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Critical Success Factors for Knowledge Management Implementation in Indonesian Banking: An Exploratory and Confirmatory Factor Analysis

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Abstract. This study investigates the critical success factors (CSFs) for Knowledge Management (KM) implementation in the banking sector to address a gap in understanding for sector-specific KM implementation. Using a quantitative approach, data were collected through surveys from 163 employees across 9 Indonesian banking organizations. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were employed to identify and validate CSFs. Results reveal four key factor groups: Human Resources, Strategic Management, Management Support, and Business Process Strategy. Human Resources and Management Support were found to be the most established factors in the sector, with IT Infrastructure being the most critical component. These findings contribute to the literature by providing a banking-specific CSF model for KM implementation and offer practical implications for banking organizations in prioritizing their KM initiatives.

Keywords: Confirmatory Factor Analysis (CFA), Critical Success Factor (CSF), Exploratory Factor Analysis (EFA), Indonesian Banking, Knowledge Management

1. Introduction

Implementation of knowledge management in the banking sector is important to increase operational efficiency, business innovation, and organizational performance. It is essential to ensure that KM practices can be implemented successfully and provide significant added value to the organization. By knowing the level of importance of factors that, it will help in identifying areas that require improvement or more attention, so that banks can take proactive action to address potential problems before they become significant obstacles (Al-Tit et al., 2019). Previous research about KM implementation in Indonesian banking company indicates that the companies still face several challenges, mainly due to cultural resistance and sharing knowledge between employees(Saide et al., 2019a).

Comparing to research on banking companies from different countries, challenges in KM implementation could come from lack of understanding of CSF importance in the banking sector, which emerge from organizational culture that reluctance to change(Chang et al., 2020), (Ozpamuk et al., 2023), barriers in communication (Alves et al., 2022), and constraints in technological aspects (Lam et al., 2021),(Sumbal et al., 2023). These challenges can be resolve by knowing success factors of knowledge management implementation in the organization, which can help organizations to focus on optimizing these factors to improve their business processes and organizational performance (Ghasemi & Valmohammadi, 2023). Therefore, the purpose of the study is to identify critical success factors (CSF) of knowledge management implementation specifically in Indonesian banking sector and its level of importance for successful knowledge management implementation.

Factors that contribute to the reluctance to change in organizational culture could involve lack of trust between employees (Ozpamuk et al., 2023) and fear of losing knowledge to other. This also comes from lack of recognition and rewards from the management, so the employees are not enough motivated to do knowledge sharing and the benefit from doing it (Miao et al., 2023). Following that, constraints in technological aspect could come from organizations which have change-resistant culture and struggle to integrate new technologies due to a fear of new technologies and a comfort level with existing technology (Sumbal et al., 2023). This could be due to a lack of understanding about the benefits of new technology and a belief that it is difficult to integrate with existing technologies. Furthermore, the complexity of technology utilized in the banking sector, as well as security concerns become barriers that might hinder the adoption of knowledge management systems, which are often easy to access and require extensive data sharing.

Identification of critical success factors for specific business sector and establishing the level of importance of each factor is required, as it can help organizations to focus on optimizing these factors to improve their business processes and organizational performance (Ghasemi & Valmohammadi, 2023). Previous research that identifies critical success factors of knowledge management implementation in different business sector (Singla & Samanta, 2022) used exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). This study (Singla & Samanta, 2022a) employs exploratory factor analysis to determine the number of factor structures without imposing a predetermined structure on the outcome and explain the observed variance in the data. Confirmatory factor analysis is used to measure data fitness to a hypothesized measurement model and validate the factors' structure established through EFA (Migdadi, 2022). Another study (Alrahbi et al., 2022) also uses factor analysis to identify critical factors and their level of importance, providing insight into factors with strong influence and weak influence, which can help organizations identify opportunities and areas for improvement.

This study uses theoretical framework from previous study about knowledge management in business sectors to determine the critical success factors of KM implementation and its factor groups. The study employs exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to identify the critical factors of knowledge management implementation in the banking sector and its level of importance. Based on the introduction of the importance of critical success factors of knowledge management implementation, the researcher identified the following research questions to be addressed:

1. How does factor analysis help to identify the critical success factors (CSF) in KM implementation in the banking sector?
2. What are the critical success factors of KM implementation in the banking sector?
3. What is the significance of critical success factors for KM implementation by their level of importance?

2. Literature Review

2.1. Knowledge Management

Knowledge management (KM) is one of the strategic pillars of companies that generate value for their shareholders since knowledge is a strategic asset for businesses. Thus, KM implementation is a crucial cornerstone for obtaining external information, accessing internal knowledge, improving efficiency, flexibility, and agility, cutting operational costs, shortening time to market, and improving business activity transparency. To improve organizational performance and create value, knowledge management (KM) necessitates a unique, systematic, and organized procedure for gathering, organizing, storing, sharing, applying, and producing explicit and tacit knowledge in employees. (Onofre & Teixeira, 2022) It concerns the reality that the creation of new information is contingent upon the utilization of implicit or tacit knowledge, which is frequently highly subjective knowledge held by a single person inside the business. (Roblek & Meško, 2020) In general, knowledge management (KM) is a process that aids businesses in finding, evaluating, organizing, and disseminating pertinent information. It has been suggested that KM is a crucial area of expertise for tasks like issue-solving, strategy planning, and decision-making. (Onofre & Teixeira, 2022)

2.2. Knowledge Management Readiness

Knowledge management (KM) readiness describes an organization’s ability to effectively incorporate knowledge management practices into their activities. This was because effective knowledge management may lead to improved organizational performance, collaboration between the employees, and better utilization of their intellectual capital. KM readiness also involves having policies to implement KM in the organization, supporting technologies, and organizational culture that promotes knowledge sharing in the organization (Galgotia & Lakshmi, 2022). Organizational readiness to implement KM can be assessed using survey and statistical methods to assess various dimensions of readiness. By knowing organization readiness, organizations can initiate improvement process to their weak areas by developing strategies related to KM activities that are practical for organizations (Sensuse et al., 2023).

2.3. Critical Success Factor

Success factors are significant aspects that most companies consider in achieving organizational goals and improving organizational performance. In the context of knowledge management, these factors can assist organizations in analyzing their ability to promote knowledge management practices internally and externally (Amelia et al., 2022). Management support, organizational culture, information technology, people aspects, organizational structure, and performance assessment are all potential success elements for knowledge management in businesses (Mousavizade & Shakibazad, 2019). Furthermore, critical success factors of knowledge management can be defined as the limited number of areas where satisfactory results ensure the organization's successful performance (Becerra-Fernandez et al., 2015).

Previous study (Stenger et al., 2023) suggest that critical success factors involve all organizational aspects and activities, including political, economic, social aspects, problem-solving, monitoring, and control procedures that may impact the business environment. These could be achieved by having sustainable CSFs that include management support for knowledge management practices (Chaurasia et al., 2020) through understanding changes in the organization environment, the use of best practices from knowledge bases and repositories, references from accessible knowledge resources, supporting IT infrastructure, and evaluation metrics to assess knowledge management practices in the organization.

This highlights the importance of knowledge management and the need for organizations to focus on the success factors of KM implementation. Previous research (Chatterjee et al., 2020) highlighted the importance of critical success factors for knowledge management to increase employee awareness of knowledge sharing, collaboration, learning, communication, and innovation within the organizations. Knowledge sharing may be improved by having effective knowledge-sharing practices and accessible knowledge resources. This will aid the learning process by providing access to resources and effective dissemination of lessons learned from previous projects. As a result, organizations may establish a collaborative culture that will lead to new ideas and innovation, as well as encourage their employees to participate in the knowledge management process.

Following the importance of critical success factors, it is critical to identify critical success factors in knowledge management to evaluate an organization's readiness to implement KM. Previous research (Sensuse et al., 2023) suggests that CSFs constitute important areas that need to be effectively managed and examined by people in organizations to successfully implement KM. Businesses can use these to identify and measure their performance on these key factors, which determine areas that need to be improved and changes that need to be made to meet their organizational performance (Ghasemi & Valmohammadi, 2023). These would also enable organizations to use CSFs to develop assessment measures and track organizational growth.

2.4. Knowledge Management in Banking Sector

Knowledge management practices in banking currently involve knowledge acquisition, knowledge storage, and knowledge sharing in the organizations, resulting in innovative capabilities for main sectors of business in banking such as product process of operation and service delivery (Edeh et al., 2022a). The innovation capability can benefit banking organizations by increasing organizational value through effective decision-making, profitability, and competitive advantage (Sofiyabadi et al., 2022), which could be supported by establishing effective knowledge management practices by the organization employee. Upper management is support also required to encourage employees to implement knowledge management practices and achieve continuous innovation capability in the banking sector (Edeh et al., 2022a). Following that, the influence of top executives in promoting knowledge management systems is critical as a strategic resource for improving organizational performance (Aldhaheri & Ahmad, 2024; Iman et al., 2023). As a result, banking organizations with established knowledge management processes can benefit from leveraging relevant knowledge about customer demand and product satisfaction to predict potential future innovation, through analyzing customer data, such as preferences and background, organizations can develop products and services that are more personalized into their customer’s needs while gaining competitive advantage for the organization (Edeh et al., 2022a).

Barriers and challenges to knowledge management practices in banking organizations include cultural resistance, leadership support, technological challenges, and data security concerns. The challenges in cultural resistance derived from employee perceptions of knowledge management practices that only add to their workload without providing immediate advantages. This leads to employee resistance to sharing information because of concerns regarding losing knowledge to others (Zhang et al., 2023). Resistant culture in the organization can result in a lack of leadership support because the upper management does not prioritize knowledge management practices or foster a supportive culture within the organization (Metwally et al., 2019). However, technological challenges in the banking sector are related to the data security concerns in organizations because they handle a vast amount of customer’s sensitive information, such as personal identifiers, financial records, and transactions history (Doğuç, 2022), (Hasan et al., 2023). These factors impact more selective adoption of successful knowledge management practices that align with data security concerns. To address this issue, (Doğuç, 2022) suggests only exchanging broad knowledge among employees and limiting the sharing of confidential information to certain departments. Regarding challenges to implementing knowledge management in the banking industry, the banking sector needs to develop effective and sustainable strategies to implement knowledge management to gain benefit and increase organizational performance.

3. Research Method

3.1. Theoretical Framework

Identifying the critical success factors (CSF) of KM implementation is crucial for assessing an organization's readiness to implement successful KM. Previous research (Sensuse et al., 2023) used CSF to assess organization readiness to implement knowledge management**.** This consists of four components: management and strategy, organizational aspect, culture, and technology. Management and strategy are made up of three parts, support and leadership, strategic management and objectives, and performance measurement. Organizational aspects include structure, procedures, activities, education, and employee training. Following that, culture includes organizational culture, motivation, communication, and work groups. Finally, technology includes IT infrastructure, integrations, and security. The KMSCF framework can be used to improve project management performance through knowledge sharing, collaboration, communication, and innovation. KMCSF may also help prioritize information management by identifying critical areas that are aligned with business objectives.

Previous research (Oliva et al., 2022) that identified various factors which influence successfulness of new businesses comprise of previous experience, solid networking that facilitates development and growth, entrepreneurial experience of the founding team, government support, and business partners. Partnerships and strategic alliances with other companies are examples of a strong network that promotes development and progress. Besides, networking can also boost productivity by connecting cross-functional teams, which will improve cooperation and communication inside the firm. Collaboration allows organizations to gain consistent knowledge exchange, which enhances the company's competitive advantage, key areas for growth, and increases profit (Keller & Lima, 2021).

Another research in businesses, specifically in financial sector (Saleh Aldehayyat & Ali Almohtaseb, 2021), identifies critical success factor such as human resource management (HRM), information technology (IT) infrastructure, organization leadership, and organization structure. Human Resources management involves practices that have a direct impact on employees, such as promoting and supporting employee's skills and knowledge, staff training and development, and performance satisfaction. Organizations should be aware of their employee satisfaction and well-being to minimize challenges in KM implementation, improve KM practices, and achieve business objectives (Mat Nor et al., 2020). IT infrastructure in organizations includes tools that are essential to business operations, such as databases, decision support systems, and communication platforms. Infrastructure is used to facilitate organizational changes, improve work experience, and improve employees' interpersonal skills of. It may provide employees with opportunities for cooperation between the youngest and oldest employees, as well as inter-age collaboration. It also helps with human resources management by enhancing employee performance and job satisfaction (Nyathi & Kekwaletswe, 2024).

Organizational leadership in this context encompasses people management within the organization, such as managing employee involvement and employee development, which leads to continual improvement. This involves the efforts of employees to attain business goals to meet customer expectations and improve company performance(Lepistö et al., 2024). Organizational leadership also covers employee's expertise, decision making, communication skills, and managerial style that positively associated with managing people through collaboration in the business process (Musonda &

Okoro, 2022). This results in influencing organizational structure that focused on knowledge management (Mat Nor et al., 2020). Aside from organizational structure, developing a culture that is aware of knowledge management in company is effective to promote knowledge sharing and foster collaboration throughout the organization. This will encourage employee to practices the knowledge management process on their business process, such as discovering new knowledge, capturing knowledge, sharing knowledge between employees and across team, and applied the knowledge in the business processes. Thus, organizations should also be aware of the importance of human factors, such as employee satisfaction and well-being to minimize the challenges in KM implementation.

Technology plays an important role in the success of KM implementation through having technology that is compatible with existing technologies and can facilitate the business needs. Technology compatibility entails adoption of technology that can be integrated with existing technology, as well as previous experiences and future requirements for new technology. Technology complexity is divided into 2 categories, internal and external factors. Internal factors are components of the technology that are required for it to function, whilst external factors are the complexity of value derived from its use. Following this, technology emphasized the importance of IT infrastructure in the context of new technology adoption, which will aid the success of KM implementation. Aside from evaluating business demands and customer's requirements, technology adoption should also provide more efficient, effective, and timely services (Zamani, 2022). Suitably, technology adoption in the business sector closely linked to the implementation of leadership and management support (Zamani, 2022), (Nyathi & Kekwaletswe, 2024), fostering collaboration and long-term relationship (Ferrer-Estévez & Chalmeta, 2023) (Soja & Soja, 2020), and improving innovation process within the organization (Ciasullo et al., 2022).

3.2. Selection of Critical Success Factors

Based on theoretical framework for the critical success factors of KM implementation in business sector, researchers selected several CSF that divided into four categories: strategic management, leadership management, human resources management, organizational attributes, and technology. Table 1 depicted the identified CSF from theoretical frameworks.

Table 1: Critical Success Factor (CSF) of KM Implementation in Business

Factors	Variables	Code	References
Strategic Management	Effective decision making	SM1	Effective business case processes (Appel-Meulenbroek & Danivska, 2023), Business process re-engineering (Musonda & Okoro, 2022), Decision-making using process mining (Novak et al., 2023), strategic management process (Sinnaiah et al., 2023)
	Strategic thinking	SM2	Effective business case processes (Appel-Meulenbroek & Danivska, 2023), Digital information product development (Keller & Lima, 2021), strategic management process (Sinnaiah et al., 2023), (Miao et al., 2023)
	Learning process	SM3	Role of big data analytics in capability and innovation (Ciasullo et al., 2022), Digital information product development (Keller & Lima, 2021), SMEs empowering of Indonesia Government (Panjaitan et al., 2021), Human Resourcesss management for organization success (Nyathi & Kekwaletswe, 2024)
	Understanding of business process	SM4	Role of big data analytics in capability and innovation (Ciasullo et al., 2022), Effective business case processes (Appel-Meulenbroek & Danivska, 2023), Importance of routines (Knol et

			al., 2019), Sustainable relationship (Ferrer-Estévez & Chalmeta, 2023), (Miao et al., 2023)
	Strong networking	SM5	Digital information product development (Keller & Lima, 2021), Sustainable relationship (Ferrer-Estévez & Chalmeta, 2023), Knowledge sharing (Saide et al., 2019b)
Leadership Management	Collaboration and coordination	LM1	Importance of routines (Knol et al., 2019), Lesson learns (Mat Nor et al., 2020), SMEs empowering of Indonesia Government (Panjaitan et al., 2021), Fostering ICT use (Soja & Soja, 2020), Business process re-engineering (Musonda & Okoro, 2022)
	Upper management support	LM2	SMEs adoption of technology (Zamani, 2022), Importance of routines (Knol et al., 2019), Role of employee participation and managers on improvement and performance (Galeazzo et al., 2021)
Human Resources Management	Employee development	HRM1	Human Resources management for organization success (Nyathi & Kekwaletswe, 2024), Role of big data analytics in capability and innovation (Ciasullo et al., 2022),
	Employee involvement	HRM2	Role of employee participation and managers on improvement and performance (Galeazzo et al., 2021), Importance of routines (Knol et al., 2019), SMEs empowering of Indonesia Government (Panjaitan et al., 2021)
	Employee satisfaction	HRM3	Human Resources management for organization success (Nyathi & Kekwaletswe, 2024), Total quality management and leadership (Lepistö et al., 2024), Lesson learn (Mat Nor et al., 2020),
	Performance measurement	HRM4	Role of employee participation and managers on improvement and performance (Galeazzo et al., 2021), SMEs adoption of technology (Zamani, 2022), Human Resources management for organization success (Nyathi & Kekwaletswe, 2024)
Organizational Attributes	Organizational culture	OA1	Lesson learns (Mat Nor et al., 2020), Role of big data analytics in capability and innovation (Ciasullo et al., 2022), Business process re-engineering (Musonda & Okoro, 2022)
	Organizational structure	OA2	KMCSF Framework (Sensuse et al., 2023), Lesson learned(Mat Nor et al., 2020), Organizational performance (Migdadi, 2022)
	Organization environment	OA3	Sustainable relationship (Ferrer-Estévez & Chalmeta, 2023), Environment changes in the organization (Edeh et al., 2022b; Lubis et al., 2022)
Technology	IT Infrastructure	TH1	Fostering ICT use (Soja & Soja, 2020), Human Resources management for organization success (Nyathi & Kekwaletswe, 2024), Sustainable relationship (Ferrer-Estévez & Chalmeta, 2023)
	Technology Complexity and Compatibility	TH2	SMEs adoption of technology (Zamani, 2022), (Iman et al., 2023), (Miao et al., 2023), High technology in industries (Yang et al., 2021), ICT and KM processes (Jarmooka et al., 2021)

Table 1 shows that the success factors for KM implementation in the banking sector could be influenced by several aspects of the organization, including Strategic Management, Leadership Management, Human Resources Management, Organizational Attributes, and Technology. The established CSF includes three management-focused factor groups, each of which focuses on a particular management component and is related to the others. Strategic Management focuses on strategic processes to ensure the successful adoption of knowledge management strategies for business operations. Leadership management emphasizes strong leadership and support from top management to promote KM activities, vision, and resources while aligning KM practices with the business objectives.

Likewise, Human Resources Management focuses on continuous employee development to improve employee abilities to apply KM processes in the organization. Aside from the management aspects, Organizational Attributes are one of the CSF factor groups that help the smooth operation of KM processes in the organization, such as organizational culture, environment, and structure. In contrast, technological aspects take part to support the successful implementation of KM in organizations which involves the availability of IT infrastructure, technology that is compatible with the existing system, and complexity of technology that matches the existing system. Based on these established factor structures, researchers then develop a list of questions for a questionnaire survey to be distributed to targeted participants in the banking organizations. Researchers will explain questionnaire development in the Data Analysis section.

3.3. Data Analysis

The study employs exploratory factor analysis to investigate factor groups from determined critical success factors from Table 1 to assess questionnaire data received from banking workers. Although EFA is typically used to find underlying links between measured variables without a preconceived structure, as in a previous study (Singla & Samanta, 2022a), this study attempted to utilize EFA to compare factor groups from the predetermined component structure in Table 1 to factor structures derived from EFA results. This is because the specified critical success elements are for KM implementation in businesses; thus, comparing the two results will reveal whether the critical success factors for businesses in general and the banking industry are the same. Afterward, researchers employed CFA to validate the identified factor structure from EFA by testing their consistency and fit to ensure the CSFs are reliable for KM implementation in the banking sector (Badenes-Ribera et al., 2020).

However, utilizing EFA and CFA results in method bias due to sample size and sampling participants, consequently the researcher should pay attention to sample size and evenly distribute participant types to represent the total population. Researchers used ten times rules to determine the sample size for this study to resolve the method bias, where the sample size is ten times from the determined variables (Hair et al., 2010) and classified participants from banking organizations into four employment levels: trainees, junior, middle, mid-to-senior, and senior. Following that, researchers develop questionnaire items based on the established factor groups in Table 1 that will be distributed to bank employees. Each variable has one to three questions to ensure that the questions accurately describe the variables' context. Researchers employ various prior studies that use questionnaires to identify crucial success elements in KM implementation (Mousavizade & Shakibazad, 2019; Saini et al., 2018; Singla & Samanta, 2022b) and gain insight into the model of the questions. There are a total of 47 questions, including 7 questions for demographic information, 7 questions about Strategic Management, 4 questions about Leadership Management, 11 questions about Human Resources Management, 9 questions about Organizational Attributes, and 9 questions about Technology.

Following the development of the questionnaire, researchers conducted a readability assessment with ten experts to ensure that the question can be easily understood and reduced the chance of misinterpretation by the targeted participants. By simplifying the wording used in the questions, the evaluation also aims to eliminate respondents' bias from misinterpreting the context of the questions (Stenger et al., 2023). The readability assessment yielded in a total of 53 questions, with modifications in demographic information changing from 7 to 10 questions, Human Resources Management changing from 11 to 13 questions, and Organizational Attributes changing from 9 to 10 questions. Changes made following the evaluation included simplifying the terms so that they could be easily understood by the participants, reorganizing the phrases, and adding questions for some variables to clearly represent the variable.

Data was obtained from Indonesian banking companies between April and May 2024, with 163 participants representing 9 banking companies. Participants comprise banking workers at the trainee, junior, middle, mid-to-senior, and senior levels to ensure that the organization's employees are well represented. Table 1 shows that trainees have less than one year of experience in the company, junior employees have 1-3 years of experience, mid-to-senior employees have 3-4 years of experience, and senior employees have more than 5 years of experience in the company. The various levels of employment can represent the population of banking employees and assist researchers in understanding how the knowledge management process is currently being applied in the banking sector. However, despite multiple employment levels, the number of participants is limited to only 163 due to the study's short duration, which could be attributed to sample size restrictions. Therefore, future research might prolong the duration of data collection and recruit an equal number of participants for each multiple employment level.

Table 2: Respondents Demographics Information

Category		Total	Percentage
Gender	Female	102	63.03%
	Male	61	36.97%
Age	17-25 years	61	37.42%
	26-35 years	77	47.24%
	36-45 years	25	15.34%
Years in the business	Less than 1 years	20	12.27%
	1-3 years	88	53.99%
	4-5 years	41	25.15%
	More than 5 years	14	8.59%
Years in the current position	Less than 1 years	17	10.43%
	1-3 years	95	58.28%
	4-5 years	41	25.15%
	More than 5 years	10	6.13%

Table 2 depicted participant's demographics information which include gender, age, years in the business, and years in the current position to know the variety of participants and their backgrounds that may affect their answer to the survey questions. Besides analyzing the demographic information, the researchers use IBM SPSS Statistics 27 to conduct descriptive analysis of collected data, including mean, standard deviation, variance, kurtosis, skewness, and standard error. The descriptive analysis conducted for 16 predetermined variables which are shown in Table 3 below. The standard deviation value indicates that there is low variation in the responses, with most respondents answering positive responses clustering around the means. This suggests consistent responses among the respondents, as it also shown by the variance values that below 1 which still considered as low. This indicates that the data points do not spread far from the mean.

For the Kurtosis value, negative value indicates that the data distribution has less outliers and relatively flat distribution, kurtosis value near 0 indicates a normal distribution, and positive Kurtosis value indicates heavy outliers. Besides, general acceptable kurtosis values for practical purposes range between -2 and 2. Therefore, from Table 3 it can be concluded that employee development, employee involvement, organizational structure, organizational environment, and IT infrastructure show high positive Kurtosis values which indicate a significant number of outliers. Following that, the Skewness values in the table shows that most of variables have negative skewness, indicating a distribution skewed to the left, which means that the responses on the higher end of the scale. However, several indicators are below acceptable for the normal distribution which range between -1 and 1 that have values below -1, such as employee development, employee involvement, organizational structure, organization environment, and IT infrastructure. This indicates that most respondents rated these variables highly.

Table 3: Descriptive Analysis

Variables	Mean		SD	Variance	Skewness		Kurtosis	
	Statistic	Standard Error			Statistic	Standard Error	Statistic	Standard Error
SM1	4.52	0.046	0.581	0.337	-0.754	0.19	-0.409	0.378
SM2	4.38	0.045	0.58	0.336	-0.291	0.19	-0.721	0.378
SM3	4.37	0.052	0.667	0.446	-0.6	0.19	-0.67	0.378
SM4	4.39	0.054	0.689	0.475	-0.696	0.19	-0.661	0.378
SM5	4.204499	0.0332442	0.424434	0.18	-0.003	0.19	-0.546	0.378
LM1	4.448	0.0373	0.4767	0.227	-0.655	0.19	-0.035	0.378
LM2	4.199	0.0419	0.5344	0.286	-0.024	0.19	-0.927	0.378
HRM1	4.318	0.0299	0.3822	0.146	-1.036	0.19	4.843	0.378
HRM2	4.259714	0.0397786	0.5078594	0.258	-1.232	0.19	2.471	0.378
HRM3	4.261	0.0418	0.5338	0.285	-0.642	0.19	0.83	0.378
HRM4	4.328	0.0259	0.331	0.11	-0.283	0.19	-0.077	0.378
OA1	4.243354	0.038163	0.4872325	0.237	-0.265	0.19	-0.847	0.378
OA2	4.304	0.0409	0.5224	0.273	-1.226	0.19	4.462	0.378
OA3	4.230	0.0481	0.6142	0.377	-1.626	0.19	5.676	0.378
TH1	4.3911	0.02795	0.35685	0.127	-1.002	0.19	2.435	0.378
TH2	4.285	0.0294	0.3757	0.141	-0.473	0.19	1.517	0.378

The analysis of Kurtosis and Skewness values revealed several indicators with potential outliers due to the asymmetrical distribution, including Employee Development (HRM1), Employee Involvement (HRM2), Organizational Structure (OA1), and Organizational Environment (OA3). As a result, researchers calculate Z-scores for each indicator and determine how to handle the outliers. The Z-score calculation allows researchers to identify outliers that are outside the threshold (-3 and 3).

After computing the Z-score, researchers did not discover outliers in variables Employee Development (HRM1) and Employee Involvement (HRM2) because of the Z-scores that are within the threshold range. However, there are outliers in variables Organizational Environment (OA3) and Organization Structure (OA1). After finding the outliers, researchers decide to employ imputation techniques to change the outliers value by replacing the outliers' value with the mean value (Ismail et al., 2022). The researchers performed two iterations to eliminate all outliers, with the first iteration removing outliers in variables Organizational Structures and the second iteration removing outliers in variables Organizational Environment. As a result, this pre-processed data will be used for factor analysis to determine critical success factors of KM implementation in the banking sector using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

3.4. Correlation Matrix

Before conducting the factor analysis, researchers use correlation matrix to understand the relationships between variables based on Pearson correlation coefficients (Field, 2019**.** The values range from -1 to -1, with negative value showing negative correlation between variables and positive value shows positive correlation between variables. Previous studies (Al-Tal & Emeagwali, 2019),(Al et al., 2023)also used correlation matrix to investigates the relationships between observed variables and determine the strength of the relationships.

Table 4: Correlation Matrix of the Observed Variables

Variables	SM1	SM2	SM3	SM4	SM5	LM1	LM2	HRM1	HRM2	HRM3	HRM4	OA1	OA2	OA3	TH1	TH2
SM1	1															
SM2	0.159	1														
SM3	0.156	0.051	1													
SM4	-0.083	0.164	0.202	1												
SM5	0.167	0.082	0.099	0.061	1											
LM1	0.117	-0.013	0.042	0.016	0.089	1										
LM2	0.172	0.081	-0.046	0.071	0.318	0.005	1									
HRM1	0.196	0.153	0.123	0.299	0.326	0.203	0.138	1								
HRM2	0.115	0.21	0.104	0.124	0.391	0.135	0.362	0.22	1							
HRM3	-0.017	-0.006	-0.054	-0.007	0.048	0.126	0.119	0.135	0.035	1						
HRM4	-0.013	-0.018	-0.016	0.026	0.221	0.189	0.203	0.283	0.114	0.344	1					
OA1	0.092	0.072	0.121	0.189	0.399	0.264	0.295	0.327	0.287	0.376	0.347	1				
OA2	0.227	0.093	0.064	0.115	0.244	0.079	0.263	0.137	0.183	0.078	0.172	0.246	1			
OA3	0.067	-0.002	0.037	0.094	0.208	0.076	0.27	0.205	0.27	0.035	0.141	0.084	-0.02	1		
TH1	0.119	0.157	0.03	0.175	0.294	0.23	0.195	0.367	0.281	0.381	0.463	0.452	0.222	0.144	1	
TH2	0.021	0.062	-0.068	0.143	0.342	0.142	0.364	0.375	0.437	0.202	0.295	0.338	0.338	0.241	0.38	1

The correlation matrix reveals coefficient values that range from 0.0 to 0.3, implying weak relationships between most pairs of variables. In the context of knowledge management, weak correlations can be influenced by complex interactions between factors that cannot represented by linear correlations (Field, 2019). However, there are also negative correlations such as between variable SM4 with SM1; variable LM1 with SM2; variable LM2 with SM3; variable HRM3 with SM1, SM2, SM3, and SM4; variable HRM4 with SM1, SM2, and SM3; and variable OA3 with SM2 and OA2. The negative correlation value may indicate inverse relationships between two variables in the context of knowledge management implementation (Wemken et al., 2021; Yang et al., 2021). This might be viewed as an indication that improvements in one area may lead to declines in other areas. The results of the matrix can be used as insight to analyze the relationships between variables after already identifying the factor structure, but relationships between studied variables cannot be determined solely from the correlation matrix due to the complexity of each variable's context (Field, 2019; Hair et al., 2010). In addition to this, factor analysis using EFA and CFA can be used to discover complex dependencies between variables.

3.5. Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) is a statistical method used to discover the underlying factor groups of a large set of variables and explain the pattern of correlations within factor groups. Several key components need to be paid attention to in conducting exploratory factor analysis, such as the extraction method, factor rotation, and interpretation of several factors (Al-Ahmad Chaar & Easa, 2021). The study uses EFA despite already having predetermined factors to compare factor groups discovered from exploratory factor analysis results that specifically from respondents in banking sectors and factor groups that are predetermined from literature review.

Researchers conducted five iterations of EFA to verify that each factor group had variables that significantly correlated with one another and had distinct characteristics. For the initial iteration of EFA, researchers discovered that variables in factor groups remain cross-correlated. Therefore, researchers adjusted the minimum factor loading from 0.4 to 0.45 (Morgan et al., 2011) to ensure that each variable only belonged to one-factor group. This results in more distinct factor groups with a higher factor loading in the following iterations. In the second iteration, the researcher discovered that the variable

HRM1 has a low correlation with each of the five identified factor groups, implying this component does not belong to any factor groups. As a result, researchers decided to eliminate this variable and run a third iteration. After removing the variable HRM1, the researchers also discovered that the variable LM1 which was previously assigned to factor group 4 had a low correlation with all factor groups.

The removal of the variable HRM1 has an impact on the content of factor groups 3, 4, and 5, which is evident by the changes in variables across the factor groups before and after the removal. Before the removal of the variable HRM1, factor group 3 consisted only of variable SM4, factor group 4 consisted of variables SM1, SM3, and LM1, and factor group 5 consisted of OA2 and SM2. Following the removal of the variable HRM1, factor group 3 now includes SM2 and OA2, which were previously in factor group 5. The presence of the same variables in the factor group shows consistency and strong correlation with one another. Following this, factor groups 4 consist of variables SM3 and SM4 which previously came from different factor groups. Finally, factor group 5 only consists of variable SM1. The changes of variables inside the factor groups indicate that the removal of a variable might disclose new correlations of each variable within a factor group and across factor group (Abid et al., 2023).

In the fourth iteration, the researchers removed variable LM1 which had a low correlation with all factor groups, revealing more reliable factor groups for groups 3, 4, and 5. Factor 3 includes variables of SM1 and OA2, factor 4 includes SM2 and SM4, while factor 5 only consists of variable SM3. Factor 5, which is made up only of one variable, implies the low correlations of variables SM3 with other variables. This can be influenced by its MSA value that is less than 0.5, implying that the variable is not well related to other factors. Consequently, such variables are often considered to be removed from the factor groups to improve the overall factorability of the data set (Willmer et al., 2019).

As a result, researchers performed the next iteration of factor analysis excluding variable SM3 and discovered that all variables in the factor groups 1, 2, 3, and 4 had remained consistent as previously. This confirms that the eliminated variable (SM3) has no significant relations with other factor groups, hence it is safe to be removed. Based on several iteration processes of factor analysis, it can be concluded that the removal of variables will alter the factor loading of each variable, with the change being caused by the new relation between variables that are closely associated. Table 5 below depicts the change in variables and factor groups throughout the iteration phase.

Table 5: Change of Factor Groups in EFA Iteration

Iteration	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
1	Employee involvement	Employee Satisfaction	Understanding Business Process	Effective Decision Making	Effective Decision Making
	Upper Management Support	Performance Measurement	Employee Development	Learning Process	Organizational Structure
	Organizational Environment	IT Infrastructure	Learning Process	Collaboration and Coordination	Strategic Thinking
	Technology Complexity and Compatibility	Organizational Culture	Strategic Thinking		
	Strong Networking	Collaboration and Coordination			
2	Employee involvement	Employee Satisfaction	Understanding Business Process	Effective Decision Making	Organizational Structure
	Upper Management Support	Performance Measurement		Learning Process	Strategic Thinking
	Organizational Environment	IT Infrastructure		Collaboration and Coordination	

	Technology Complexity and Compatibility	Organizational Culture			
	Strong Networking				
3	Employee involvement	Employee Satisfaction	Organizational Structure	Learning Process	Effective Decision Making
	Upper Management Support	Performance Measurement	Strategic Thinking	Understanding Business Process	
	Organizational Environment	IT Infrastructure			
	Technology Complexity and Compatibility	Organizational Culture			
	Strong Networking				
4	Employee Satisfaction	Employee involvement	Organizational Structure	Strategic Thinking	Learning Process
	Performance Measurement	Upper Management Support	Effective Decision Making	Understanding Business Process	
	IT Infrastructure	Organizational Environment			
	Organizational Culture	Technology Complexity and Compatibility			
		Strong Networking			
5	Employee Satisfaction	Employee involvement	Organizational Structure	Strategic Thinking	-
	Performance Measurement	Upper Management Support	Effective Decision Making	Understanding Business Process	
	IT Infrastructure	Organizational Environment			
	Organizational Culture	Technology Complexity and Compatibility			
		Strong Networking			

During the multiple iterations of the factor analysis, researchers also examined various components of exploratory factor analysis, including the KMO value, Barlett's Test, MSA (Measuring Sample Adequacy) value, Communalities, and factor loading. The KMO value, Barlett's Test value, and Communalities that meet the threshold suggest that researchers could continue the factor analysis and perform several iterations. Following the final iteration, researchers obtain the final factor groups, which consist of four-factor groups as illustrated in Table 6.

Table 6: Results of Factor Identification using EFA

Factor 1	Factor Loading	Factor 2	Factor Loading	Factor 3	Factor Loading	Factor 4	Factor Loading
Employee Satisfaction	0.761	Organizational Environment	0.706	Organizational structure	0.749	Understanding of Business Process	0.778
Performance Measurement	0.717	Employee involvement	0.691	Effective Decision Making	0.572	Strategic thinking	0.671
IT Infrastructure	0.704	Upper Management Support	0.634				
Organizational Culture	0.648	Complexity and Compatibility	0.595				
		Strong Networking	0.579				

EFA consists of several processes of analysis, the first one is Kaiser-Meyer-Olkin (KMO) and Barlett's Test which evaluates the adequacy of the sample gathered from data collection. The KMO value for the final iteration is 0.781 greater than 0.7, which is above the generally considered acceptable for factor analysis (Yan et al., 2023). Following this, Barlett's Test showed a significant result ($p < 0.001$) which supported the suitability of their data for factor analysis (Fischer-Suárez et al., 2022). The value of KMO and Barlett's test indicates that the variables are significantly intercorrelated and appropriate for factor analysis to explore the underlying factors. After assessing the KMO and Barlett's test value, the researchers also examined the Measuring Sample of Adequacy (MSA) value to determine the acceptability of the data to conduct factor analysis. The MSA value for all variables exceeds 0.5, which indicates that the sample size is adequate and can be represented by the observed variables (Willmer et al., 2019).

Researchers also found that all variables in this study had Communalities values which are above the threshold (0.4), with the lowest value being 0.441 and the highest being 0.687. This threshold is used to ensure that the items retained in the factor analysis were significant and contributed meaningfully to the identified factors (Abbas et al., 2024) This implies that a significant percentage of the variable's variance is shared with other variables in the dataset and can be explained by the identified factors later (Morgan et al., 2011). As a result, this final iteration of EFA produced four factors from the Eigenvalues and the constituent variables can be seen in the rotated component matrix.

Based on the results of factor groups in Table 6, it shows that the result of factor analysis has different factor structures than predetermined factor structures created by researchers in Table 1. Therefore, researchers used a correlation matrix to examine the differences between the newly identified variables and predetermined factors from the theoretical framework. It also helps to discover the relationship between new factor groups with predetermined factor groups based on its theoretical framework. The value used in the correlation matrix in Table 7 below is the Pearson correlation coefficient, which quantifies the linear relationship between two variables (Field, 2019). By examining the Pearson correlation coefficients in the matrix, researchers can understand how changes in one variable are associated with changes in another variable.

Table 7: Correlation Matrix Between Predetermined Factor Groups and EFA Results

Factor Groups	1	2	3	4
Strategic Management	0.043	0.253	0.429	0.635
Leadership Management	0.270	0.530	0.236	-0.023
Human Resources Management	0.781	0.401	0.060	0.071
Organizational Attributes	0.422	0.597	0.291	0.124
Technology	0.648	0.491	0.120	0.216

The correlation matrix shows that factor groups 1 are strongly correlated with Human Resources Management and Technology. This is because these factor groups include several factors from both factor groups, such as Employee Satisfaction, Performance Measurement, IT Infrastructure, and Organizational Culture. This implies that employee growth is closely related to organizational aspects as supportive elements. The correlation matrix also revealed that factor group 2 was substantially related to Leadership Management and Organizational Attributes. This indicates that there are relationships between factors in Leadership Management and Organizational Attributes, implying that leadership management is assisted by organizational attributes.

Following that, factor group 3 has the most significant correlation with Strategic Management while having a very low correlation with the other factor groups. This is because group 3 comprises just two variables: Effective Decision Making and Organizational Structure, with Effective Decision Making having a greater loading factor than Organizational Structure. Afterward, factor group 4 has a significant correlation with Strategic Management because the factors in this group are all from Strategic Management factor groups. These findings suggest that examining factor structures using exploratory factor analysis can reveal connections between variables that were previously unknown when leveraging a literature review. Therefore, although researchers have already selected factor groups from literature review, it is needed to do factor analysis and use correlation matrix to confirm the factor groups and discover correlations between factors (Singla & Samanta, 2022b). For the next step, researchers will further examine the correlation between factors inside the factor groups in the Confirmatory Factor Analysis (CFA).

3.6. Confirmatory Factor Analysis (CFA)

Researchers employed Confirmatory Factor Analysis (CFA) to assess the reliability and validity of each factor group and its associated variables after identifying them during exploratory factor analysis. CFA also used to develop a model from exploratory factor analysis results to confirm that the data fits a given factor structure by analyzing the model's fit using goodness-of-fit. Afterward, CFA results will help in determining whether the hypothesized model is consistent with the observed data, as well as information on how each measured variable represents the latent constructs (Hair et al., 2010). Based on the final factor groups of critical success factors using EFA in Table 6, researchers construct a measure model for CFA shown in Figure 1.

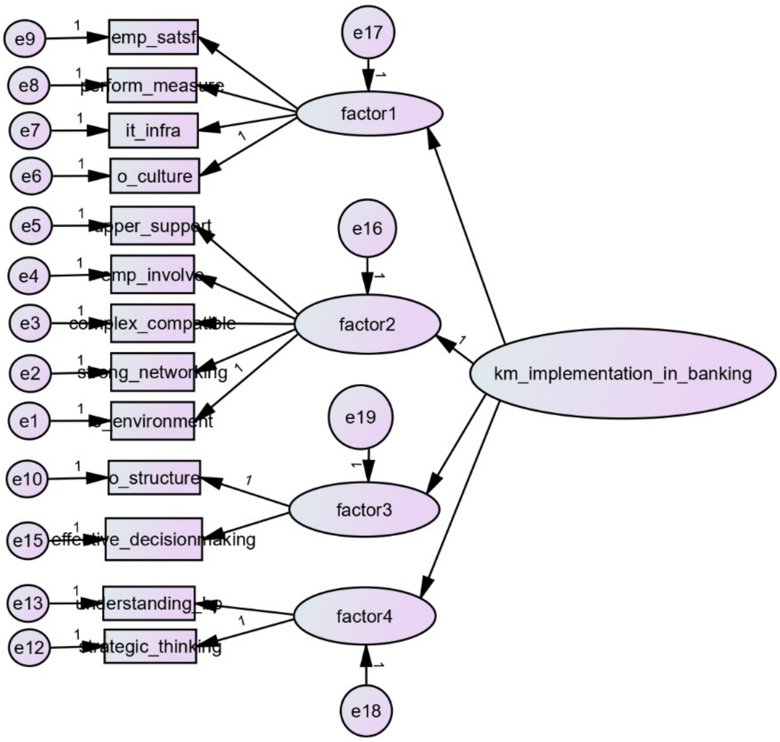

Fig. 1: Measurement Model of CSF Identification for KM Implementation in Banking Sector

Researchers examine the model's fitness in Figure 1 using various components of Goodness of Fit analysis which is detailed in Table 8 below. The model fitness can be confirmed by the Chi-Square and Degrees of Freedom values, which suggest that the dataset has sufficient information to estimate the model fit. The Comparative Fit Index (CFI) that compares the fit of the specified model to an independent (null) model, is likewise more than 0.90, indicating a good fit for the model (Kline, 2015). This is further shown by the Tucker-Lewis Index (TLI) result for this model, which compares the fit of the specified model to a null and gives a value close to the acceptable threshold but still acceptable as a moderate fit (Kline, 2015). Following that, the Goodness of Fit Index (GFI) for the model is more than 0.90 which indicates that the proportion of variables variance can be determined using the dataset (Kline, 2015). As a result, it can be concluded that the Goodness of Fit analysis for the model provides a reasonable presentation of the data and indicates a good fit for the CFA model.

Table 8: Goodness of Fit Analysis

Measure	Estimate	Threshold	Interpretation
Chi-Square	76.596	Closer to 0	Model fit to the data
Degree of Freedom (DF)	61		Sufficient information to estimate parameters and test model fit
Chi-Square/DF	1.256	Between 1 and 3	Good fit
CFI	0.952	>0.9	Good fit
GFI	0.935	>0.9	Good fit
AGFI	0.903	>0.9	Good fit
RMSEA	0.040	<0.06	Good fit
TLI	0.810	>0.90	Moderate fit

Following the model fitness analysis, the researchers also computed the Composite Reliability (CR) and Average Variance Extracted (AVE) values for each variable to determine the validity and reliability of variables and factors. CR assesses the internal consistency of the variables representing the factor groups, considering the actual factor loadings. The generally acceptable threshold for CR value is 0.7, which means the value below this threshold indicates that the variables do not reliably measure the underlying factor groups. Following that, AVE calculated the amount of variance captured by the factor groups and explained how it represents the variables inside the factor groups. The lower AVE value might indicate that the indicators may not represent the factor groups adequately, while the generally accepted threshold is 0.5 (Hair et al., 2010). Table 9 below shows the factor loading, CR value, and AVE value of identified factor groups and their constituent variables.

Table 9: Factor Groups and Variables Analysis

Factor Groups	Factor Loading	Variables	Factor Loading	CR	AVE
Factor 1	0.704	Employee Satisfaction	0.501	0.704	0.444
		Performance Measurement	0.587		
		IT Infrastructure	0.741		
		Organizational Culture	0.662		
Factor 2	0.895	Organizational Environment	0.357	0.437	0.328
		Employee involvement	0.63		
		Upper Management Support	0.563		
		Technology Complexity and Compatibility	0.685		
		Strong Networking	0.573		
Factor 3	0.585	Organizational structure	0.753	0.453	0.329
		Effective Decision Making	0.301		
Factor 4	0.494	Understanding of Business Process	0.434	0.283	0.165
		Strategic Thinking	0.377		

Table 9 reveals that Factor 1 has a factor loading of 0.704, implying a strong correlation between the observed variable and the latent construct. CR value that is greater than 0.7 indicates good reliability, implying that the construct's indicators are measured consistently. This also implies that the construct is measured accurately and consistently across its variables. However, the AVE value that is below the generally accepted indicates that the construct does not capture as much of the underlying factor groups which will lead to concerns about its convergent validity. Regardless of the AVE value that is below the threshold, it could be still considered acceptable because the other indices suggest that the model is a good fit (Kline, 2015). While Factor 2 shows a high factor loading (0.895) for the factor groups, it has considerably low CR and AVE values. It can be interpreted that the variables are not consistently measuring the same construct which could be influenced by one of the variables with low-factor loadings, which indicates the variables have low correlation with other variables in the factor groups. This shown in Table 9 where the variable Organizational Environment has the lowest factor loading, with a value of 0.357, compared to other variables that have factor loading more than 0.5.

Following this, Factor 3 has a factor loading of 0.585 with a CR value of 0.283 and an AVE value of 0.165, indicating a possible issue with the factor groups despite having a moderately acceptable factor loading. The CR value for these factor groups indicates poor internal consistency to represent the same factor groups and the AVE value indicates poor convergent validity. This can be influenced by the variable Effective Decision Making which has a low factor loading (0.301), implying it is not strongly correlated with the variable Organizational Structure in the factor group. It can be concluded that this indicator may not be relevant to the factor groups and may not capture the same underlying factor groups uniformly. This problem can be resolved by assessing the relevance of indicators and developing new indicators that are more accurate with factor groups 3.

Factor 4 also has considerably low CR and AVE values below the acceptable threshold with a CR value of 0.283 and an AVE value of 0.165. This is caused by the low factor loading of two constituent variables that are not strongly correlated, with the variable Understanding of Business Process value being 0.434 and the variable Strategic Thinking value being 0.377. From the confirmatory factor analysis results, researchers tried to modify the model by aligning the variables using theoretical frameworks which only resulted in lower CR and AVE values for each factor group.

Based on the CFA results, researchers decided to use the current CFA model shown in Figure 2 based on the model Goodness-of-Fit results that show that the model is a good fit. Goodness-of-Fit measures, such as the Goodness of Fit Index (GFI), the Comparative Fit Index (CFI), the Root Mean Square Error of Approximation (RMSEA), and the Tucker-Lewis Index (TLI), collectively demonstrated that the model meets the criteria for an acceptable fit, thereby validating the overall structure of the model (Kline, 2015), (Steenkamp & Maydeu-Olivares, 2023) Furthermore, the model can correctly specify the correlations within the factor groups despite having some variables that have low factor loadings. The inclusion of variables with low factor loadings can be justified in confirmatory factor analysis (Hair et al., 2010). While high factor loadings are generally preferred as they signify strong correlations between observed variables and their underlying latent constructs, low factor loadings do not necessarily invalidate the model. These factor loadings can still provide meaningful information about the constructs being measured, especially if the overall fit indices are satisfactory.

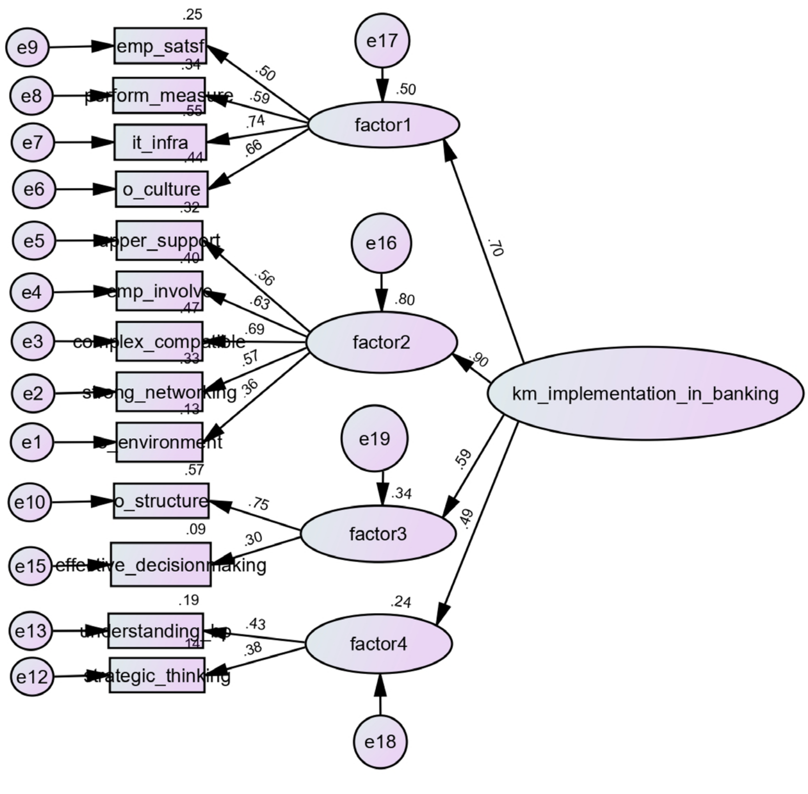

Fig. 2: Structural Model of CSF Identification for KM Implementation in Banking Sector

4. Results and Discussion

Addressing the first research question, exploratory factor analysis and confirmatory factor also applied to discover complex dependencies between variables that not represented when only use correlation matrix (Field, 2019; Hair et al., 2010). EFA allowed researchers to identify factor groups based on their correlations while ensuring that each factor group was distinct through several iterative processes. Each process involves several adjustments, such as increasing the minimum factor loading for the rotated component matrix (Morgan et al., 2011)and removing weakly correlated variables (Abid et al., 2023), such as Employee Development, Collaboration and Coordination, and Learning Process. This iterative process to refine the factor group identification using EFA indicates that factor analysis using EFA can effectively discern the critical success factors by continuously improving the factor structure until a stable and interpretable solution is achieved. As a result, the exploratory factor analysis identified 4 factor groups and 13 variables.

While EFA is used to establish structures based on their correlation using factor loadings, CFA is used to assess the reliability of variables representing the factor groups as well as the strength of each variable's correlations. The Goodness of Fit findings reveal that the structural model in Figure 2 for the model represents the data properly and indicates a good fit for the CFA model, even though some variables have low factor loadings. While high factor loadings are generally preferred because they represent strong correlations between observed variables and their underlying latent constructs, these factor loadings can still provide meaningful information about the constructs being measured, especially if the overall fit indices are satisfactory (Steenkamp & Maydeu-Olivares, 2023).

The second research question regarding CSF for KM implementation in the banking sector can be answered by the structural model from the confirmatory factor analysis in Figure 2. These factors included 4 factor groups and 13 variables depicted in Table 10 below. Factor 1 consists of Employee Satisfaction, Performance Measurement, IT Infrastructure, and Organizational Culture, Factor 2 consists of Upper Management Support, Employee Involvement, Technology Complexity and Compatibility, and Strong Networking, Factor 3 consists of Organizational Structure and Effective Decision Making, and Factor 4 consists of Understanding of Business Process and Strategic Thinking. The correlation between variables constructing the factor groups, theoretical framework, and results from correlation matrix in Table 7 can determined what the factor group represents. Factor 1 mostly represents Human Resources, Factor 2 mostly represents Management Support, Factor 3 mostly represents Strategic Management, and Factor 4 mostly represents Business Process Strategy.

Table 10: Critical Success Factors of KM Implementation in the Banking Sector

Factor 1: Human Resources	Factor 2: Management Support	Factor 3: Strategic Management	Factor 4: Business Process Strategy
Employee Satisfaction	Organizational Environment	Organizational structure	Understanding of Business Process
Performance Measurement	Employee involvement	Effective Decision Making	Strategic thinking
IT Infrastructure	Upper Management Support		
Organizational Culture	Complexity and Compatibility		
	Strong Networking		

Following the identification of factor groups, the level of importance of each factor groups can be determined by factor loadings value, composite reliability (CR), and average variance extracted (AVE). Factor loadings use to represents the correlation between observed variables and their factor groups, with high loading factor indicates that the variable is strongly correlated with a particular factor group (Morgan et al., 2011). Factor loadings of each variable in the identified success factors indicate how the variables correlated with other variables in the factor groups, Therefore, it can provide researchers with insight into variables influence to its factor groups and how well it already implemented in the banking sector (Singla & Samanta, 2022a) ,(Yamany et al., 2024). Meanwhile, CR value and AVE value presented information on the reliability and validity of each factor group and its constituent variables (Cheung et al., 2023).

The factor loadings from CFA results in Table 9 implies that Factor 1 is strongly correlated with each other and reliable in representing the factor groups. This also implies that the Human Resources factor has the greatest impact on the important success aspects of knowledge management implementation in the banking sector as it has already been well established in Indonesian banking companies (Lubis et al., 2022). Meanwhile, Factor 2 has the highest factor loading among other factor groups while having the CR and AVE values that are still below the acceptable threshold due to one variable with a low factor loading (variable Organizational Environment). It indicates that Factor 2 also has the second level of importance for the knowledge management implementation in the banking sector. However, variable Organizational Environment that has lowest factor loading in this factor groups implies that it not yet established in Indonesian banking companies (Lubis et al., 2022).

Following that, factor groups 3 and 4 have lower factor loadings compared to Factor 1 and 2. This implies that Strategic Management and Business Process Strategy are still not considered as important as Human Resources and Management Support in implementing knowledge management in Indonesian banking companies. Meanwhile, these factors are critical for improving business process efficiency and streamlining operations by eliminating redundant steps and automating repetitive tasks (Edeh et al., 2022b). Strategic Management and Business Process Strategy may also build a culture of continuous improvement and encourage innovation in products and services within the organizations, resulting in a competitive advantage for the organizations (Erena et al., 2023).

5. Conclusion

This study provides empirical evidence on the critical success factors for KM implementation in the Indonesian banking sector. Our findings demonstrate that Human Resources and Management Support are the most established factors in the banking industry, with IT Infrastructure playing a crucial role. These results extend the existing literature by highlighting sector-specific CSFs and their relative importance in banking organizations. The study has important implications for both theoretical and practical. The theoretical implications of this study are added to contribute to our understanding of how KM implementation factors differ in the banking context compared to other industries. This is shown by the difference between factor groups from factor analysis results and predetermined factor groups using a theoretical framework generally for the business sector. Following that, the findings also focus on the banking industry, specifically in Indonesia, because of challenges in implementing knowledge management in Indonesian banking companies.

The practical implication of this study is it suggests that banking organizations should prioritize their IT infrastructure and human resource strategies to implement knowledge management practices. This significant impact of IT infrastructure emerges from its ability to facilitate the seamless flow of knowledge across the organizations, allowing for effective communication among employees, and supporting daily operational activities that require dependable technology. As for the human resources strategies, banking companies can focus on employee skill development and having a culture and structure that facilitates the KM implementation. Aside from the main factors, banking firms might adopt the established CSF model to focus on finding areas for improvement and establishing strategies to improve their ability to apply knowledge management. Based on the conclusion, future research in this area could be addressed by investigating CSFs in smaller banking organizations, conducting comparative studies with banking organizations from different countries, and conducting longitudinal studies to understand how CSFs for KM implementation will evolve. These could provide a greater understanding of success factors for KM practices in the banking sector from different perspectives and develop strategies to enhance organizational performance.

6. Limitations and Future Research

Limitations of this study is its focus on large-scale banks in Indonesia and its cross-sectional nature. This was because the banking organizations used in this study were the only large-scale organizations that Indonesian citizens were familiar with, which created the possibility of overlooking significant insights from smaller-sized banking organizations that could not be represented in the current study. Aside from that, the cross-sectional nature of the study emerges from the limited time of data collection.

Future research could explore these CSFs in smaller banking institutions to identify CSFs that may be more specific for different scales of banking organizations and compare them with those from across various countries. Future research could also use the longitudinal study to understand how the important success factors of KM implementation in the banking sector could evolve to ensure that the findings are applicable in the long term. Despite these limitations, this study provides valuable insights into the critical factors for successful KM implementation in the banking sector, offering a foundation for future research and practice in this important area.

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