,0.4)}
		IDE2 (0.15)	{(A,0.8),(VG,0.2)}	{(A,0.2),(G,0.6),(VG,0.2)}	{(P,0.2),(A,0.2),(G,0.4),(VG,0.2)}
		IDE3 (0.07)	{(A,0.8),(G,0.2)}	{(A,0.4),(G,0.4),(VG,0.2)}	{(A,0.6),(VG,0.4)}
		IDE4 (0.35)	{(A,0.6),(G,0.4)}	{(G,0.8),(VG,0.2)}	{(P,0.2),(A,0.4),(VG,0.4)}
	PRO (0.02)	PRO1 (0.44)	{(A,0.6),(G,0.4)}	{(G,0.8),(VG,0.2)}	{(A,0.2),(G,0.4),(VG,0.4)}
		PRO2 (0.29)	{(A,0.4),(G,0.4),(VG,0.2)}	{(G,0.8),(VG,0.2)}	{(A,0.2),(G,0.6),(VG,0.2)}
		PRO3 (0.12)	{(A,0.4),(G,0.4),(VG,0.2)}	{(G,0.8),(VG,0.2)}	{(A,0.4),(G,0.2),(VG,0.4)}
		PRO4 (0.16)	{(A,0.6),(G,0.2),(VG,0.2)}	{(G,0.8),(VG,0.2)}	{(P,0.2),(A,0.2),(G,0.2),(VG,0.4)}
	MAR (0.06)	MAR1 (0.17)	{(A,0.4),(G,0.2),(VG,0.4)}	{(G,0.4),(VG,0.6)}	{(A,0.2),(G,0.2),(VG,0.6)}
		MAR2 (0.39)	{(A,0.4),(G,0.4),(VG,0.2)}	{(G,0.8),(VG,0.2)}	{(A,0.4),(G,0.6)}
		MAR3 (0.24)	{(A,0.4),(G,0.6)}	{(G,0.8),(VG,0.2)}	{(A,0.4),(G,0.4),(VG,0.2)}
		MAR4 (0.21)	{(A,0.4),(G,0.4),(VG,0.2)}	{(G,0.6),(VG,0.4)}	{(G,0.8),(VG,0.2)}
	RAD (0.08)	RAD1 (0.39)	{(A,0.4),(G,0.6)}	{(G,0.6),(VG,0.4)}	{(A,0.2),(G,0.6),(VG,0.2)}
		RAD2 (0.10)	{(A,0.4),(G,0.4),(VG,0.2)}	{(G,1.0)}	{(A,0.4),(G,0.4),(VG,0.2)}
		RAD3 (0.37)	{(A,0.6),(G,0.2),(VG,0.2)}	{(G,0.6),(VG,0.4)}	{(A,0.4),(G,0.6)}
		RAD4 (0.15)	{(A,0.6),(G,0.2),(VG,0.2)}	{(G,0.8),(VG,0.2)}	{(B,0.2),(G,0.8)}
	COO (0.05)	COO1 (0.11)	{(G,1.0)}	{(G,1.0)}	{(G,0.8),(VG,0.2)}
		COO2 (0.40)	{(P,0.4),(G,0.4),(VG,0.2)}	{(G,1.0)}	{(A,0.2),(G,0.4),(VG,0.4)}
		COO3 (0.17)	{(A,0.4),(G,0.6)}	{(G,0.8),(VG,0.2)}	{(G,0.8),(VG,0.2)}
		COO4 (0.32)	{(P,0.4),(G,0.6)}	{(G,1.0)}	{(A,0.2),(G,0.6),(VG,0.2)}
	POR (0.02)	POR1 (0.12)	{(G,0.8),(VG,0.2)}	{(G,0.6),(VG,0.4)}	{(G,0.6),(VG,0.4)}
		POR2 (0.45)	{(P,0.4),(G,0.4),(VG,0.2)}	{(G,0.8),(VG,0.2)}	{(G,0.6),(VG,0.4)}
		POR3 (0.26)	{(A,0.4),(G,0.4),(VG,0.2)}	{(G,0.8),(VG,0.2)}	{(G,1.0)}
		POR4 (0.17)	{(A,0.4),(G,0.4),(VG,0.2)}	{(G,1.0)}	{(G,0.8),(VG,0.2)}
	KNO (0.09)	KNO1 (0.35)	{(G,0.4),(VG,0.6)}	{(G,1.0)}	{(G,0.8),(VG,0.2)}
		KNO2 (0.32)	{(A,0.4),(G,0.4),(VG,0.2)}	{(G,0.8),(VG,0.2)}	{(G,0.8),(VG,0.2)}
		KNO3 (0.11)	{(A,0.4),(G,0.4),(VG,0.2)}	{(G,1.0)}	{(A,0.2),(G,0.6),(VG,0.2)}
		KNO4 (0.22)	{(G,0.4),(VG,0.6)}	{(G,1.0)}	{(A,0.2),(G,0.8)}
	TEC (0.10)	TEC1 (0.08)	{(G,0.6),(VG,0.4)}	{(G,0.8),(VG,0.2)}	{(A,0.4),(G,0.4),(VG,0.2)}
		TEC2 (0.50)	{(A,0.6),(G,0.2),(VG,0.2)}	{(G,0.8),(VG,0.2)}	{(A,0.6),(VG,0.4)}
		TEC3 (0.27)	{(A,0.4),(G,0.4),(VG,0.2)}	{(G,0.6),(VG,0.4)}	{(A,0.6),(VG,0.4)}
		TEC4 (0.14)	{(A,0.8),(VG,0.2)}	{(G,0.8),(VG,0.2)}	{(A,0.2),(G,0.4),(VG,0.4)}

Notes: *Values in parentheses following the VIMPs and the sub-VIMPs are their corresponding weights.*

4.4 Calculating the overall evaluation of IC and ranking

4.4.1 Based on data formulation 1

Table 4.7 displays the results of computing the maturity degrees of each bank's 11 VIMPs by applying Eq. (3.4). Eq. (3.5) was then applied to calculate the three banks' ICIs. As a result, the ICIs of Bank b_1, Bank b_2, and Bank b_3 were 3.800, 4.230, and 4.035, respectively. Based on this result, Bank b_2 is ranked as the most innovative bank, Bank b_3 is the next, and Bank b_1 is the least innovative bank among the three banks in the sample (as shown in Table 4.8).

Table 4.7: Maturity degrees of VIMPs at three banks in Vietnam

VIMPs	STR	RES	ORG	IDE	PRO	MAR	RAD	COO	POR	KNO	TEC
Bank b_1	4.170	3.642	3.754	3.300	3.630	3.824	3.656	3.436	3.668	4.256	3.654
Bank b_2	4.490	4.204	4.140	3.970	4.242	4.352	4.374	4.034	4.190	4.064	4.212
Bank b_3	4.240	4.208	3.788	3.872	4.096	3.946	3.812	4.136	4.262	4.090	3.818

Table 4.8: ICIs and ranking of three banks in Vietnam

Rank	ICI	Bank
1	4.230	Bank b_2
2	4.035	Bank b_3
3	3.800	Bank b_1

4.4.2 Based on data formulation 2

The overall assessments for the three banks' ICs were found by coding a MATLAB program to compute the weighted probability and combination operations via a bottom-up approach along the hierarchical tree (Fig. 4.1).

For each bank, the assessments for the sub-VIMPs were weighted by applying the weighted probability operation with their corresponding weights. Table 4.9 displays the weighted masses of STR1, STR2, STR3, and STR4 with the corresponding weights of 0.45, 0.09, 0.14, and 0.32, respectively for the case of Bank b_1. The same process was then followed to yield the weighted masses of the sub-VIMPs of other VIMPs at Bank b_1.

Table 4.9: Weighted evaluations for sub-VIMPs of STR of Bank b_1

Sub-VIMPs	Weighted mass
STR1	{(A,0.090),(G,0.090),(VG,0.270),($\mathcal{G}$,0.550)}
STR2	{(A,0.018),(G,0.036),(VG,0.036),($\mathcal{G}$,0.910)}
STR3	{(A,0.028),(G,0.112),($\mathcal{G}$,0.860)}
STR4	{(A,0.128),(G,0.064),(VG,0.128),($\mathcal{G}$,0.680)}

The weighted assessments for the sub-VIMPs of each VIMP at each bank were then joined by applying Dempster's rule of combination to find each VIMP's aggregated assessment. Consequently, Table 4.10 shows the aggregated assessments for the 11 VIMPs of Bank b_1.

Table 4.10: Aggregated evaluations for VIMPs of Bank b_1

VIMPs	Aggregated mass
STR	{(A,0.177),(G,0.187),(VG,0.314),($\mathcal{G}$,0.322)}
RES	{(P,0.057),(A,0.254),(G,0.231),(VG,0.137),($\mathcal{G}$,0.321)}
ORG	{(A,0.369),(G,0.171),(VG,0.156),($\mathcal{G}$,0.304)}
IDE	{(A,0.547),(G,0.156),(VG,0.012),($\mathcal{G}$,0.286)}
PRO	{(A,0.380),(G,0.249),(VG,0.063),($\mathcal{G}$,0.308)}
MAR	{(A,0.326),(G,0.351),(VG,0.125),($\mathcal{G}$,0.199)}
RAD	{(A,0.374),(G,0.249),(VG,0.076),($\mathcal{G}$,0.301)}
COO	{(P,0.244),(A,0.049),(G,0.508),(VG,0.049),($\mathcal{G}$,0.151)}
POR	{(P,0.122),(A,0.165),(G,0.383),(VG,0.162),($\mathcal{G}$,0.167)}
KNO	{(A,0.099),(G,0.285),(VG,0.309),($\mathcal{G}$,0.306)}
TEC	{(A,0.494),(G,0.205),(VG,0.173),($\mathcal{G}$,0.128)}

Similarly, the weighted probability operation was used for the assessments for STR, RES, ORG, IDE, PRO, MAR, RAD, COO, POR, KNO, and TEC at each bank with their corresponding importance weights of 0.28, 0.19, 0.05, 0.05, 0.02, 0.06, 0.08, 0.05, 0.02, 0.09, and 0.10, respectively. For instance, Table 4.11 outlines the weighted masses for Bank b_1's 11 VIMPs. The weighted assessments for the 11 VIMPs at each bank were then brought together using Dempster's rule of combination to achieve an aggregated assessment of IC for each bank. Consequently, Table 4.12 shows the three banks' IC aggregated assessments.

Table 4.11: Weighted evaluations for VIMPs of Bank b_1

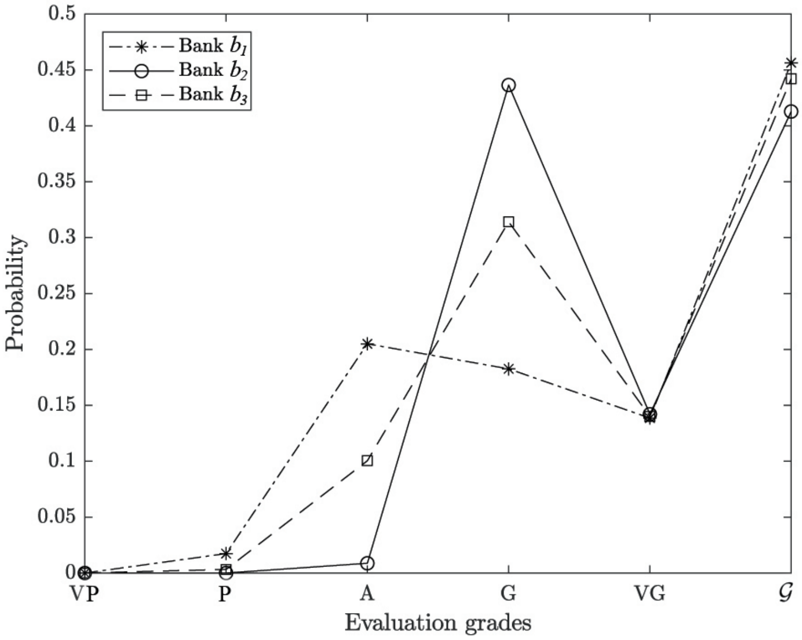
VIMPs	Weighted mass
STR	{(A,0.049),(G,0.052),(VG,0.088),($\mathcal{G}$,0.810)}
RES	{(P,0.011),(A,0.048),(G,0.044),(VG,0.026),($\mathcal{G}$,0.871)}
ORG	{(A,0.018),(G,0.009),(VG,0.008),($\mathcal{G}$,0.965)}
IDE	{(A,0.027),(G,0.008),(VG,0.001),($\mathcal{G}$,0.964)}
PRO	{(A,0.008),(G,0.005),(VG,0.001),($\mathcal{G}$,0.986)}
MAR	{(A,0.020),(G,0.021),(VG,0.007),($\mathcal{G}$,0.952)}
RAD	{(A,0.030),(G,0.020),(VG,0.006),($\mathcal{G}$,0.944)}
COO	{(P,0.012),(A,0.002),(G,0.025),(VG,0.002),($\mathcal{G}$,0.958)}
POR	{(P,0.002),(A,0.003),(G,0.008),(VG,0.003),($\mathcal{G}$,0.983)}
KNO	{(A,0.009),(G,0.026),(VG,0.028),($\mathcal{G}$,0.938)}
TEC	{(A,0.049),(G,0.021),(VG,0.017),($\mathcal{G}$,0.913)}

Table 4.12: Aggregated evaluations on IC for three banks in Vietnam

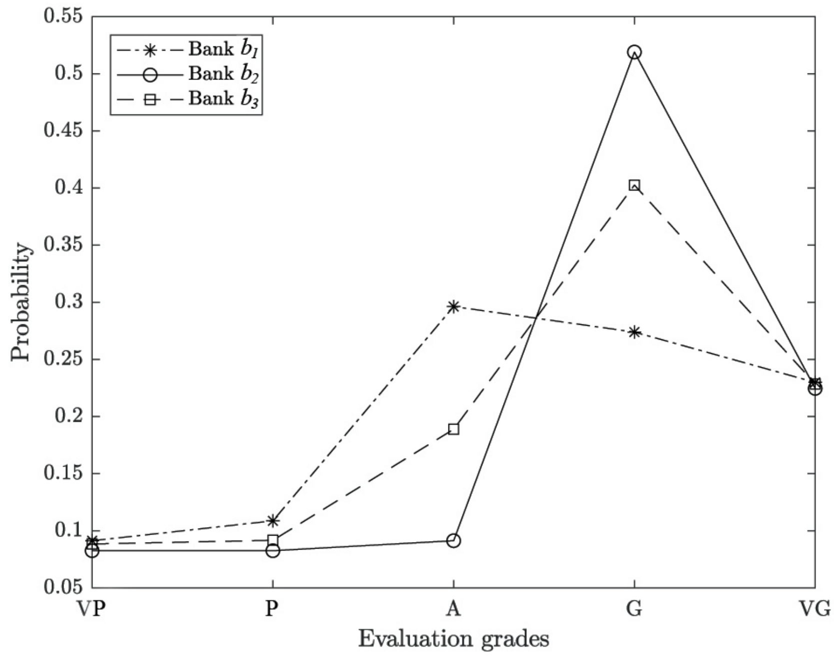
Bank	Overall assessment on IC
b_1	{(P,0.017),(A,0.205),(G,0.183),(VG,0.139),($\mathcal{G}$,0.456)}
b_2	{(A,0.009),(G,0.436),(VG,0.142),($\mathcal{G}$,0.413)}
b_3	{(P,0.003),(A,0.100),(G,0.314),(VG,0.140),($\mathcal{G}$,0.443)}

Lastly, the pignistic transformation and expected utility function were used to figure out the banks' ranking in terms of their ICs. Fig. 4.2 shows the distributions of the aggregated evaluations on the IC of the three banks, plus their approximations obtained from pignistic transformation. The expected performances of the three banks on IC were then calculated to be 0.413, 0.518, and 0.464, respectively. The overall outcome is that Bank b_2 has a higher IC level than Bank b_3, while Bank b_1 is the worst. Significantly, this result is the same as the ranking of three banks found using data formulation 1.

Notably, while both methods to the data formulation produce the consistent final ranking of the three banks according to their ICs, they vary in operation and as such offer differing analytical insights into the IC of banks. The first method of data formulation quantitatively handles the collected data in the numerical form and uses a simple process of computation, particularly by applying the weighted sum for aggregating multiple criteria to obtain the final results of the banks' IC levels. However, it could not capture the inter-individual variance in the experts' assessments of innovation practices, which are primarily qualitative in nature. As such, it does not provide bank managers any revelations regarding the in-depth analysis for the strengths and weaknesses of innovation practices that most add to the IC level of a bank. The restrictions in the first method can be solved in the second method of data formulation, which processes the collected data in the linguistic form. It sees multi-expert assessments on innovation practices as uncertain judgments because different experts with different backgrounds and perspectives may have different judgments even on the same practices of a bank. Such uncertainties are modeled by mass functions in the D-S theory to signify the ambiguity in the experts' assessments of innovation practices. With the data presented in this way, bank managers can refer to particular criteria to identify which practices are strong or weak, and thus suggest appropriate strategies to improve each one. Crucially, when the experts' assessments on the same criteria at the same bank do not have consensus, bank managers should reassess issues linked to these criteria in order to enhance the evaluation process.



(a)



(b)

Figure 4.2: Overall IC evaluations for three banks in Vietnam: (a) Aggregated evaluations (b) Approximate evaluations by pignistic transformation

Chapter 5

Alternative Approaches

In this chapter, we will introduce two approaches to fully understand the IC of banks using another method and under another perspective. The first approach is to develop another method based on the DEA model (an objective IC evaluation method) for evaluating the IC of the three banks in Vietnam using the same data collected in Chapter 4. The second approach is based on another perspective (customer perspective) to evaluate Service Innovation (SI) as a concept positively correlated with IC.

5.1 Using DEA-like model

In this section, we aim to see how the ranking of the three banks in terms of their IC levels changes when applying an objective IC evaluation method developed based on the DEA model. Instead of determining the weights of VIMPs and sub-VIMPs using the AHP based on subjective judgments of experts, we try to define the optimal weights of VIMPs and sub-VIMPs for each bank based on the data of sub-VIMPs which are then used to compute the overall IC evaluation of each bank [145].

5.1.1 Objective IC evaluation approach

As IC is a multi-dimensional concept that was decomposed into 11 VIMPs with their corresponding 44 sub-VIMPs, the IC evaluation can be treated as a MCDM problem. In such a MCDM problem, there are two main tasks that need to be done: weighting and aggregating to ultimately produce a composite indicator [146]. In our proposed methodology in Chapter 3, determining the weights of sub-VIMPs and VIMPs were based on the subjective judgments of experts following the AHP. By this method, the common weights were applied for all banks. It may cause controversy among banks since each bank may have its own innovation strategies that result in different preferences in investing into specific VIMPs and sub-VIMPs. In addition, when changing to another set of weights, the ranking results may change as well. Therefore, we aim to develop a more objective weighting method that can endogenously drive the optimal weights of VIMPs and sub-VIMPs for each bank based on the collected data of sub-VIMPs without referring to any prior or external information for fairly evaluating the IC of banks.

As described in subsection 2.5.3, the main idea of the DEA model is to automatically drive the best possible weights of criteria for each alternative in MCDM problems. For each alternative, the optimal weights are chosen to maximize the aggregated score of this alternative. This means, higher weights will be assigned for better criteria. By this way, we do not apply the same weights for all alternatives. The optimal weights are determined for each alternative based on its data, which helps ensure the objectiveness in the evaluation as well as disclose which criteria each alternative is focusing on or ignoring. Based on the main idea of the DEA model, we will then develop a data-driven weighting method to solve the IC evaluation problem in subsection 5.1.3.

5.1.2 IC evaluation hierarchy

Let us summarize the problem of evaluating IC in the case of the three banks in Vietnam, enormously called Bank b_1, Bank b_2, and Bank b_3. The IC concept is decomposed into the 11 VIMPs (STR, RES, ORG, IDE, PRO, MAR, RAD, COO, POR, KNO, TEC) each of which is measured by the 4 sub-VIMPs. The maturity degree of sub-IMPs at each bank were rated by the five experts separately using a five-point scale (from 1 - *very poor* to 5 - *very good*). As shown in Table 4.5, the scores of the 44 sub-IMPs at the three banks in Vietnam were obtained by averaging the rating scores of the five experts.

5.1.3 Data-driven weighting method

As shown in Fig. 5.1, there are two levels of aggregations to produce the overall IC evaluations for the three banks in Vietnam. The lower level aggregation is to aggregate the 4 sub-VIMPs of each VIMP to determine the maturity degree of this VIMP at each bank. The upper level aggregation is to aggregate the 11 VIMPs to derive the overall IC evaluation of each bank (ICI).

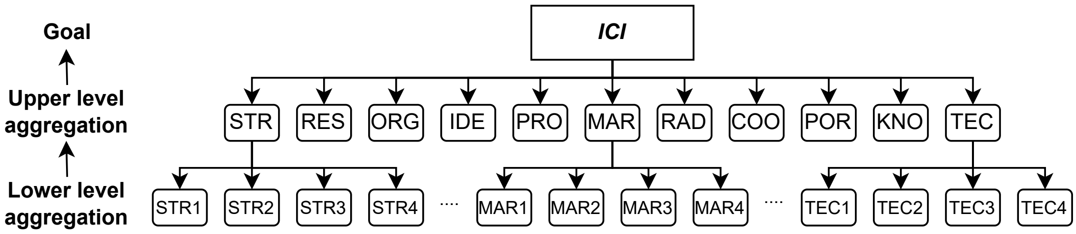


Figure 5.1: IC evaluation with two levels of aggregations

The problem here is to find the optimal weights of the 4 sub-VIMPs of each VIMP for each bank and then compute the aggregated scores of VIMPs of each bank. Subsequently, we need to find the optimal weights of the 11 VIMPs for each bank and then compute the aggregated IC evaluation for each bank (ICI). We now propose a data-driven weighting method based on the DEA model to compute aggregated indicators in the IC evaluation. Nonetheless, in our formulation, there is no input in the proposed DEA-like model (DEA without input) and there are several revisions in constraint conditions in comparison with the original DEA model as described in subsection 2.5.3.

5.1.3.1 Aggregation in the lower level

Suppose B is the set of all banks to be evaluated. Considering a bank $b \in B$, $W_t^{(b)} = \{w_{tk}^{(b)} | k = 1, \ldots, K_t\} = \{w_{t1}^{(b)}, \ldots, w_{tK_t}^{(b)}\}$ is the optimal set of weights of K_t sub-VIMPs of VIMP t for maximizing the score of VIMP t of bank b. To solve the problem of identifying the optimal weights of K_t sub-VIMPs with regard to VIMP t for bank b, $t \in \{1, ..., T\}$, we propose an optimization problem as follows:

$$\text{Maximize} \quad a_t^{(b)} = \sum_{k=1}^{K_t} w_{tk}^{(b)} s_{tk}^{(b)}, \quad k = 1, ..., K_t \tag{5.1}$$

subject to

$$0 \leq w_{tk}^{(b)} \leq 1 \quad \text{and} \quad \sum_{k=1}^{K_t} w_{tk}^{(b)} = 1, \quad k = 1, ..., K_t \tag{5.2}$$

where $a_t^{(b)}$ is the maturity degree of VIMP t at bank b, $a_t^{(b)} \in [1, 5]$; $s_{tk}^{(b)}$ is the score of sub-VIMP k of VIMP t of bank b, $s_{tk}^{(b)} \in [1, 5]$; K_t is the quantity of sub-VIMPs linked with VIMP t, K_t=4 in this study; T is the number of VIMPs, $T = 11$ in this study; $w_{tk}^{(b)}$ with $k = 1, ..., K_t$ is the optimal weights of sub-VIMPs related to VIMP t for bank b.

We can notice that with only the objective function (5.1) and the constraint conditions (5.2), extreme weighting will occur, that means, the highest weight of 1 will be assigned for the best performance sub-VIMP. To overcome this shortcoming, we employed the concept of entropy that shows the state of disorder in data [147] to obtain the high-entropy set of weights $W_t^{(b)}$. The entropy value of the set of weights $W_t^{(b)}$, denoted by $H(W_t^{(b)})$, is calculated as:

$$H(W_t^{(b)}) = -\sum_{k=1}^{K_t} w_{tk}^{(b)} \log_2^{w_{tk}^{(b)}} \tag{5.3}$$

It is clear that, the entropy value of the set of weights when extreme weighting occurs is 0. To avoid the case of extreme weighting, we added one more objective function to solve the above optimization problem (5.1), that is:

$$\text{Maximize} \quad H(W_t^{(b)}) \tag{5.4}$$

The above multi-objective optimization problem can be solved by a library called pymoo as multi-objective optimization in Python. Table 5.1 shows the optimal weights of the sub-VIMPs related to the 11 VIMPs for each bank that is then used to compute the aggregated scores of the 11 VIMPs at each bank.

Table 5.1: Optimal weights of sub-VIMPs and aggregated scores of 11 VIMPs for each bank

Bank	VIMPs	sub1	sub2	sub3	sub4	Aggregated score
Bank b_1	STR	0.697	0.208	0.082	0.013	4.304
	RES	0.200	0.346	0.288	0.166	3.850
	ORG	0.219	0.636	0.098	0.047	3.889
	IDE	0.108	0.353	0.205	0.334	3.337
	PRO	0.191	0.292	0.308	0.209	3.682
	MAR	0.712	0.130	0.054	0.104	3.932
	RAD	0.065	0.568	0.170	0.198	3.714
	COO	0.433	0.241	0.216	0.110	3.681
	POR	0.518	0.068	0.207	0.208	3.980
	KNO	0.572	0.019	0.001	0.409	4.585
	TEC	0.394	0.153	0.291	0.162	3.941
Bank b_2	STR	0.780	0.115	0.072	0.034	4.556
	RES	0.196	0.201	0.385	0.217	4.275
	ORG	0.364	0.210	0.155	0.271	4.138
	IDE	0.182	0.306	0.235	0.277	3.972
	PRO	0.250	0.250	0.250	0.250	4.200
	MAR	0.274	0.261	0.221	0.244	4.359
	RAD	0.315	0.191	0.247	0.248	4.274
	COO	0.273	0.204	0.323	0.199	4.065
	POR	0.270	0.233	0.261	0.236	4.207
	KNO	0.213	0.379	0.219	0.189	4.076
	TEC	0.196	0.230	0.374	0.200	4.275
Bank b_3	STR	0.110	0.076	0.543	0.271	4.543
	RES	0.192	0.354	0.269	0.185	4.428
	ORG	0.195	0.366	0.166	0.272	3.856
	IDE	0.574	0.091	0.204	0.131	3.985
	PRO	0.255	0.258	0.251	0.235	4.004
	MAR	0.354	0.121	0.201	0.324	4.118
	RAD	0.676	0.164	0.091	0.068	3.903
	COO	0.357	0.217	0.396	0.030	4.194
	POR	0.250	0.250	0.250	0.250	4.250
	KNO	0.366	0.408	0.172	0.055	4.144
	TEC	0.199	0.201	0.074	0.526	4.011

5.1.3.2 Aggregation in the upper level

To aggregate the 11 VIMPs in the upper level for each bank, the optimal weights of the 11 VIMPs for each bank needs to be calculated based on the data of VIMPs obtained in the lower level aggregation. In the same manner to compute the weights of sub-VIMPs in the lower level aggregation, we can compute the optimal set of weights of the 11 VIMPs for bank b, denoted by $W^{(b)} = \{W_t^{(b)} | t = 1, \ldots, T\} = \{W_1^{(b)}, \ldots, W_T^{(b)}\}$ by solving a multi-objective optimization problem that tries to find an optimal set of weights of VIMPs to maximize the ICI of bank b while maximize $H(W^{(b)})$ where $H(W^{(b)})$ is the entropy value of the optimal set of weights of VIMPs for bank b, with the constraint conditions including $0 \leq W_t^{(b)} \leq 1$ and $\sum_{t=1}^{T} W_t^{(b)} = 1$, $t = 1, ..., T$, $T = 11$ in this study. Based on the optimal set of weights of VIMPs of each bank, we can point out which VIMPs each bank is focusing on (strengths) or ignoring (weaknesses).

Consequently, Table 5.2 presents the optimal weights of the 11 VIMPs for each bank that are then used to compute the aggregated evaluation of IC level (ICI) for each bank. In particular, Bank b_1 was found to focus more on KNO and STR, Bank b_2 was found to pay attention to STR and MAR, and Bank b_3 was was found to better at RES and STR. As we can infer from the results, the three banks all focus on STR, which may reveal that STR is a significant IMP in innovation management in banking.

Table 5.2: Optimal weights of 11 VIMPs and ICI for each bank

Bank	STR	RES	ORG	IDE	PRO	MAR	RAD	COO	POR	KNO	TEC	ICI	Rank
b_1	0.116	0.088	0.097	0.042	0.069	0.114	0.089	0.093	0.093	0.120	0.080	3.962	3
b_2	0.250	0.090	0.107	0.076	0.082	0.137	0.053	0.073	0.055	0.014	0.060	4.291	1
b_3	0.111	0.115	0.092	0.088	0.104	0.094	0.090	0.085	0.084	0.074	0.060	4.147	2

5.1.4 Discussion of IC ranking results

As a final result, the ICI values of Bank b_1, Bank b_2, and Bank b_3 were determined to be 3.962, 4.291, and 4.147, respectively using each bank's optimal sets of weights of sub-VIMPs and VIMPs. According to that, Bank b_2 is ranked best, Bank b_3 is ranked second, and Bank b_1 is ranked worst.

To ensure the fairness in ranking the three banks with regard to their IC levels, we averaged the three sets of optimal weights of VIMPs of the three banks to obtain a set of common weights of VIMPs that are used to recompute the IC of the three banks. As a result, the common weights of the 11 VIMPs (STR, RES, ORG, IDE, PRO, MAR, RAD, COO, POR, KNO, TEC) were determined to be 0.159, 0.098, 0.098, 0.069, 0.085, 0.115, 0.077, 0.084, 0.078, 0.069, and 0.068, respectively. The ICIs of the three banks were then computed based on the common weights. Consequently, the ICIs of Bank b_1, Bank b_2, and Bank b_3 were found to be 3.929, 4.252, and 4.166, respectively. We can see that the ranking of the three banks based on the common weights still keep the same as the ranking computed based on the optimal weights of each bank.

By the both ways, the IC ranking results of the three banks based on the DEA-like model is the same as the IC ranking result obtained from our proposed methodology based on combining the AHP and the ER approach. By this alternative approach for IC evaluation, the ranking results in Chapter 4 was firmly confirmed.

5.2 Using customer survey

In this section, we aim evaluate the IC of banks via SI performance evaluated from customers' perspectives. In the literature, IC and SI were found to have a positive relationship. Additionally, because customers may not have enough information to evaluate such a complex IC problem based on multiple IMPs, we tend to ask their assessment on the SI problem that is more familiar to them. Seeing that customers are the final consumers of innovative services, they will be the ones who can contribute convincing assessments for the SI performance of banks. Thus, we tend to rely on customers' perspectives to evaluate SI.

This section is devoted to develop a new SI evaluation method in banking using customer surveys. In details, we will attempt to solve three specific problems as follows:

- To understand how customers view the SI of banks.
- To highlight which SI indicators are more important in customers' perceptions.
- To determine the ranking of banks in terms of SI performance based on customers' assessments.

5.2.1 SI in relationship with IC

There have been various definitions of SI in the literature (see Table 5.3). Generally, SI can be defined as the changing in the concepts, processes of delivering, and technological systems to provide new or improved services to customers.

Table 5.3: Definitions of SI

Author	Definition
Thakur and Hale [148]	"New services and/or new ways of delivering services"
Tajeddini and Trueman [149]	"The adoption of new concepts, processes, or technologies to provide customers superior products or services to satisfy the changing customer needs, and thereby sustain organizational competitive advantages."
YuSheng and Ibrahim [4]	"A multidisciplinary process of designing, realizing and marketing combinations of existing and/or new services with the final attempt to create valuable customer experiences."
Ndubisi et al. [150]	"The development of new processes, technologies, products, and services that meet market preferences."
Woo et al. [7]	"Customer-oriented activities aimed at providing new value and benefit to customers through technology, and promoting cooperation between the firm and its customers."

As mentioned in section 2.2, IC can be defined as dynamic abilities of an organization to continuously facilitate the creation of new or improved products or services, processes, and systems based on a process of multiple IMPs [68, 70, 71, 79, 151]. SI has been confirmed to be positively affected by IC. For evidences, Cheng, Rajapathirana and Hui, and Kiani et al. confirmed that IC has positive effects on SI in Taiwanese service firms [152], insurance companies in Sri Lanka [97], and Pakistani cellular companies [153], respectively. Cheng stated that in the development of dynamic service IC, organizations increase new services discovery, knowledge accumulation for SI, and personnel training, which makes them acquire the ability to catch up with new trends, evaluate new techniques and use them for designing new services [152]. According to Subramaniam and Youndt, IC shapes the fate of innovation success of companies either in the form of incremental innovation or radical innovation by maintaining and retaining the gained knowledge [154,155]. In the same line with that, Lavie and Rosenkopf claimed that a high level of dynamic service IC could facilitate greater exploitation of existing knowledge, thus producing incremental SI [156]. Because dynamic service IC is imbued and accumulated in routinized activities of organizations over time, which makes it difficult to imit, valuable, and non-substitutable and therefore become an important source to achieve SI [152, 153].

5.2.2 SI measurement

SI is typically a multi-dimensional concept that can be characterised by multiple qualitative criteria. In the study of Mahmoud et al. [157] about the associations between SI, customer value creation, and customer satisfaction in the telecommunication sector, SI is rated in terms of three dimensions comprising new service concept innovation, new service process innovation, and new technological system innovation. Edvardsson [158] also stated that service development process focuses on developing service concept, service system, and service process. Table 5.4 shows three constructs of SI, namely, new service concept innovation , new service process innovation, new technological system innovation, each of which is measured by five measurement indicators adapted from [157]. This scale was adapted and validated by [4, 159], which ensures its validity and reliability.

Table 5.4: Constructs and measurement indicators for SI

Constructs	Measurement indicators
New service concept innovation	SI1: Creative service packages
	SI2: Customized service options according to customer needs
	SI3: Differences in service concept and design as compared to previous services
	SI4: Differences in service experiences as compared to previous services
	SI5: Differences in service concept and design, as compared to other banks' services
New service process innovation	SI6: Efficient online support processes
	SI7: Automated service options
	SI8: Adopting of new media to interact with customers
	SI9: Attractive marketing campaigns at special occasions and events
	SI10: Quick and simple support services via call center
New technological system innovation	SI11: Constantly updating of new features
	SI12: Modern technology equipment and infrastructure
	SI13: Pioneering new technologies on the market
	SI14: Service development based on the latest technology applications
	SI15: Always striving to improve service quality

5.2.3 Customer-driven SI evaluation method

As SI is characterised by multiple qualitative indicators, the proposed method for SI evaluation is essentially a multi-attribute evaluation method that is capable of handling inherent uncertainty and imprecision due to qualitative nature of SI indicators and subjectivity in human judgments. In this subsection, we will develop a method for evaluating SI in banking under uncertainty based on customer surveys that is then applied in the case study of the three banks in Vietnam (Bank b_1, Bank b_2, and Bank b_3) to see how their ranking is in terms of SI. We first distribute a questionnaire to customers who have been using the services of at least a bank among the three banks. The participating customers are asked to provide some profile information related to their experiences in using banking services, rate the performance of the 15 SI indicators for the banks they have been using, and also rate the importance of the 15 SI indicators. We then propose an appropriate formulation to estimate the different belief on customers' assessments based on their profile data. Because of the qualitative nature of SI as well as the differences in customers' perspectives and experiences in using banking services, the subjective evaluations of SI indicators from different customers may be inconsistent even on the same criterion at the same bank. Hence, we use the means of the so-called mass functions in the D-S theory of evidence [160,161] to represent such uncertainty. After that, the relative weights of the 15 SI indicators reflecting their contribution to SI are then computed based on the perceptions of all customers participating in the survey. Next, the ER approach in terms of the D-S theory of evidence is applied to combine the uncertain subjective evaluations of the 15 SI indicators into the aggregated evaluations representing the SI levels of the three banks taking the relative importance of SI indicators into account. Finally, we will establish a ranking among banks in terms of their SI performance based on the so-called pignistic transformation [124] and expected utility [36].

The process of evaluating the SI levels of the three banks including 6 stages as follows:

Stage 1. Designing and distributing questionnaire

A questionnaire survey was developed based on the 15 SI indicators as shown in Table 5.4. To ensure the questionnaire is suitable for the banking context, two experts in service science and five experienced banking officers were invited to check the content validity and the clarity of wording of the questions. The questionnaire was then revised based on their suggestions and then translated into Vietnamese for data collection via the platform of Google Form. A pilot study was conducted with five bank customers to ensure that they all understood the study and could answer all questions in the questionnaire. After the pre-testing, we had two banking officers working in each evaluated bank help to ask their customers to participate in the survey. Each banking officer was given a "Thank You" voucher for online shopping of 500,000 VND for their support in data collection. They were also promised to share the research findings for use in improving their innovation policies.

The questionnaire comprises three sections: customers' experiences in banking service usage, customers' evaluations on SI indicators, and customers' perceptions on the importance of these indicators:

- The first section of the questionnaire asks three following questions to capture customers' experiences:

  P_1 : Which bank(s) have you been using?
  P_2 : How long have you been using the services of the bank(s)?
  P_3 : Which service(s) of the bank(s) have you been using?

  Such information of customers' experiences will be used to estimate the belief over their evaluations on SI indicators. Besides that, demographic variables consisting of gender and age are also included.
- The second section is for customers to rate the performance of the evaluated banks on the 15 SI indicators using a five-point scale: *very dissatisfied (VD), very dissatisfied (D), neutral (N), satisfied (S), very satisfied (VS)*, denoted by $\mathcal{L}_{SI}$.
- The third section asks customers to rate the importance of the 15 SI indicators when selecting new banking services, using a five-point scale that ranged from 1 – *not important at all* to 5 – *very important*, denoted by $\mathcal{L}_I$.

Adopting a convenience sampling technique, the questionnaire was distributed to 60 customers of each bank among the three banks. Depending on the number of banks that responders have been using, the average time to complete the questionnaire is from 5 minutes to 15 minutes. The survey process was conducted over a period of one month. Of 180 distributed questionnaires, 145 responses were collected, with a completed response rate of 80.56%. However, only 113 responses were valid and retained for analysis (after excluding 32 invalid responses because the participants answered all questions the same). In particular, there are 6 customers using the services of Bank b_1, Bank b_2, and Bank b_3, 8 customers using the services of Bank b_1 and Bank b_2, 3 customers using the services of Bank b_1 and Bank b_3, 18 customers using the services of Bank b_2 and Bank b_3, 21 customers using the services of only Bank b_1, 32 customers using the services of only Bank b_2, and 25 customers using the services of only Bank b_3, which is graphically displayed in Figure 5.2. In terms of demographic variables, the majority of responders were female (53.982%) and older than 30 years old (52.212%). Table 5.5 shows the demographic profile of the participants in the survey.

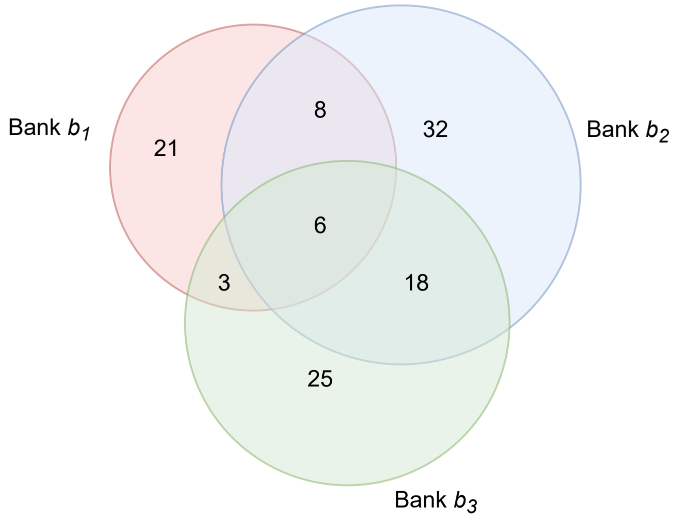


Figure 5.2: Distribution of customers by banks

Table 5.5: Demographic variables

Category	Frequency	Percentage (%)
Gender		
Male	52	46.018
Female	61	53.982
Total	113	100
Age		
≤30	54	47.788
≥31	59	52.212
Total	113	100

Stage 2. Estimating the belief over customers' evaluation:

Considering the different belief in different customers' assessments can be regarded as an advantage of this method because most previous research based on customer surveys weighted customers' assessments equally. It is reasonable that customers who have been using more bank(s) and/or using the services of the evaluated bank(s) for a longer time, and/or using more services of the bank(s) should have higher weights in deciding the performance of SI indicators of the bank(s) as they have better understanding of the bank(s).

The data of customer c's experiences collected by using the questions P_1, P_2 and P_3 will then be used to estimate the belief over customer c's evaluation as follows.

Let us define $\mathcal{H}_1, \mathcal{H}_2$, and $\mathcal{H}_3$ as the sets of possible answers to the questions P_1, P_2, and P_3, respectively. In this study, $\mathcal{H}_1 = \{1, \ldots, n_1\} = \{1, 2, 3\}$ is the number of banks that a customer has been using, $\mathcal{H}_2 = \{1, \ldots, n_2\} = \{1, 2, 3, 4\}$ is the period of time in years that a customer has been using services, and $\mathcal{H}_3 = \{1, \ldots, n_3\} = \{1, 2, 3, 4, 5, 6, 7\}$ is the number of services that a customer has been using.

Assume that the answers of customer c to the questions P_1, P_2 and P_3 are n_c^1, n_c^2 and n_c^3, respectively. We then define the belief over customer c's evaluation (β_c) by the following relation:

$$\beta_c = \gamma + (1-\gamma)\frac{1}{3}\left(\frac{n_c^1}{n_1} + \frac{n_c^2}{n_2} + \frac{n_c^3}{n_3}\right)$$

where $\gamma \in [0, 1]$ is interpreted as the belief over customer c's assessment when we do not have information about customer c's profile, for example $\gamma = 0.5$. That is, by definition, the more experiences a customer has with using banking services, the higher belief β_c is in this customer's judgment.

Fig. 5.3 shows the distributions of the belief over customers' evaluations for the SI indicators of the three banks. In general, most of the evaluations of customers using the services of Bank b_2 and Bank b_3 obtain high belief values. It can be referred from Fig 5.2, the probability of customers using the services of Bank b_2 or Bank b_3 and also using the services of the remaining two banks is high. In addition, based on the collected data, the averaged time period that customers have been using the services in the case of Bank b_2 is the highest while the averaged number of services that customers of Bank b_3 have been using is the highest.

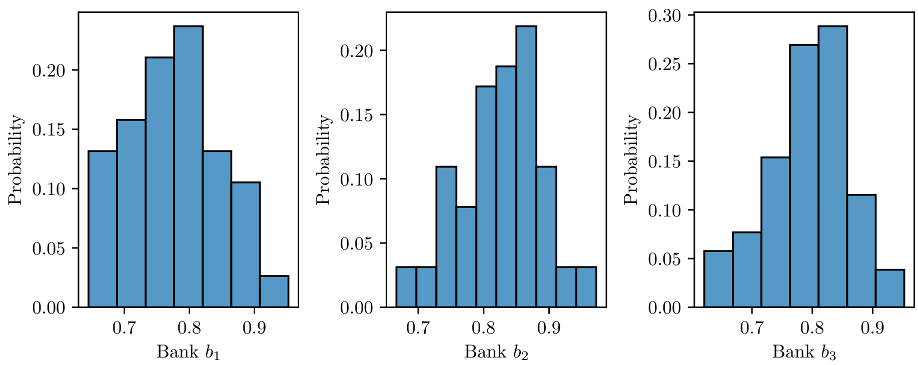


Figure 5.3: Distributions of the belief over customers' evaluation

Stage 3. Formulating the mass function for customers' evaluations of SI indicators:

Customers' assessments on each SI indicator at each bank are modeled as a distribution that captures the uncertainty in evaluating a qualitative concept like SI. For each SI indicator SI_k with $k = 1, \ldots, K$, $K = 15$ in this study, we now model customers' evaluations on SI_k of bank b based on the so-called mass function in the D-S theory of evidence [161] defined as

$$m_k^b : 2^{\mathcal{L}_{SI}} \to [0, 1]$$

such that

$$m_{l,k}^b = \frac{1}{N_b} \sum_{c:\ c(SI_k)=l} \beta_c, \text{ for } l \in \mathcal{L}_{SI} \tag{5.5}$$

$$m_{\mathcal{L}_{SI},k}^b = 1 - \sum_{l \in \mathcal{L}_{SI}} m_{l,k}^b \tag{5.6}$$

where m_k^b is a mass function that captures the differences in customers' evaluations regarding SI_k of bank b; $m_{l,k}^b$ is the probability that SI_k of bank b is rated at the level l over N_b customers taking the belief in their judgments into account; N_b is the total number of customers who provide evaluation for bank b; $c(SI_k) = l$ means that the performance of bank b at SI_k is rated at the level l by customer c; and β_c is the belief over customer c's assessment for bank b.

Intuitively, the $m_{l,k}^b$ for $l \in \mathcal{L}_{SI}$ represents the average belief of the population for the performance of bank b with respect to SI_k being at the level l, while $m_{\mathcal{L}_{SI},k}^b$ quantifies the ignorance resulting from missing evaluations due to a lack of knowledge.

As such, for K SI indicators we obtain a tuple of K mass functions

$$\left[m_1^b, m_2^b, \ldots, m_K^b\right] \tag{5.7}$$

where

$$m_k^b = \{m_{l,k}^b\} \cup \{m_{\mathcal{L}_{SI},k}^b\} \quad \text{ for } l \in \mathcal{L}_{SI} \tag{5.8}$$

referred to customer-oriented evaluation profile of SI for bank b.

Table 5.6 shows the distributions for customers' evaluations on the 15 SI indicators of the three banks in the sample.

Stage 4. Deciding the relative importance of SI indicators:

Next, we use the data of customers' perceptions on the importance of SI indicators for estimating their relative importance. For each SI indicator SI_k, $k = 1, ..., K$, we first define its expected importance denoted by w_k as follows.

$$w_k = \sum_{l^* \in \mathcal{L}_I} \frac{|c : c(SI_k) = l^*|}{N} \times l^* \tag{5.9}$$

Table 5.6: Evaluation matrix of SI indicators for three banks in Vietnam

Indicators	Bank b_1	Bank b_2	Bank b_3
SI1	(D,0.111),(N,0.365),(S,0.352),($\mathcal{L}_{SI}$,0.172)	(D,0.078),(N,0.423),(S,0.242),(VS,0.081),($\mathcal{L}_{SI}$,0.175)	(D,0.046),(N,0.400),(S,0.303),(VS,0.077),($\mathcal{L}_{SI}$,0.174)
SI2	(D,0.131),(N,0.364),(S,0.289),(VS,0.045),($\mathcal{L}_{SI}$,0.172)	(D,0.103),(N,0.434),(S,0.206),(VS,0.082),($\mathcal{L}_{SI}$,0.175)	(VD,0.014),(D,0.032),(N,0.355),(S,0.316),(VS,0.109),($\mathcal{L}_{SI}$,0.174)
SI3	(D,0.021),(N,0.363),(S,0.444),($\mathcal{L}_{SI}$,0.172)	(D,0.026),(N,0.335),(S,0.435),(VS,0.029),($\mathcal{L}_{SI}$,0.175)	(D,0.017),(N,0.332),(S,0.397),(VS,0.080),($\mathcal{L}_{SI}$,0.174)
SI4	(N,0.409),(S,0.372),(VS,0.047),($\mathcal{L}_{SI}$,0.172)	(N,0.304),(S,0.479),(VS,0.042),($\mathcal{L}_{SI}$,0.175)	(D,0.048),(N,0.285),(S,0.383),(VS,0.110),($\mathcal{L}_{SI}$,0.174)
SI5	(D,0.022),(N,0.499),(S,0.284),(VS,0.023),($\mathcal{L}_{SI}$,0.172)	(D,0.039),(N,0.433),(S,0.310),(VS,0.043),($\mathcal{L}_{SI}$,0.175)	(D,0.097),(N,0.344),(S,0.288),(VS,0.097),($\mathcal{L}_{SI}$,0.174)
SI6	(D,0.063),(N,0.449),(S,0.293),(VS,0.023),($\mathcal{L}_{SI}$,0.172)	(VD,0.012),(D,0.090),(N,0.354),(S,0.313),(VS,0.056),($\mathcal{L}_{SI}$,0.175)	(VD,0.014),(D,0.033),(N,0.393),(S,0.242),(VS,0.143),($\mathcal{L}_{SI}$,0.174)
SI7	(D,0.045),(N,0.430),(S,0.285),(VS,0.069),($\mathcal{L}_{SI}$,0.172)	(D,0.039),(N,0.349),(S,0.367),(VS,0.069),($\mathcal{L}_{SI}$,0.175)	(D,0.033),(N,0.268),(S,0.380),(VS,0.145),($\mathcal{L}_{SI}$,0.174)
SI8	(D,0.153),(N,0.472),(S,0.156),(VS,0.047),($\mathcal{L}_{SI}$,0.172)	(D,0.051),(N,0.377),(S,0.317),(VS,0.081),($\mathcal{L}_{SI}$,0.175)	(D,0.066),(N,0.328),(S,0.306),(VS,0.126),($\mathcal{L}_{SI}$,0.174)
SI9	(VD,0.020),(D,0.064),(N,0.458),(S,0.264),(VS,0.023),($\mathcal{L}_{SI}$,0.172)	(VD,0.026),(D,0.053),(N,0.408),(S,0.286),(VS,0.052),($\mathcal{L}_{SI}$,0.175)	(D,0.083),(N,0.406),(S,0.290),(VS,0.047),($\mathcal{L}_{SI}$,0.174)
SI10	(VD,0.020),(D,0.105),(N,0.479),(S,0.224),($\mathcal{L}_{SI}$,0.172)	(VD,0.023),(D,0.170),(N,0.391),(S,0.202),(VS,0.039),($\mathcal{L}_{SI}$,0.175)	(VD,0.048),(D,0.094),(N,0.382),(S,0.192),(VS,0.110),($\mathcal{L}_{SI}$,0.174)
SI11	(D,0.045),(N,0.353),(S,0.429),($\mathcal{L}_{SI}$,0.172)	(D,0.053),(N,0.321),(S,0.412),(VS,0.040),($\mathcal{L}_{SI}$,0.175)	(D,0.033),(N,0.251),(S,0.397),(VS,0.145),($\mathcal{L}_{SI}$,0.174)
SI12	(N,0.461),(S,0.368),($\mathcal{L}_{SI}$,0.172)	(D,0.053),(N,0.345),(S,0.362),(VS,0.065),($\mathcal{L}_{SI}$,0.175)	(D,0.080),(N,0.299),(S,0.339),(VS,0.109),($\mathcal{L}_{SI}$,0.174)
SI13	(VD,0.021),(D,0.021),(N,0.571),(S,0.193),(VS,0.022),($\mathcal{L}_{SI}$,0.172)	(D,0.088),(N,0.426),(S,0.284),(VS,0.026),($\mathcal{L}_{SI}$,0.175)	(D,0.033),(N,0.330),(S,0.335),(VS,0.128),($\mathcal{L}_{SI}$,0.174)
SI14	(D,0.043),(N,0.417),(S,0.368),($\mathcal{L}_{SI}$,0.172)	(D,0.053),(N,0.399),(S,0.334),(VS,0.039),($\mathcal{L}_{SI}$,0.175)	(N,0.364),(S,0.352),(VS,0.111),($\mathcal{L}_{SI}$,0.174)
SI15	(D,0.063),(N,0.330),(S,0.413),(VS,0.022),($\mathcal{L}_{SI}$,0.172)	(D,0.053),(N,0.337),(S,0.382),(VS,0.053),($\mathcal{L}_{SI}$,0.175)	(VD,0.014),(D,0.032),(N,0.257),(S,0.376),(VS,0.146),($\mathcal{L}_{SI}$,0.174)

where $|c : c(SI_k) = l^*|$ is the number of customers who rate the importance of SI_k by the level l^*, $l^* \in \mathcal{L}_I = \{1, ..., 5\}$; N is the number of all customers participating in the survey. The relative importance of SI_k is then defined by normalization as

$$\overline{w}_k = \frac{w_k}{\sum_k w_k} \tag{5.10}$$

That is, we obtain the following weighting vector for K SI indicators used in SI evaluation:

$$[\overline{w}_1, \overline{w}_2, \ldots, \overline{w}_K] \tag{5.11}$$

Note that the weighting vector (5.11) reflecting relative importance of SI indicators is incorporated into the model of SI evaluation for banks participating in the comparison.

As a result, the expected importance of the 15 SI indicators is shown in the first row of Table 5.7. The relative importance of the 15 SI indicators can then be determined as shown in the second row of Table 5.7. Relying on the opinions of 133 banking customers in Vietnam, it was explored that the most important factor affecting customers' selection for new banking services is new technological system innovation, the next is new service process innovation, and after that new service concept innovation.

Table 5.7: Expected importance and relative importance of SI indicators

Indicators	SI1	SI2	SI3	SI4	SI5	SI6	SI7	SI8	SI9	SI10	SI11	SI12	SI13	SI14	SI15
w_k	358	340	390	414	407	466	450	411	398	477	457	463	448	458	496
$\overline{w}_k$	0.056	0.053	0.061	0.064	0.063	0.072	0.070	0.064	0.062	0.074	0.071	0.072	0.070	0.071	0.077

Stage 5. Computing the overall performance of banks

Having obtained the customer-oriented evaluation profile (5.7) for a bank b and the weights associated with SI indicators as defined by Eq. (5.11), we are now ready to aggregate the mass functions representing SI indicators' evaluations taking their weights into account to derive an overall performance of SI for bank b using the ER approach in terms of the D-S theory of evidence. In particular, we will apply the so-called weighted probability operation and Dempster's rule of combination to derive the aggregated SI evaluation as follows.

First, by considering m_k^b as the belief quantified from the source of evidence SI_k and interpretation of weight $\overline{w}_k$ as the "degree of contribution" of SI_k in evaluating SI of bank b, the weighted probability operation is applied to m_k^b with the weight $\overline{w}_k$ to obtain a new mass function, denoted by $\overline{w}_k \otimes m_k^b : 2^{\mathcal{L}_{SI}} \to [0, 1]$, that is defined by

$$\overline{w}_k \otimes m_{l,k}^b = \overline{w}_k m_{l,k}^b, \quad \text{for } l \in \mathcal{L}_{SI} \tag{5.12}$$

$$\overline{w}_k \otimes m^b_{\mathcal{L}_{SI},k} = 1 - \sum_{l \in \mathcal{L}_{SI}} \overline{w}_k \otimes m^b_{l,k} \tag{5.13}$$

Then, Dempster's rule of combination is applied to combine all new mass functions $\overline{w}_k \otimes m^b_k$, for $k = 1, \ldots, K$, to obtain an aggregated mass function, denoted by m^b, that is formally defined as

$$m^b = \bigoplus_{k=1}^{K} \overline{w}_k \otimes m^b_k \tag{5.14}$$

where $\oplus$ is Dempster's rule of combination.

The resulting mass function m^b is considered as the aggregated evaluation for the SI performance of bank b.

A MATLAB program was coded to automatically compute the weighted probability and combination operations, the overall evaluations regarding the SI of the three banks were then obtained. The assessments for SI1, SI2, SI3, SI4, SI5, SI6, SI7, SI8, SI9, SI10, SI11, SI12, SI13, SI14, and SI15 at the three banks were first weighted with their corresponding relative weights of 0.056, 0.053, 0.061, 0.064, 0.063, 0.072, 0.070, 0.064, 0.062, 0.074, 0.071, 0.072, 0.070, 0.071, and 0.077, respectively. For instance, Table 5.8 shows the weighted masses for the 15 SI indicators of Bank b_1 applying their corresponding weights. The weighted assessments of the 15 SI indicators of the three banks were next combined using Dempster's rule of combination to get the aggregated assessments on the SI of the three banks (see Table 5.9).

Table 5.8: Weighted evaluations for SI indicators of Bank b_1

Indicators	Weighted mass
SI1	(D,0.006),(N,0.02),(S,0.02),($\mathcal{L}_{SI}$,0.954)
SI2	(D,0.007),(N,0.019),(S,0.015),(VS,0.002),($\mathcal{L}_{SI}$,0.956)
SI3	(D,0.001),(N,0.022),(S,0.027), ($\mathcal{L}_{SI}$,0.95)
SI4	(N,0.026),(S,0.024),(VS,0.003),($\mathcal{L}_{SI}$,0.947)
SI5	(D,0.001),(N,0.032),(S,0.018),(VS,0.001),($\mathcal{L}_{SI}$,0.948)
SI6	(D,0.005),(N,0.033),(S,0.021),(VS,0.002),($\mathcal{L}_{SI}$,0.94)
SI7	(D,0.003),(N,0.03),(S,0.02),(VS,0.005),($\mathcal{L}_{SI}$,0.942)
SI8	(D,0.01),(N,0.03),(S,0.01),(VS,0.003),($\mathcal{L}_{SI}$,0.947)
SI9	(VD,0.001),(D,0.004),(N,0.028),(S,0.016),(VS,0.001),($\mathcal{L}_{SI}$,0.949)
SI10	(VD,0.001),(D,0.008),(N,0.036),(S,0.017),($\mathcal{L}_{SI}$,0.939)
SI11	(D,0.003),(N,0.025),(S,0.031),($\mathcal{L}_{SI}$,0.941)
SI12	(N,0.033),(S,0.026),($\mathcal{L}_{SI}$,0.94)
SI13	(VD,0.001),(D,0.001),(N,0.04),(S,0.013),(VS,0.002),($\mathcal{L}_{SI}$,0.942)
SI14	(D,0.003),(N,0.03),(S,0.026),($\mathcal{L}_{SI}$,0.941)
SI15	(D,0.005),(N,0.025),(S,0.032),(VS,0.002),($\mathcal{L}_{SI}$,0.936)

Table 5.9: Aggregated evaluations on SI for three banks in Vietnam

Bank	Overall performance on SI
b_1	(VD,0.003),(D,0.042),(N,0.384),(S,0.268),(VS,0.015),($\mathcal{L}_{SI}$,0.288)
b_2	(VD,0.003),(D,0.049),(N,0.327),(S,0.285),(VS,0.039),($\mathcal{L}_{SI}$,0.297)
b_3	(VD,0.005),(D,0.036),(N,0.284),(S,0.283),(VS,0.091),($\mathcal{L}_{SI}$,0.301)

Stage 6. Making a ranking among banks:

Finally, to establish a ranking among banks in terms of their SI performance, we first employ the pignistic transformation [124] for m^b to obtain approximate distribution for the overall SI evaluation of each bank. Namely, the pignistic transformation of m^b results in the following distribution p^b : $\mathcal{L}_{SI} \to [0, 1]$ such that

$$p^b_l = m^b_l + \frac{m^b_{\mathcal{L}_{SI}}}{|\mathcal{L}_{SI}|}, \quad \text{for } l \in \mathcal{L}_{SI} \tag{5.15}$$

in this study, $|\mathcal{L}_{SI}| = 5$.

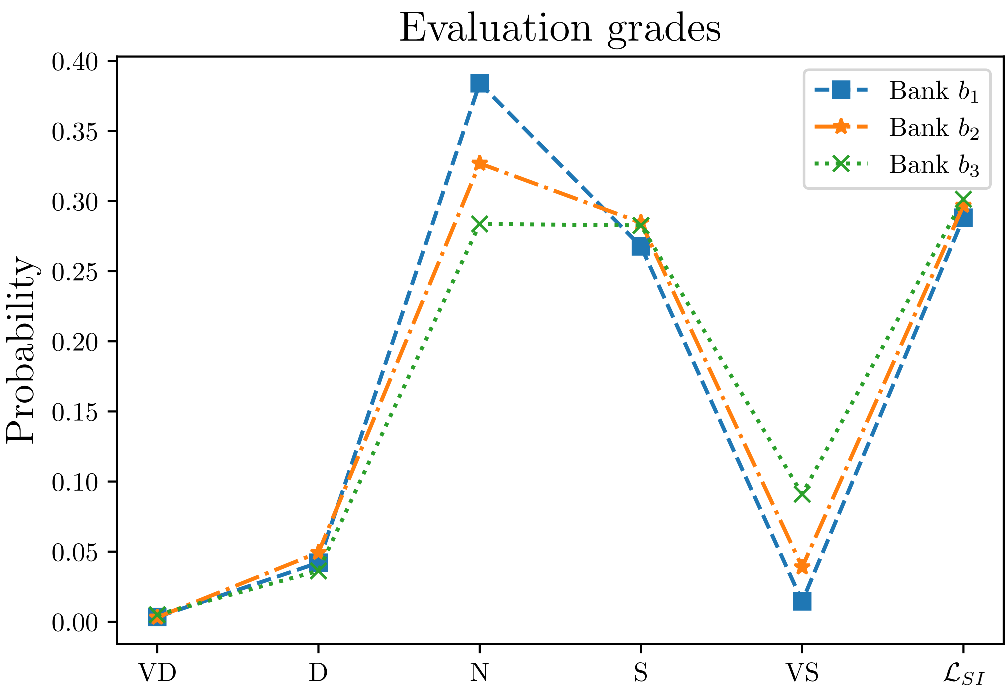
Then, the expected performance of bank b on SI is determined by

$$u^b_{SI} = \sum_{l \in \mathcal{L}_{SI}} p^b_l \times u(l) \tag{5.16}$$

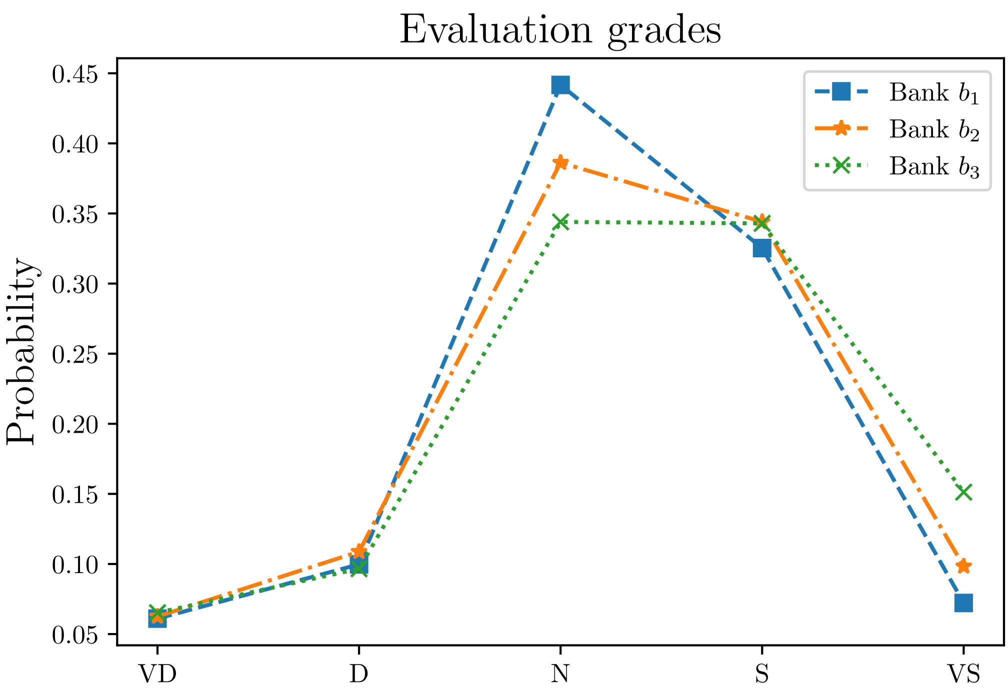
for ranking, where $u : \mathcal{L}_{SI} \to [0, 1]$ is a utility function as used in [33, 36–38]:

$$\begin{aligned}
&u(VD) = 0,\\
&u(D) = 0.35,\\
&u(N) = 0.55,\\
&u(S) = 0.85,\\
&u(VS) = 1
\end{aligned}$$

Fig. 5.4 displays the distributions of the aggregated evaluations on the SI overall performance of the three banks and their approximations via pignistic transformation. The expected overall performances of Bank b_1, Bank b_2, and Bank b_3 on SI were finally specified to be 0.627, 0.641, and 0.666, respectively. As a final result, Bank b_3 has the highest SI performance among the three banks, Bank b_2 is ranked second, and Bank b_3 stands last.



(a)



(b)

Figure 5.4: Overall SI evaluations for three banks in Vietnam: (a) Aggregated evaluations (b) Approximate evaluations via pignistic transformation

5.2.4 Discussion of SI ranking results

In terms of SI levels, Bank b_3 was ranked as the best, Bank b_2 is in the second position, and Bank b_1 is the worst. However, as shown in Chapter 4, the ranking results with regard to IC levels of the three banks reveals that Bank b_2 is the most innovative bank, Bank b_3 is the next, and Bank b_1 is the least innovative bank. This inconsistency in the ranking in terms of IC and SI may be due to the following reasons: *First*, the two studies on IC and SI were based on two different points of view: the IC evaluation relies on experts' judgments while the SI evaluation depends on customers' assessments. *Second*, the two studies were conducted at different time. *Second*, the two studies used different measurement indicators. *Fourth*, the implementation speed of innovation of the banks are different. *Last*, even a bank has high IC level, but the success of SI depends on the context where the innovations take place.

Chapter 6

Discussions and Conclusions

6.1 Summary

Assessing IC in banking allows bank managers to review their innovation management processes, identify how well or poorly their banks are doing with IC, plus highlight their banks' strengths and weaknesses in their innovation management as well as important areas to be focused for improvement of their IC. Such insights can assist bank managers to devise novel approaches to benefit their banks' ICs. Our study offers an integrated approach founded on the combination of several methods to respond to the IC evaluation challenge in the banking industry. Specifically, the Pareto analysis was implemented first to detect the pertinent VIMPs that can be applied in banking including idea management, cooperative learning, marketing management, strategic management, technology management, resource management, organization management, process improvement, R&D, portfolio management, and knowledge management from previous studies. The AHP was next used to determine the importance weights of VIMPs and their sub-VIMPs. The results show that strategic management, resource management, and technology management are the most crucial practices for banking innovation. Strategies act as frameworks for all activities of a bank, which results in a comprehensive and timely approach for creating innovation developments throughout the bank. Hence, as per Geschka [125], the innovation management process should commence with devising an innovation strategy for planning strategic orientations, overarching objectives, and targeted guidance for the growth and advancement of an organization. Further, strategic leadership is vital in enabling the discovery and utilisation of new products or processes [126]. Additionally, resource management is needed to assign the required resources such as employees, capital, and organizational infrastructure to apply innovation practices. Resource management was found to be the secondary vital element in Wang and Chang's innovation value diagnosis system model while process innovation is the first vital element [75]. Their study was conducted regarding the high-tech sector, which may have specific interests in approaches for enhancing the process by which to produce and deliver new or upgraded products with less production spending, shorter delivery time, and enhanced standards and proficiency. Matroushi et al. [162], in alignment with our findings also discovered that by implementing an AHP method, that the chief aspects that encourage innovation in organizations are innovation policy, followed by opportunity recognition and finance. Next, the data of the maturity degrees of sub-VIMPs at the evaluated banks was collected using a questionnaire and done by experts in banking-related fields. Last, the weighted sum method was applied to combine the data formulated in the numeric form and the ER method was implemented to combine the data formulated in the linguistic form. Particularly, we found the ER approach established by Yang and Singh [35] to be a useful way to manage scenarios in which the judgments of a group of experts are subjective and conflicting. It offers a valuable aggregation means to direct the aggregated evaluations on the IC of banks within an uncertain or imprecise environment.

Additionally, we implemented the proposed methodology for IC evaluation to test the IC of three banks in Vietnam (Bank b_1, Bank b_2, Bank b_3) plus to find useful lessons for management regarding innovation in banking. The use of both numeric and linguistic forms, that is, adopting two methods of processing the gathered data, allowed us to determine that the end results arrived at the same conclusion regarding the three banks' ranking. Therefore, both found that Bank b_2 is the most innovative bank, Bank b_3 is the second most, and Bank b_1 is the least. With small alternations, our suggested methodology can be used for a variety of appraisals of other sectors' IC.

6.2 Implications for theory

This study offers many contributions to progress theories of IC. *First*, it undertakes a detailed appraisal of the extensive body of relevant literature on the topics of innovation and IC management to highlight the most typical IMPs and their related measurement indicators, which offers a wide-ranging theoretical foundation that is helpful for researchers in the innovation research field. *Second*, this research provides insights into the innovation management issue in the banking sector, a field in which there is presently scant comprehensive research on IC, by illuminating the importance roles of IMPs in banking innovation. *Third*, in terms of methodology, this study brings together several methods to create a novel integrated framework for evaluating IC in banking in an uncertain and vague environment. The key contribution of this research is an ER-based multi-criteria evaluation approach to the IC as applicable to banks in Vietnam. As far as we are aware, this study could be considered as the first study to use the ER combining with the AHP for IC evaluation.

As explained in section 2.4, the literature typically involves a multiple criteria approach for IC evaluation, though different authors adopt different data gathering and aggregation techniques. Rejeb et al. [74] and Boly et al. [15] created an IC measuring framework that takes into account several IMPs evaluated by numerous observable criteria that are scored 1 if existing or 0 if not. This approach is restricted by the fact that it only reveals that an innovation practice exists but does not offer any information regarding the development level with which this practice is accomplished. The averages of the criteria's values are acquired to determine the value for the related IMP. Handling the data in this way, however, cannot account for the uncertainty and inaccuracy in the IC evaluation process. Further, such computations of the value for an IMP do not account for the various importance weights within the criteria. Lastly, a value test is used to determine the typical weight vectors of the IMPs for four innovative classes. These are then applied to calculate the IC indices of companies. We observe that the calculation of the value test must have minimum one company in a class. As a result, this method cannot be applied to a small research sample. Wang et al. [13] created a combined method of the non-additive measure and the Choquet integral to assess technological IC in terms of five aspects comprising several criteria. Qualitative criteria are assessed using linguistic variables signified by triangular fuzzy numbers. The final rating of each criterion judged by several experts is found using the fuzzy averaging technique and a defuzzification method. Non-additive Choquet integral is then implemented to find the overall aggregated IC performance of firms. While their method based on non-additive Choquet integral does not necessitate the assumption of mutual independence among criteria, it is a major obstacle to detect the non-additive measure while considering dependency between criteria. Additionally, the computational intricacy of this undertaking is exponential in terms of the number of criteria, creating challenges for practical application. Using a range of linguistic models with various fuzzy numbers also means the evaluators must possess the professional competency to differentiate between qualitative terms. In addition, we notice that in the case of additive weights, Choquet integral becomes the weighted sum that is used in Eq. (3.5) for calculating a bank' ICI in terms of data formulation 1. Cheng and Lin [14] assessed the performance of technological IC in an attempt to identify the optimal alternative using various fuzzy criteria based on a combined method of fuzzy set and a MCDM technique—TOPSIS. TOPIS does encounter numerous challenges, however, including different normalization and distance measurement techniques applied finding different outcomes [163]. Compared to prior studies, this one presents a new integrated method to assess IC in banking in an uncertain environment by bringing together the AHP and the ER approach in terms of the D–S theory of evidence. Data of IMPs can be easily gathered from various evaluators using the five-point linguistic scale (from *very poor* to *very good*), which assists to overview the development degree of IMPs in the evaluated banks from a range of points of view. In data formulation, data signified by means of mass functions in the D-S theory of evidence can effectively reveal the nature of uncertainty in the evaluation process of qualitative criteria. This creates additional understanding regarding the evaluation criteria than expressing the data in crisp or fuzzy numbers. By adopting the AHP to levels of criteria and sub-criteria, we take into account both the different importance weights of sub-criteria regarding criteria and the various importance weights of criteria regarding the goal. Additionally, our suggested approach can be used for all sample sizes.

6.3 Implications for practice

Innovation is a main priority in all industries, so banks must constantly innovate their services by enhancing their IC on an ongoing basis. There are many significant managerial consequences that can be gathered from our research for use in innovation management in banking.

First, IC evaluation in banking have to take into account numerous dimensions at the same time. IC is not linked to one element alone, such as novel technologies, new strategies, or new ideas, but instead should be perceived as a blend of several innovation activities. Our suggested framework can offer bank managers a way to create a comprehensive overview of VIMPs in their banks, methodically appraise and assess these practices, and as a result, enhance innovation strategies to elevate their IC levels to maintain their competitive position.

Second, it is recommended that banks should target to pay more attention to and invest more into the most important VIMPs for banking innovation including managing innovation strategies, resources, and technologies in order to upgrade their ICs more efficiently. It is apparent that, of the three banks, the most innovative bank (Bank b_2) has the greatest strategic management practices, with a score being 4.490 (see Table 4.7). Bank b_2 also has the most advanced technology management practices, with a score being 4.212. While the resource management practices of Bank b_2 (4.204) are somewhat weaker than Bank b_3's (4.208), they are better than those of Bank b_1 (3.642). This analysis shows that the more innovative banks target the development of the more important VIMPs, which leads to higher IC levels.

Third, by taking into account the mass functions signifying the experts' assessments of each bank's sub-VIMPs (see Table 4.6), managers can point to which sub-VIMPs receive assessments that the experts disagree on. Experts' different backgrounds and experiences will create varying views and perspectives, meaning their thoughts about the same sub-VIMPs at a bank may not match those of others'. When such sub-VIMPs are highlighted, the banks should re-assess their innovation management process to enhance those innovation practices. For instance, the evaluations for RES4 of Bank b_1 and IDE4 of Bank b_3 revealed apparent discrepancies among the five experts, as displayed in Fig. 6.1. As such, Bank b_1 and Bank b_3 may work with the experts who judged P for these sub-VIMPs to find out which points caused problems so as to refine these innovation practices at their banks and obtain more universal credit from all of the experts.

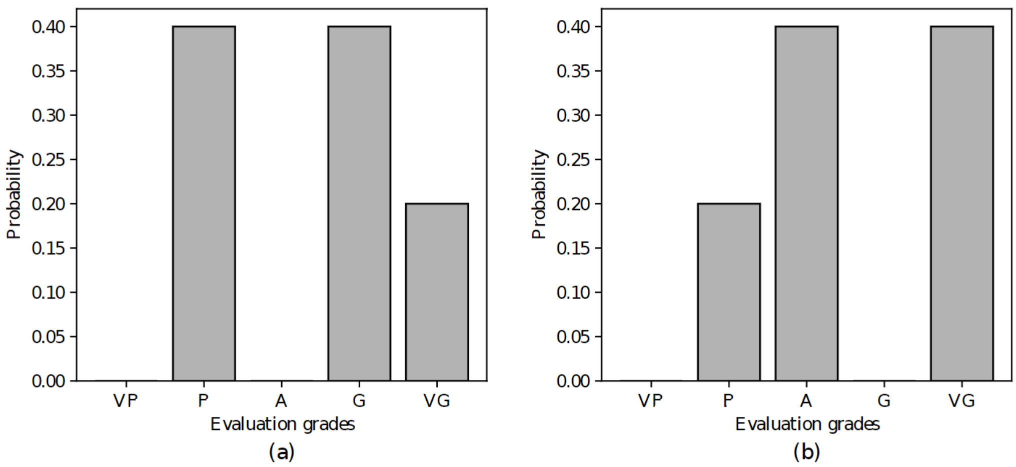


Figure 6.1: Differences among expert evaluations: (a) Evaluations for RES4 at Bank b_1 (b) Evaluations for IDE4 at Bank b_3

Last, the outcome for the IC evaluation may alter over time. The maturity levels of VIMPs in conjunction with their importance for IC enhancement in banking will respond to adjustments in the dynamic business market and as such may be anticipated to shift constantly. By comparing the banks' current IC status against themselves in the past and against other banks, they can see how they have improved and can learn from mistakes and successes from their own and rivals. Additionally, focus should be given to novel IMPs to monitor emerging trends. Hence, banks should undertake IC evaluations regularly and change their innovation management strategies based on any shifts so their IC status remains relevant.

Overall, for banking innovation management, bank managers should consider numerous IMPs simultaneously to gain a complete perspective on their innovation management process. The managers also need to regularly assess the development levels of these IMPs, check the importance of these IMPs in terms of the shifting business context, and then alter innovation tactics toward focusing more resources on the most crucial IMPs to enhance their IC. Additionally, they should consider to update new IMPs so that their banks can take advantages in the highly competitive innovation race. As IC is by its nature nonconcrete and indeterminate, it is challenging to judge precisely. Each expert may have varying views on a bank's IMP; as such, bank managers must use the recommendations of various experts to enhance their innovation management systems.

6.4 Limitations and suggestions for future research

Of course, this research faced several limitations as follows:

First, because we only used the IMPs found in prior studies, new or unique IMPs may have emerged in the banking sector that are not referred to in this research. In future studies, more detailed interviews with experts in banking innovation fields would allow greater exploration of up-to-date IMPs that better fit with the context of banking innovation.

Second, the use of the AHP presumes that the weights of IMPs and sub-IMPs are crisp and additive, yet in real-world scenarios weight information can also be unpredictable, as shown by probability distributions [164]. As such, future research is needed to enhance the suggested approach so that it can work with uncertain and imprecise weight information.

Third, given the qualitative nature of sub-IMPs and subjectivity in experts' evaluations, experts may sometime face challenges in communicating their judgments precisely by selecting one option among multiple grades when replying to a question in the questionnaire adopted for data collection. For this reason, new methods able to suitably capture uncertainty and ambiguity in such subjective judgments are required when experts select several linguistic terms to communicate their judgments of qualitative sub-IMPs.

Last, complex decision making founded only on experts' judgments may be inadequate. The authors in [165, 166] suggested that, in organizational decision making, we should depend on quantitative evidence and apply instinctive judgments as a way to incorporate other elements to replace, add to, translate, and recontextualize the existing data. As such, future research should take into account not solely experts' perception but also quantitative evidence, situational analysis, and other data sources including those available through forums and professional platforms to arrive at a final decision regarding the banks' ranking and thus limit lack of consensus about the ranks.

Publications

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