

Research on Digital Maturity Model for Financial Shared Service Center in Chinese State-Owned Enterprise

PhD

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October 2025

Declaration of Original Authorship

Declaration:

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

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Abstract

This study develops a Digital Maturity Model for Financial Shared Service Center (FSSC), addressing the absence of clear and tailored frameworks to determine and improve the development level of digitalization of FSSC in Chinese state-owned enterprise. Guided by the Design Science Research paradigm and a mixed-methods approach, the study integrates theoretical rigor and practical relevance through a five-phase procedure for model design: problem definition, initial development, model improvement, weight determination, and model evaluation.

Drawing on model combination and systems theory, six key process areas (Strategy and Organization, Infrastructure, Process Management, Data Management, Digital Performance, and External Environment) are identified within an evaluation indicator system for digital maturity, accompanied by five defined digital maturity levels (Initial, Repeatable, Defined, Managed, Optimizing). Through literature analysis and Delphi consultations involving 50 academic and industry experts, the system is finally refined into a four-layer hierarchy comprising six key process areas, 19 first-level, 47 second-level, and 131 third-level indicators, each weighted by the Analytic Hierarchy Process to ensure consistency and comparability.

The model is then validated through case studies of five representative FSSCs in Chinese state-owned enterprises. Survey data from 107 respondents are analyzed using the Fuzzy Comprehensive Evaluation to determine digital maturity scores for each center. The results verify the reliability, validity, and practical applicability of the model, with the participating FSSCs distributed between the Defined and Optimizing levels. Based on feedback, a refined eight-level maturity framework is introduced to enhance the model's discriminatory power and benchmarking precision.

The final model consists of two integrated components: a complete evaluation indicator system and a refined maturity framework. Together, they provide both a comprehensive theoretical framework and a practical evaluation tool, enabling FSSCs in Chinese state-owned enterprises to systematically assess their current digital maturity, identify strengths and weaknesses, and develop targeted strategies to advance toward the next level of digitalization. It contributes to the broader understanding of digitalization in finance by bridging research and practice through a structured and data-driven model.

Acknowledgement

This doctoral journey would not have been possible without the invaluable support and encouragement of many people to whom I am deeply indebted.

First and foremost, I would like to express my heartfelt gratitude to my supervisors, Professor Yinshan Tang and Professor Hongbo Duan, for their unwavering guidance, trust, and encouragement throughout this research. Their insightful advice, patient mentorship, and continuous support have not only shaped the direction of my study but also strengthened my confidence in the topic I have pursued with passion.

My sincere appreciation also goes to Henley Business School and the Department of Digitalisation, Marketing and Entrepreneurship at the University of Reading. In particular, I would like to thank Ms. Cindy Zhang, whose administrative assistance and thoughtful help made many things much easier during my study.

I am deeply grateful to all the experts who participated in the Delphi and Analytic Hierarchy Process procedures, as well as to the managers and staff members from the five FSSC case enterprises who generously shared their time and insights. Their contributions were essential to the empirical foundation of this research.

I also wish to extend my warmest thanks to my dear friends Sherri Chen, Caroline Ning, and Gina Fu for their company, encouragement, and countless moments of support during the most crucial final year of my PhD. I am equally thankful to my best friend Kevin Wong in China, whose understanding and help have accompanied me throughout these years.

Finally, I owe my deepest gratitude to my beloved parents, Yongfeng Meng and Aijun Jiang, for their unconditional love, patience, and encouragement that sustained me through every stage of this long journey.

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Chapter 1 Introduction

1.1 Research Background

Over the past two decades, digitalization in China has undergone a gradual and stage-based development, evolving from the early construction of information systems to deeper integration of digital technologies with organizational management and value creation. In the early 2000s, digital development in Chinese enterprises primarily focused on informatization, which emphasized the deployment of basic information systems such as enterprise resource planning and financial management systems. At this stage, digital technologies were mainly used to support routine operations and improve basic efficiency, with limited impact on organization structure and decision-making processes (Wei and Liu, 2015; Accenture Consulting, 2018).

Since the 2010s, driven by rapid technological advancement and economic restructuring, digitalization in China has entered an accelerated development stage. A range of digital technologies has been increasingly adopted by enterprises to support process integration, data sharing, and management innovation. Digitalization has gradually expanded from technical infrastructure to core business and management functions, becoming an important means for enterprises to enhance operational efficiency and competitiveness (Chen and Ma, 2018). In recent years, with the emergence of more advanced data analytics, digitalization in China has further progressed toward deeper integration, characterized by data-driven decision-making, intelligent management, and value creation based on data resources (Peng and Tao, 2022; Zheng and Jiang, 2022).

A distinctive feature of digitalization in the Chinese context is the strong role played by national strategies and institutional arrangements. Policies such as the “Made in China 2025” initiative and the “Digital China” strategy explicitly emphasize the importance of digital innovation in achieving economic modernization and global competitiveness (Wei and Liu, 2015; Peng and Tao, 2022). Under these policy frameworks, state-owned enterprises are regarded as important carriers of national digitalization strategies and are expected to take the lead in exploring digital transformation paths. As a result, digitalization in Chinese state-owned enterprise is not only motivated by efficiency improvement and cost reduction, but also serves broader objectives related to governance enhancement, regulatory compliance, and long-term strategic development (Lu and Pan, 2016; Peng et al., 2023). Within this broader digitalization context, financial management has increasingly been recognized as a foundational component of enterprise digitalization in China, because financial data constitute the core of enterprise data resources and provide essential support for operational management and strategic decision-making. In Chinese state-owned enterprises, the

requirements for transparency, standardization, and centralized control further strengthen the importance of restructuring and digitalizing financial management systems (Wei and Huang, 2018; Chen and Guo, 2022).

Against this background, the Financial Shared Service Center (hereafter referred to as FSSC) has become a key organizational arrangement for centralizing financial processes, integrating financial data, and supporting enterprise-wide management. In China, the FSSC is primarily adopted by state-owned enterprises and has evolved over many years. According to Zeng (2021), more than half of state-owned enterprises in China have established and developed FSSCs since the early 2000s. Historically, Chinese state-owned enterprises have faced numerous challenges such as rising costs, inefficient processes, fragmented financial management systems, and inadequate control over subsidiaries, especially as they expanded in scale and responded to economic globalization. In response, the FSSC is intended to address these issues by consolidating key financial functions, including accounts payable, accounts receivable, expense reimbursement, general ledger management, and financial reporting, into a centralized and standardized financial service center. Ultimately, by providing the above financial services, FSSCs in Chinese state-owned enterprises play a key role in optimizing resource allocation, ensuring compliance with regulatory standards, enhancing overall financial performance, and creating greater value for the entire enterprise (Zhang et al., 2012; Li et al., 2020).

However, within the context of ongoing digitalization, it has become increasingly evident that the existing form of FSSC in many Chinese state-owned enterprises faces fundamental practical limitations. Although FSSCs have been established and operated for many years, most of them remain primarily focused on centralized transaction processing and operational efficiency, rather than contributing to strategic management and value creation. As a result, the implementation of FSSCs has not yielded the expected benefits for state-owned enterprises. Specifically, improvements in overall financial performance have been limited, and employees in both FSSCs and business departments often experience increased workloads rather than efficiency gains (Chen and Ma, 2018; Liu and Liu, 2019). More importantly, FSSCs are generally unable to effectively support strategic management and data-driven decision-making, as financial data generated and processed within FSSCs are often fragmented, backward-looking, and insufficiently integrated with business operations. Accordingly, FSSC outputs cannot be effectively transformed into actionable insights for front-end business departments or enterprise-level strategic planning (He and Zhou, 2013; Chen and Guo, 2022; Liu et al., 2022). These practical limitations are further reflected in organizational, process, and technological dimensions, including unclear organizational hierarchies and role definitions, insufficient process re-engineering, and continued reliance on fragmented and outdated information systems (He and Cao, 2009; Hu et al., 2013; Zhang et

al., 2017). Therefore, the current form of FSSC is misaligned with the evolving requirements of digital transformation, where finance is expected to function as a strategic partner and a data-driven decision-making hub. This misalignment creates a strong internal need for Chinese state-owned enterprises to advance the digitalization of FSSC.

In addition to internal needs, external factors have also contributed to the digitalization of FSSC. First, the emergence and development of digital technologies such as the Internet of Things, big data, cloud computing, blockchain, and artificial intelligence have provided the technical foundation for FSSCs to begin digitalization (Madakam et al., 2015; Addo-Tenkorang and Helo, 2016; Berdik et al., 2021). Furthermore, the Chinese government has played an important role in promoting the digitalization of state-owned enterprises by providing a favorable policy environment and financial incentives for the transformation of FSSCs (Wei and Liu, 2015; Lu and Pan, 2016; Ding, 2020). Moreover, globalization and the expansion of cross-border operations have created new challenges in areas such as regulatory compliance, tax reporting, and currency risk management, all of which require higher levels of process standardization and automation in FSSCs. At the same time, the growing complexity of audit and risk management has led FSSCs to adopt digital solutions for improving compliance and control (Kohlhase and Pierk, 2020). Finally, growing external pressures, including increasing market competition and the necessity of benchmarking against industry leaders, have prompted state-owned enterprises to adopt more advanced financial management models, thus accelerating the digitalization of FSSC (Bounfour, 2016; Kane et al., 2017; Eller et al., 2020). Therefore, driven by technological progress, policy support, globalization, regulatory pressures, and market competition, FSSC is transitioning toward a new stage of digitalization.

The digitalization of FSSC aims to transform FSSC into a centralized big data center that supports data-driven decision-making in state-owned enterprises. Specifically, digital technologies are being used to automate fundamental financial processes and to collect, store, analyze, and visualize large volumes of heterogeneous data from both internal and external sources. This not only enhances efficiency but also provides more comprehensive and detailed data for front-end business operations and strategic decision-making. Ultimately, digitalized FSSCs in Chinese state-owned enterprises can facilitate the integration of financial and business processes, create greater data value, and advance both financial and enterprise digitalization (Chen and Guo, 2020). According to Zhang (2020), most state-owned enterprises in China have been undertaking the digitalization of their FSSCs since the 2010s. Therefore, as more Chinese state-owned enterprises have embarked on the digitalization of their FSSCs, it becomes increasingly necessary for these centers to develop a systematic and in-depth understanding of their digitalization process, in order to determine their current stage of digitalization and identify effective strategies for further improvement.

1.2 Research Problem

However, many FSSCs in Chinese state-owned enterprises lack a clear and structured understanding of the digitalization of FSSC. As a result, they face substantial difficulties in determining their current stage of digitalization and in making further progress toward higher levels of development. These challenges arise from two closely related gaps: a theoretical gap, reflected in the lack of relevant literature, and a practical gap, reflected in the absence of effective guidance.

From a theoretical perspective, the existing literature on the digitalization of FSSCs in Chinese state-owned enterprises remains extremely limited. First, many studies overlook the fact that FSSC has already entered the stage of digitalization. Instead, FSSC is still predominantly viewed as a department responsible for handling basic financial processes consolidated from other business units, with research primarily focusing on performance evaluation and operational optimization (Ulrich, 1995; Bergeron, 2002; Wu and Zhou, 2015). Such studies remain at a foundational level and fail to capture the evolving role of FSSC in the digital era. Second, although a growing body of research has examined the factors influencing enterprise digitalization and financial digitalization, and has developed evaluation systems to assess their development levels, there is still a clear lack of studies that specifically focus on the digitalization of FSSCs (Schumacher et al., 2016; De Carolis et al., 2017; Du, 2023; Zhang, 2024). In particular, few studies have attempted to identify the key influencing factors of the digitalization of FSSC or to develop evaluation models tailored to its unique characteristics. This theoretical gap is partly attributable to the fact that many researchers neglect the role of financial digitalization as a foundation of enterprise digitalization, as well as the central position of FSSC within the process of financial digitalization (Ma, 2017; Zhang and Sheng, 2022; Li, 2023). Moreover, existing studies conducted in the Chinese context mainly focus on performance analysis of FSSCs or on the digitalization of financial functions in small and medium-sized enterprises, while largely overlooking state-owned enterprises, which are in fact the primary adopters and key developers of FSSC digitalization in China (Chen and Guo, 2020; Zhang, 2020). As a result, the existing literature provides the fragmented and incomplete understanding of digitalization of FSSC in Chinese state-owned enterprise, including what it entails, how it evolves over time, and how it should be assessed.

From a practical perspective, the digitalization of FSSCs in Chinese state-owned enterprises is constrained by the absence of a specialized and structured framework and evaluation system. In practice, FSSCs lack a clear reference that can guide them in determining where they currently stand in the digitalization process, which critical capabilities are missing, and how digitalization efforts should be systematically advanced. As

a result, the digitalization of FSSC in Chinese state-owned enterprise is often implemented in a fragmented manner, particularly among FSSCs that are initiating or are in the early stages of digitalization, which frequently encounter various challenges during the transformation process. Specifically, many FSSC leaders lack sufficient awareness and understanding of digitalization, which undermines the formulation of well-defined digitalization strategies. These strategies often fail to align with the broader digital strategies of the enterprise, leading to unclear direction (Kane et al., 2019; AlNuaimi et al., 2022). Second, the organization structures within many FSSCs remain rigid and hierarchical, failing to match the structural requirements of digitalization, which demand flatter, more decentralized, and functionally specialized structures (He and Zhou, 2013; Hu et al., 2013). Third, finance-related processes in many FSSCs are not effectively integrated with system interfaces, resulting in unstable connections and partial or inconsistent execution of workflows, which in turn prevents the full automation and digitalization of these processes (Reijers and Mansar, 2007; Owens, 2013). Fourth, the application of advanced technologies such as cloud platforms for in-depth data mining and analysis, artificial intelligence for decision-making support, and blockchain for enhancing data security remains limited (Chen and Metawa, 2020; Berdik et al., 2021; Faccia and Petratos, 2021).

More importantly, these challenges do not merely reflect technical and operational difficulties, but indicate that FSSCs at an early or intermediate stage of digitalization continue to operate in a constrained functional form. Although certain digital initiatives may have been introduced, these FSSCs remain transaction-oriented, with limited capability to support strategic and data-driven decision-making. Data generated within FSSCs is mainly used for retrospective financial reporting and operational control, rather than being transformed into forward-looking insights to inform managerial and strategic actions. Consequently, even after the initiation of digitalization, many FSSCs fail to achieve a substantive shift from an efficiency-driven service unit to a strategic, value-creating, and decision-support center (Richter and Brühl, 2017; Liu and Liu, 2019; Liu et al., 2022; Soni et al., 2022). This persistent gap between digitalization initiatives and functional transformation highlights limitations in the current implementation of digitalization of FSSC in Chinese state-owned enterprise.

Therefore, the fragmented understanding of digitalization of FSSC reflected in the existing literature, together with the fragmented implementation observed in practice, underscore a clear need for academic research that develops a structured and stage-based practical framework to guide the digitalization of FSSC in Chinese state-owned enterprise. Such a framework should enable a systematic evaluation of the digitalization process by identifying key influencing factors, conceptualizing digitalization as a progressive and staged transformation, and determining the current stage of digitalization.

To address these research gaps, an appropriate methodological approach is required to support a rigorous evaluation of the digitalization of FSSC in Chinese state-owned enterprise. Given that digitalization is inherently a dynamic and progressive transformation rather than a one-time event, this study introduces the maturity model as its core theoretical foundation. The maturity model provides a structured methodology for assessing staged development and has been widely applied to guide complex and long-term transformation processes. The maturity model originated in the software industry and was initially developed to support continuous improvement in software development processes, including implementation, testing, and upgrading. By defining progressive maturity levels and corresponding capability requirements, it facilitates the transition from immature and disorganized practices to standardized and optimized processes (Paulk et al., 1993; Lee et al., 2007). Over time, the maturity model has been extended to various organizational and management domains due to its strength in constructing indicator systems that dynamically assess evolving objectives and capabilities (Morgan, 2007; Chrissis et al., 2011). In particular, it has proven effective in evaluating and guiding digitalization processes. Similarly, the digitalization of FSSC can be conceptualized as a multi-stage process of capability development, ranging from initial implementation to advanced integration and value creation (Kane et al., 2017; Chanias et al., 2019). As a result, the maturity model serves as a useful reference for developing an evaluation framework for digitalization. While several maturity models have been proposed for enterprise and financial digitalization, there is a clear need to develop a maturity model specifically for the digitalization of FSSC in Chinese state-owned enterprise to assess its maturity level, thereby enabling accurate evaluation of its development level and promoting its advancement.

1.3 Research Question

Based on the research problems outlined above, this study aims to investigate the following main research question:

How can a maturity model be developed to evaluate and support the digitalization of FSSC in Chinese state-owned enterprise?

To address this main question, the study proposes the following sub-questions:

1. What are the key factors that can be used to determine the maturity of digitalization of FSSC?
2. How can the maturity of digitalization of FSSC be systematically classified into progressive levels?

3. How can the current maturity level of digitalization of FSSC be determined and further improved?

1.4 Research Aim and Objective

Based on the research questions outlined above, this study establishes the following ultimate aim:

To develop a digital maturity model for determining and improving the development level of digitalization of FSSC in Chinese state-owned enterprise.

To achieve this aim, the study sets the following specific objectives:

1. To construct an evaluation indicator system for the digital maturity of FSSC by identifying relevant key process areas and indicators, and by determining their relative weights.

2. To classify the digital maturity of FSSC into multiple progressive levels, ranging from low to high maturity.

3. To validate the developed digital maturity model by applying it to selected FSSCs in Chinese state-owned enterprises, determining their digital maturity levels, and providing guidance for improvement.

1.5 Research Contribution

1.5.1 Theoretical Contribution

This study makes several important contributions to the theoretical understanding of financial shared service and digitalization. First, it broadens the traditional research scope of financial shared service by extending it into the digital era and framing the digitalization of FSSC as a core component of financial and enterprise digitalization. Specifically, it not only clarifies the definition and connotation of digitalization in the context of FSSC, but also reinterprets the evolving nature and strategic role of FSSC in the age of digital transformation. This conceptual redefinition provides a solid theoretical basis for understanding how FSSC can serve as a central hub for data-driven value creation through digitalization, rather than merely a center for basic financial processing. Second, this study responds to the absence of literature and lack of theoretical references that have hindered Chinese state-owned enterprises from understanding and guiding the digitalization of their FSSCs. By identifying

the key factors influencing the digitalization of FSSC and analyzing the transformation path from a multi-stage perspective, it addresses a major cognitive gap among enterprises regarding what digitalization of FSSC entails, why it matters, and how it can be achieved systematically. In doing so, this research lays a theoretical foundation for the development and application of evaluation systems and transformation frameworks for digitalization of FSSC.

Furthermore, the study contributes to the literature on maturity models by developing a digital maturity model specifically tailored to the FSSC in Chinese state-owned enterprises. Unlike previous models that focus on general enterprise or financial digitalization, this model captures the unique structural, operational, and technological characteristics of FSSC. Most importantly, it offers a structured and reliable framework for the construction of maturity evaluation indicator systems, particularly in the identification and refinement of key process areas and their associated indicators, the categorization of maturity levels, and the selection of appropriate model development methods in future studies. Therefore, it meaningfully extends and complements existing maturity model frameworks within the context of digitalization research.

1.5.2 Practical Contribution

From a practical perspective, this study offers timely and actionable insights for managers of FSSCs, particularly in Chinese state-owned enterprises, by addressing the critical issue of lack of reference during the digitalization of FSSCs. The absence of relevant literature and frameworks has long left FSSCs with no clear guidance, resulting in fragmented understanding, inconsistent implementation, and repeated strategic or operational missteps. This study fills that gap by offering a structured framework and evaluation tool that helps FSSCs develop a comprehensive and in-depth understanding of their own digitalization process.

Specifically, through the application of the digital maturity model proposed in this study, FSSCs in Chinese state-owned enterprises can accurately determine their current stage of digitalization, benchmark themselves against best practices or industry leaders, and understand the specific gaps and limitations in their current digital capabilities. Based on this understanding, FSSCs in Chinese state-owned enterprises are better positioned to identify necessary conditions and actions required for the successful implementation of digitalization, helping them overcome the challenges previously highlighted in the research problem section. For instance, the model can guide FSSC leaders in aligning digital strategies with enterprise objectives, optimizing organization structures to enhance cross-functional collaboration, integrating financial processes with information systems to improve automation and

workflow stability, and enhancing data management capabilities, including data analysis, decision-making, and security, by adopting appropriate technologies.

Therefore, this digital maturity model serves as a practical roadmap that not only supports evaluation but also promotes the development of digitalization of FSSC in Chinese state-owned enterprise. It enables managers of FSSCs to move beyond abstract goals and adopt a concrete, stage-based approach toward subsequent improvement in digitalization and ultimately successful digital transformation. Furthermore, although the model is designed for Chinese state-owned enterprises, its methodological framework and evaluation dimensions can be adapted by FSSCs in other types of enterprises or regions, thereby offering broader international applicability and contributing to the global discourse on digital shared service.

1.6 Thesis Structure

This thesis is structured into eight chapters, each of which is designed to progressively achieve the research objectives and contribute to the development of a digital maturity model for FSSC in Chinese state-owned enterprise. The structure is outlined as follows.

Chapter 1 outlines the research background, problem statement, research questions, aim and objectives, and expected theoretical and practical contributions. It highlights the pressing need for a digital maturity model specifically tailored to FSSC in Chinese state-owned enterprise. Chapter 2 critically reviews the existing literature on financial shared service, digitalization, maturity models, and systems theory. It identifies key research gaps in evaluating the digital maturity of FSSC, especially in Chinese state-owned enterprise, and introduces the Input-Processing-Output model as the theoretical foundation for developing the proposed digital maturity model. Chapter 3 outlines the research paradigm, approach, and method adopted in this study. It justifies the adoption of the Design Science Research Paradigm combined with a Mixed Research Approach and Method, and then introduces a five-phase procedure for model design. Chapter 4 presents the initial development of the digital maturity model, the second phase of the procedure for model design. It defines five digital maturity levels and constructs a preliminary three-layer evaluation indicator system for digital maturity, comprising key process areas, first-level and second-level indicators. Chapter 5 focuses on the improvement of the initial digital maturity model, the third phase of the procedure for model design. It refines the three-layer evaluation indicator system and extends it into a complete four-layer framework by introducing and revising third-level indicators through expert consultation. Chapter 6, as the fourth phase of the procedure for model design, determines the relative weights for all key process areas and three-level indicators by applying the Analytic Hierarchy Process. The weighting process ensures that the digital maturity model reflects expert consensus on the most critical factors influencing

digitalization. Chapter 7, as the final phase of the procedure for model design, tests the developed digital maturity model by applying it to five FSSCs in different Chinese state-owned enterprises. Based on the calculated digital maturity levels and feedback from these FSSCs, the model is refined and its reliability, validity, and practical applicability are verified. Chapter 8 summarizes the key findings, theoretical and practical contributions, and limitations of the study, and provides recommendations for future research on the further refinement and application of the digital maturity model.

Chapter 2 Literature Review

This chapter systematically reviews existing literature on financial shared service, enterprise and financial digitalization, maturity model, and systems theory, including studies on evaluation systems and assessment indicators. It identifies key research gaps, particularly the lack of a dedicated digital maturity model for evaluating the digitalization of FSSC in Chinese state-owned enterprise.

2.1 Financial Shared Service

2.1.1 Concept and Development

Shared service refers to the consolidation and centralization of common business functions within an organization, involving the pooling of resources, processes and expertise from various departments or business units to deliver specific services centrally (Ulrich, 1995; Bergeron, 2002). In addition, this concept has gained prominence in management literature due to its potential to enhance organizational performance, particularly in terms of cost reduction and service improvement (Hamari et al., 2018). Furthermore, the shared service has evolved significantly over the years, driven by technological advancements and changing business landscapes (Richter and Brühl, 2017).

Financial shared service originated from the concept of shared service and becomes the specific application of shared service in the field of accounting and finance (Bangemann, 2017). In general, financial shared service is an innovative financial management approach that integrates key elements such as personnel, technology and processes, centralizing and standardizing finance-related businesses in the enterprise, in order to achieve and maintain a competitive advantage (Gunn et al., 1993; Bergeron, 2002). Specifically, it refers to the process of extracting dispersed and highly repetitive finance-related activities from individual unit within the enterprise and concentrating them in a new financial department for standardized processing and unified management (Janssen and Joha, 2008; Rothwell et al., 2011).

2.1.2 Function and Performance Evaluation

Financial Shared Service Center (referred to as FSSC) is a centralized unit within the enterprise originating from the financial shared service model (Keith and Hirschfield, 1996). First of all, FSSC is responsible for consolidating and standardizing a wide range of financial processes such as accounts payable, accounts receivable, general ledger accounting, financial reporting, and financial analysis. It delivers these finance-related services to multiple entities,

business units and subsidiaries within the enterprise, often across different geographic locations (Gospel and Sako, 2010; Seal and Herbert, 2013). Moreover, the primary objectives of establishing FSSC should be aligned with the overarching goals of the enterprise, which include, but are not limited to, improvements in operational efficiency, internal control, service quality, and decision-making (Girdea and Nilsson, 2010; Rothwell et al., 2011). Finally, the operation of FSSC is influenced by multiple factors, mainly including strategic planning, personnel management, organizational restructuring, process re-engineering, and information systems construction. In addition, FSSC can generate significant value for the whole enterprise based on the effective combination of the above factors (Janssen and Joha, 2008).

Furthermore, establishing a specialized performance evaluation system by effectively leveraging these influencing factors is critical to ensuring the successful operation of FSSC (Qian and Liu, 2019). With regard to evaluation methods, the two primary approaches involve the identification of key performance indicators and the implementation of balanced scorecard framework according to the Institute of Management Accountants (2014). In terms of evaluation dimensions, the performance level of FSSC can be evaluated through five key aspects: standardization, service level, quality management, operational efficiency, and on-site management (Chen and Dong, 2008). At present, the majority of FSSCs adopt a performance evaluation system based on the balanced scorecard framework, which encompasses four key dimensions: financial, customer, internal process, and learning and growth. Specifically, the four dimensions evaluate: first, the extent to which cost and budget objectives are met; second, the degree of customer satisfaction and the strength of the relationship between FSSC and its internal customers; third, the internal operational and process management capabilities; finally, the effectiveness of team development, staff training, and routine personnel management (Ulbrich et al., 2008; Zhang et al., 2012; Wu and Zhou, 2015). Subsequently, additional dimensions such as strategy and technology, particularly information systems, have been integrated into the performance evaluation system to further improve the performance of FSSC (Owens, 2013).

Therefore, much of the existing research remains narrowly focused on performance evaluation and operational optimization based on traditional frameworks, as researchers continue to view FSSC primarily as a centralized department responsible for handling basic and repetitive financial processes aggregated from other units. While these studies have provided a solid foundation and valuable insights for more in-depth exploration of FSSC-related issues, they remain at a basic level and fail to reflect the changes brought about by digital technologies. These technologies have already begun to reshape how FSSC operates and creates value, and are leading FSSC toward digitalization. As a result, it is necessary to re-examine the role of FSSC in the digital era and to develop new research

perspectives that better reflect its current functions, strategic importance, and transition toward a more intelligent, data-driven, and value-generating unit.

2.2 Digitalization

Digitization was originally defined as the process of converting analog information into digital form, enabling its storage, processing, and transmission through electronic devices and computer systems. This transformation involves the representation of data as discrete elements or digits, typically using binary code (Boole, 2021). However, digitization has gradually developed into the process of using digital technology and digital information to change the way of value creation in fields other than information technology (hereafter referred to as IT), including business and society (Manyika et al., 2016; Sjödin et al., 2018; Sheninger, 2019). As a result, the process of digitization and its subsequent impacts are always described as digitalization. Digitalization, often referred to as the digital transformation, is distinct from digitization, representing the integration of digital technology into diverse areas such as enterprise management, economic and social systems, and public policy and governance. Ultimately, it can lead to fundamental changes in how individuals, organizations, and governments operate and interact (Berman, 2012; Bounfour, 2016; Rogers, 2016).

2.2.1 Enterprise Digitalization

Enterprise digitalization represents the strategic integration and utilization of digital technologies across all departments or business units of the enterprise to drive innovation, enhance efficiency and deliver value to stakeholders. On the one hand, it encompasses a broad spectrum of technologies, including the Internet of Things (hereafter referred to as IoT), big data, cloud computing, blockchain, and artificial intelligence (hereafter referred to as AI) (Westerman et al., 2012). On the other hand, the organization structure, business model, and customer experience can be fundamentally reshaped through the automation and digitization of existing business and financial processes (Wischnevsky and Damanpour, 2006; Kotter, 2007; Kane et al., 2017). Ultimately, the enterprise is able to engage in data-driven decision-making and build an ecosystem to realize value co-creation (Lenka et al., 2017; Pflaum and Gölzer, 2018; Hess et al., 2020). Furthermore, a variety of internal and external factors have been identified as influencing the process of enterprise digitalization. From a resource-based view, resources such as IT, employee skills, and digital strategies available to enterprise significantly impact the progress of digitalization (Eller et al., 2020). From the perspective of data lifecycle management, dynamic capabilities, data elements, and innovations in technology and business models need to be effectively integrated and coordinated throughout enterprise digitalization (Frank et al., 2019; Jiao et al., 2021).

Moreover, next-generation digital technologies, evolving competitive patterns, accumulation of new types of human capital, and corresponding institutional reforms constitute the external influencing factors of enterprise digitalization (Vial, 2021; Zheng and Jiang, 2022).

Therefore, developing an evaluation system based on the rational integration of these influencing factors plays a vital role in determining the development level of enterprise digitalization (Sethi and King, 1994; Qin et al., 2016). Such systems are typically evaluated from the perspectives of value chain, architecture, organizational capability, and maturity. For instance, based on innovation value chain theory, an evaluation system for assessing the digitalization of manufacturing enterprise is developed from three aspects: digital input, digital application, and digital benefit (Li, 2019). Based on architecture theory, Wan et al. (2020) constructed another evaluation system, considering seven key dimensions: strategic and organizational alignment, digital infrastructure, application of digital technologies, business integration, enterprise-wide integration, industrial collaborative innovation, and effectiveness and efficiency. Moreover, drawing on dynamic capability theory, the capability of enterprise digitalization can be evaluated through technological change, organizational change, and management change (Chen and Xu, 2020; Soluk et al., 2021; Wang and He, 2022). More importantly, from a maturity-based perspective, Blatz et al. (2018) evaluated the digitalization of small and medium-sized enterprise by measuring the maturity levels of six factors, including strategy and leadership, organization and culture, IT infrastructure, data maturity, processes and operation, and product. Together, these evaluation systems help ensure the effective and successful implementation of enterprise digitalization.

2.2.2 Financial Digitalization

Financial digitalization, as the premise of enterprise digitalization, can be conceptualized as a process involving the application of technology, process re-engineering, organizational restructuring, and value creation. Specifically, it refers to the integration of digital technologies into both traditional financial processes and financial organization structure, to achieve their transformations and create value for the entire enterprise (Soluk et al., 2021; Vial, 2021). When discussing the key factors influencing financial digitalization, most existing studies focus on four main perspectives: strategy and leadership, technological capability, organization and culture, and business process. Firstly, leaders are the primary drivers of financial digitalization. Their depth of understanding of digitalization has a direct impact on how strategic resources are allocated. Additionally, they can develop financial transformation strategies based on the current situation of enterprise and guide financial staff in their future development (Chanas et al., 2019; Kane et al., 2019; Singh and Hess, 2020). Secondly, digital technologies can enhance financial management and control by increasing the efficiency and quality of financial operations. The effectiveness of their application

depends on the degree of alignment between technologies and financial processes. For instance, the development of data platform requires deep integration with financial decision-making (Chen and Guo, 2022; Zhang and Song, 2025). Thirdly, organizational structure and culture can provide foundational support for the effective implementation of financial digitalization. Accordingly, enterprise should focus on developing interdisciplinary talent to establish a strong digital finance team with clearly defined roles and responsibilities. At the same time, efforts should be made to create a positive culture, promote digital thinking, and encourage innovation in financial management (Kotter, 2013; Soluk et al., 2021; Zhu and Xia, 2022). Lastly, it is important to redesign financial processes, innovate financial analysis methods, and develop new financial models. As a result, the standardization and automation of processes can enable finance teams to shift their focus from routine tasks to strategic analysis (Baiyere et al., 2020; Wang, 2021; Zhu and Xia, 2022).

Therefore, to determine the development level of financial digitalization, it is essential to build an evaluation system that integrates these influencing factors in a structured way. Some studies have proposed certain evaluation methods and key factors that should be taken into consideration. For instance, Song et al. (2025) innovatively proposed the “Compass Model”, which divides the process of financial digitalization into three dimensions: awareness, capability, and stage. By measuring the indicators within these dimensions, the model enables a precise assessment of the whole process. Building on this foundation, Wang (2025) further developed an evaluation indicator system with a hierarchical structure, offering a more detailed framework for assessing both the degree and effectiveness of financial digitalization. The degree of financial digitalization is assessed through awareness, infrastructure, application, and innovation. Meanwhile, the effectiveness of financial digitalization is measured using four outcome indicators: breakthrough in market value, improvement in financial efficiency, enhancement of financial service, and sustainable development. More importantly, from the perspective of maturity, Du (2023) evaluated the financial digitalization of oil enterprise by measuring the maturity levels of seven indicators, including strategy and organization, infrastructure, intelligent financial operation, data value creation, comprehensive integration, financial risk control, and digital performance. Accordingly, these evaluation systems facilitate the effective and successful implementation of financial digitalization.

2.2.3 Digitalization of FSSC

Furthermore, as the core department responsible for finance-related services, FSSC should also enter the stage of digitalization (Miller and Mork, 2013; Zilic and Cosic, 2016). The digitalization of FSSC can be summarized as the application of digital technologies to adjust the structure and digitize all processes in FSSC, with the aim of managing the entire

data value chain from data collection and storage to data analysis and visualization. Specifically, first of all, FSSC typically employs technologies such as radio frequency identification (hereafter referred to as RFID) and data warehouses to collect, store, and process large volumes of complete and heterogeneous data from both internal and external sources (Brewer and Johnson, 2010; Madakam et al., 2015). Secondly, tools such as cloud platforms, data mining techniques, and robotic process automation (hereafter referred to as RPA) are commonly applied to analyze data, visualize results, and ultimately extract value from data by enabling data-driven decision-making (Onggo et al., 2021; Soni et al., 2022). As a result, the whole process can support the construction of big data center, facilitate comprehensive financial digitalization, and enhance the decision-making function of management accounting (Brynjolfsson and McElheran, 2016; Ahmed et al., 2020). Therefore, digital technologies, data value chain, and financial processes should be considered as the most important factors influencing the digitalization of FSSC.

Moreover, the digitalization of FSSC requires appropriate strategy, culture, structure, and relationships with stakeholders (Colli et al., 2018). Specifically, first of all, well-defined strategies provide clear direction and long-term goals for digitalization. These strategies ensure that digital initiatives are aligned with the overall business objectives of the enterprise, allowing FSSC to prioritize resources and set measurable targets (Lam and Law, 2019; Hess et al., 2020). Secondly, supportive organizational culture plays a critical role in embracing change and encouraging innovation. When employees are open to adopting digital tools and processes, and when management fosters a culture of learning and adaptation, the chances of successful transformation significantly increase (Herbert and Seal, 2012; Fulton and Parchure, 2018). Thirdly, effective structural design ensures that FSSC operates with clarity, efficiency, and flexibility. For instance, streamlined and agile organizational structure allows for quicker decision-making, improved internal collaboration, and better integration of digital technologies into daily operations (Janssen and Joha, 2008; Chanias and Hess, 2016; Sova et al., 2022). Lastly, strong relationships with stakeholders such as business units, IT departments, and external partners are essential for gaining cooperation, securing resources, and ensuring that digital solutions meet real business needs. In addition, open communication and cross-functional collaboration enable FSSC to co-create value and respond effectively to changing demands (Buntak et al., 2021; Petrova et al., 2021).

However, there is a lack of in-depth academic understanding of digitalization of FSSC, particularly in the context of Chinese state-owned enterprises. First, one major gap lies in the absence of research that explores the specific factors influencing digitalization in the unique context of FSSC. This is largely because most of the influencing factors discussed in the existing literature are not unique to digitalization of FSSC, but are instead derived from broader frameworks of enterprise and financial digitalization. Second, there is limited

literature focused on developing a robust framework for evaluating the development level of digitalization of FSSC, due to the underestimation of its importance and prevalence. Although there have been many studies on the evaluation of development levels of digitalization in both the enterprise and financial function levels, research specifically focusing on digitalization of FSSC remains extremely limited. Existing evaluation systems tend to treat financial departments as a homogeneous whole, without accounting for the distinct role of the FSSC as a centralized service unit with unique structural, operational, and technological characteristics. As a result, they often fail to reflect the specific pathways, stages, and capabilities involved in the digitalization of FSSC. Furthermore, most current studies overlook the fact that FSSC serves not only as a basic financial processing center, but also increasingly as a strategic hub for automation, data-driven decision-making, and value creation within the enterprise. Therefore, it is crucial to build a clear and practical framework to evaluate the digitalization of FSSC.

2.3 Maturity

Maturity, as an important evaluation indicator, often refers to the state or level of development, completeness or sophistication that an individual, organization, process or concept achieves over time (Gottschalk, 2009; Mettler, 2011; Maier et al., 2011). Specifically, the maturity model is typically characterized as continuous, progressive and irreversible, as it usually divides the development process of entities listed above into multiple levels ranging from low to high, each of which is based on the further improvement of the previous level.

2.3.1 Capability Maturity Model

Capability maturity model (hereafter referred to as CMM) evolved from the maturity model and was initially developed by the Software Engineering Institute at Carnegie Mellon University in 1987. The CMM provides a structured approach for organizations to evaluate the capability maturity of specific development processes, identify areas for improvement, and progress to higher levels of maturity, particularly in the context of software and systems engineering (Paulk et al., 1993; Lee et al., 2007). Moreover, the CMM has evolved into a widely adopted model for assessing the maturity of process capability across various industries such as manufacturing and finance, and functional domains including human resource, marketing, project management, and financial management (Grant and Pennypacker, 2006; Morgan, 2007; Doss et al., 2008; Chrissis et al., 2011).

More importantly, implementing the CMM requires the division of maturity levels, the construction of maturity evaluation indicator system, and the selection of appropriate model development methods (Paulk et al., 1993; Fraser et al., 2002; Marx et al., 2012). First of all,

maturity levels represent the progressive stages of capability development within the model. The number of maturity levels typically ranges from three to six, with five levels being the most commonly adopted structure in existing models. This five-level structure offers a balanced framework, from initial and unmanaged stages to fully optimized performance. In addition, the specific number of levels should align with the design purpose and application context (Chrissis et al., 2011). Secondly, in the evaluation indicator system, key process areas (hereafter referred to as KPA) and their corresponding indicators should be clearly identified, as they constitute the core components of each maturity level. Specifically, each maturity level is associated with a defined set of KPAs that must be fulfilled in order to attain that level. Each KPA reflects a critical area of process capability and defines the specific problems that must be addressed, as well as the objectives to be achieved, in order for an organization to progress to the corresponding maturity level. Moreover, the number of KPAs typically varies depending on the scope of the model and the complexity of the domain (Mettler, 2011). Based on the above structure, appropriate model development methods should be employed to construct a reliable and comprehensive CMM. These methods, which can be either qualitative or quantitative, are essential for designing maturity levels, identifying relevant KPAs, and ensuring that the evaluation indicator system reflects both theoretical soundness and practical applicability (De Bruin et al., 2005; Becker et al., 2009).

Finally, several studies have applied the CMM to the field of financial management, particularly in FSSC, to assess the capability maturity level of their development processes more precisely. Table 2.1 presents nine representative models on the capability maturity of FSSC, serving as key references. Therefore, a review of the existing CMM for FSSC shows that while most studies adopt the fundamental components of classical CMM frameworks, they differ in the design of evaluation indicators. The models listed in Table 2.1 demonstrate the following characteristics. Firstly, the number of KPAs typically ranges between four and six. Commonly included KPAs are strategic planning, personnel management, information systems, process management, and operation management, encompassing essential aspects of activities in FSSC. Secondly, most models adopt a five-level maturity structure, with typical stages labeled as initial, repeatable, defined, managed, and optimizing, or similar terms. Thirdly, most models employ a combination of Analytic Hierarchy Process and Fuzzy Comprehensive Evaluation methods for model construction and validation. This methodological combination enables both systematic structuring and quantitative evaluation, and reflects a dominant trend across the maturity models included in this category. Fourthly, some models are designed to assess the overall capability maturity of financial management systems within an enterprise. In contrast, others are specifically focused on evaluating the capability maturity of FSSC, which is only a component of the broader financial function. Finally, many models are developed for the FSSC of a single enterprise, making them useful only in specific cases. These models often lack general applicability and may not be suitable

for use across different FSSCs.

2.3.2 Digital Maturity Model

Digital maturity is considered an application of the CMM in the current context of digitalization, since digitalization is not a one-time event but rather a progressive and multi-stage development process. It is commonly defined as the current state of digitalization of organization, in which the term of maturity is used to describe the degree of completion of its digitalization (Chantias et al., 2019). In addition, the significance of digital maturity is to guide the organization in systematically preparing for and adapting to the continuous digital transformation (Kane et al., 2017). Furthermore, some scholars divide digital maturity into digital readiness, digital intensity, and digital contribution (Berghaus and Back, 2016; De Carolis et al., 2017; Remane et al., 2017; Canetta et al., 2018). Specifically, digital readiness refers to the preparation of organization for digitalization, including its technological infrastructure, employee digital capability, leadership awareness, and organizational culture. Digital intensity reflects the actual level of digital technology usage within the organization. It encompasses the degree to which digital tools, platforms, and processes are integrated into core business operations and decision-making. Digital contribution focuses on the measurable value created through digitalization, including improvements in efficiency, customer satisfaction, innovation, and financial performance.

This paper argues that the digital maturity model is a framework used to assess and enhance the organization's capability for digitalization across various dimensions. It provides a structured approach for organizations to evaluate the current maturity level of its digitalization, identify areas for improvement, and develop strategies to navigate the complexities of digitalization. As a result, the digital maturity model helps the organization track the progress of digitalization and prioritize investments in digital capabilities. It also supports continuous improvement by providing a step-by-step path toward higher levels of digital performance, thereby facilitating better decision-making and long-term value creation. Most importantly, digital maturity models have already been applied to enterprise digitalization since the rise of Industry 4.0 in 2011, when most enterprises, especially in the manufacturing sector, began their digital and intelligent transformation. Therefore, many researchers have begun helping enterprises assess the overall development levels of their digitalization by establishing specific digital maturity models, whereas some of them have paid much more attention to the maturity of financial digitalization, developing dedicated digital maturity models for financial management. Table 2.2 and 2.3 present representative models on the digital maturity of enterprise and of finance respectively, serving as main references.

A review of digital maturity models developed for enterprise reveals that most follow the basic structure of traditional CMM frameworks. However, differences still exist in the design of specific KPAs, the classification of maturity levels, and the application of development methods. The representative models listed in Table 2.2 share the following characteristics. In terms of KPAs, most models contain between four and nine core areas. These KPAs commonly include dimensions such as strategy and leadership, organizational culture, employee capability, digital infrastructure, smart operation, product innovation, and customer, covering the key aspects involved in enterprise digitalization, including both organizational and technical elements. With regard to maturity levels, most models define between two and six levels to describe the progression of enterprise digitalization. These levels often range from an initial or basic stage to an optimized or leading stage. Some models use descriptive labels such as outsider, beginner, intermediate, experienced, and expert, while others adopt more abstract numeric or performance-based classifications. In terms of development methods, models are developed using qualitative, quantitative, or mixed methods. Qualitative methods often involve literature analysis, expert interview, or case study to identify and refine KPAs and related indicators. Quantitative methods are typically based on structured questionnaires using Likert scales to collect the data. When analyzing the data, some models simply use the total scores of each dimension to represent maturity, whereas others employ advanced statistical tools to dynamically weight KPAs and corresponding indicators for more accurate assessment. Furthermore, in several studies, Design Science Research is employed as a mixed-methods approach that integrates both qualitative insights and quantitative validation to ensure theoretical soundness and practical value. Regarding the scope of application, some models are designed to assess digital maturity within a single enterprise, focusing on internal transformation, system integration, and process digitization. Others are intended for broader application across industry clusters, especially in the manufacturing sector, where digitalization often follows similar patterns in the context of Industry 4.0. Therefore, those variations illustrate the differences in complexity and operational difficulty across various digital maturity models.

A review of the existing digital maturity models for enterprise finance shows that most studies draw from classical maturity model structures but tailor them to the specific context of financial digitalization. The representative models listed in Table 2.3 exhibit the following characteristics. First of all, these three models include five to seven KPAs, covering areas such as strategy and organization, infrastructure, financial operation, IT application, data management, and digital performance. These KPAs represent the key components of financial digitalization, involving both technological capabilities and managerial effectiveness. Secondly, all models adopt five maturity levels. While naming conventions vary slightly, these levels commonly describe a progression from early-stage digital capability to fully integrated, intelligent financial systems. Thirdly, all models adopt a

combination of Analytic Hierarchy Process and Fuzzy Comprehensive Evaluation methods for weight determination, as well as for model application and validation. Lastly, all models are developed for financial digitalization within a single enterprise, often based on specific case studies. As a result, their practical value may be limited to the originating enterprise, and they often lack general applicability across different enterprises or sectors.

2.3.3 Model Limitation

Through a comparison of the representative maturity models cited above, it can be observed that substantial progress has been made in both the theoretical research and practical application of CMM for FSSC, as well as digital maturity models for enterprise and finance. Nevertheless, this study also identifies several limitations in the existing research.

Firstly, there is still an evident gap in the literature regarding digital maturity model for FSSC in Chinese state-owned enterprise. Most of the literature has only built CMM for FSSC to evaluate its overall development and performance, while overlooking the impact of digitalization on its evolution. As a result, few studies have explored the level of digitalization in the development of FSSC in depth. Although there have been studies on digital maturity models for enterprise and finance, research specifically focusing on digital maturity model for FSSC is still almost blank. Existing digital maturity models tend to assess financial digitalization at the enterprise level, without isolating FSSC as a distinct functional unit. Consequently, they often overlook the unique pathways, challenges, and requirements of digitalization associated with FSSC operations. Among them, the Chinese literature primarily focuses on analyzing the maturity of FSSC capabilities and financial digitalization in small and medium-sized enterprises, while paying insufficient attention to state-owned enterprises, which heavily rely on and continue to develop FSSC. This narrow focus limits their practical reliability and generalizability.

Secondly, regarding the determination of KPAs in the maturity evaluation indicator system and the division of maturity levels, most models tend to directly apply both KPAs and maturity levels published by professional institutions. This practice not only leads to models sharing similar typical components, mainly including strategy, culture, personnel, structure, technology, process, and performance, but also results in selected indicators being insufficiently comprehensive. For instance, only a few digital maturity models consider the contribution of digitalization to enterprise performance and the implementation of digital security protection as part of their evaluation dimensions. Moreover, most models consider only internal factors and fail to account for external elements such as the establishment of ecosystems, relationships with stakeholders in the external supply chain, and the supportive activities within the enterprise value chain. Lastly, it is worth noting that KPAs selected in

Table 2.1 Representative Capability Maturity Models for FSSC

No.	Authors	Models	KPAs	Maturity Levels	Development Methods
1	Ai, 2015	Financial Management Maturity Model	Integrated Management, Budget and Cost management, Tax Management, Fund Management, Accounting Management, Financial Systems	–	–
2	Zhang, 2015	Finance Capacity Maturity Model	Planning and Execution, Performance and Decision, Transaction Processing, Financial Reporting, Compliance Control, Corporate Governance	Initial, Developing, Standardized, Optimizing, Leading	–
3	Zhang, 2016	FSSC-CMM	Personnel Management, Process Management, Information Technology, Operation Management	Initial, Repeatable, Defined, Managed, Optimizing	Extended Analytic Hierarchy Process; Fuzzy Comprehensive Evaluation
4	Ma, 2017	FSSC-CMM	Strategic Planning, Process Management, Information Systems, Personnel Management	Initial, Managed, Defined, Predictable, Optimizing	Analytic Hierarchy Process; Fuzzy Comprehensive Evaluation
5	Wei and Huang, 2018	Advanced FSSC-CMM	Personnel Management, Internal Process, Information Technology, Operation Management	Disordered, Simple, Upgraded, Quantitatively Managed, Continuously Improving, Independent Sharing	Fuzzy Comprehensive Evaluation
6	Jin, 2022	Financial Capability Maturity Model	Strategic Layout, Business Process, Personnel Learning, Information Systems	Initial, Standard, Normative, Optimizing, Perfect	Analytic Hierarchy Process; Fuzzy Comprehensive Evaluation
7	Zhang and Sheng, 2022	FSSC-CMM	Organization Personnel, Business Process, Operation Management, Information Systems	Initial, Repeatable, Defined, Managed, Optimizing	Analytic Hierarchy Process; Fuzzy Comprehensive Evaluation

No.	Authors	Models	KPAs	Maturity Levels	Development Methods
8	Li, 2023	FSSC-CMM	Process Setting, Information Systems, Personnel Management, Operation Management, Strategic Planning	Initial, Repeatable, Defined, Managed, Optimizing	Analytic Hierarchy Process; Fuzzy Comprehensive Evaluation
9	Wang, 2023	Intelligent Finance Maturity Model	Strategy, Financial Management Process, Organization and Personnel, Next-Generation Digital Technology	Initial, Developing, Standardized, Optimizing, Leading	Analytic Hierarchy Process; Fuzzy Comprehensive Evaluation

Table 2.2 Representative Digital Maturity Models for Enterprise

No.	Authors	Models	KPAs	Maturity Levels	Development Methods
1	Lichtblau et al., 2015	Industrie 4.0 Readiness	Strategy and Organization, Smart Factory, Smart Operation, Smart Product, Data-driven Service, Employee	Outsider, Beginner, Intermediate, Experienced, Expert, Top Professional	Literature Analysis Method; Survey Research Method
2	Gill and VanBoskirk, 2016	Digital Maturity Model 4.0	Culture, Organization, Technology, Insight	Skeptic, Adopter, Collaborator, Differentiator	Survey Research Method
3	Leyh et al., 2016	System Integration Maturity Model Industry 4.0	Vertical Integration, Horizontal Integration, Digital Product Development, Cross-Sectional Technology Criteria	Basic, Cross Departmental, Horizontal and Vertical, Full, Optimized Full	Literature Analysis Method
4	Schumacher et al., 2016	Industry 4.0 Maturity Model	Strategy, Leadership, Governance, Culture, Personnel, Product, Customer, Operation, Technology	Levels 1-5: Never Achieving to Fully Achieving	Design Science Research

No.	Authors	Models	KPAs	Maturity Levels	Development Methods
5	De Carolis et al., 2017	Digital Readiness Assessment Maturity Model	Design and Engineering, Production Management, Quality Management, Maintenance Management, Logistics Management	Initial, Managed, Defined, Integrated and Interoperable, Digital-Oriented	Design Science Research
6	Accenture, 2018	Digital Transformation Index Model for Chinese Enterprise	Digital Marketing, Intelligent Manufacturing, Intelligent Control, Product Innovation, Digital Business Model, Digital Investment	General Enterprise, Transformation Leader	–
7	Bandara et al., 2019	Industry 4.0 Maturity Model in Banking Sector	Product and Service, Technology and Resource, Strategy and Organization, Operation, Customer, Governance, Employee	Initial, Managed, Defined, Established, Digital Oriented	Literature Analysis Method; Case Study Method
8	Gökalp and Martinez, 2021	Digital Transformation Capability Maturity Model	Strategic Governance, Information and Technology, Digital Process Transformation, Workforce Management	Incomplete, Performed, Managed, Established, Predictable, Innovating	Literature Analysis Method; Expert Interview Method; Case Study Method
9	Kljajić Borštnar and Pucihar, 2021	Multi-attribute Model	Digital Technology, Role of Informatics, Digital Business Model, Strategy, Human Resource, Organizational Culture, Management	No Capability, Planning, Limited, Full Capability	Design Science Research
10	Wang et al., 2021	Digital Maturity Evaluation System	Strategy and Organization, Infrastructure, Business Process and Management Digitalization, Comprehensive Integration, Digital Performance	Initial, Growing, Upgraded, Comprehensively Integrated, Continuously Improving	Literature Analysis Method; Delphi Method

Table 2.3 Representative Digital Maturity Models for Enterprise Finance

No.	Authors	Models	KPAs	Maturity Levels	Development Methods
1	Du, 2023	Evaluation Model for Financial Digital Maturity of Petroleum Enterprise	Strategy and Organization, Infrastructure, Intelligent Financial Operation, Data Value Creation, Comprehensive Integration, Financial Risk Control, Digital Performance	Initial, Growing, Upgraded, Comprehensively Integrated, Continuously Improving	Analytic Hierarchy Process; Fuzzy Comprehensive Evaluation
2	Li, 2023	Finance Digital Maturity Model	Strategic Planning, Organizational Change, Financial Service Support, Effectiveness and Efficiency, Data Management, IT Application	Original, Basic, Standard, Mature, Intelligent	Analytic Hierarchy Process; Fuzzy Comprehensive Evaluation
3	Zhang, 2024	Evaluation System for Digital Maturity of Enterprise Finance	Organization, Technology, Data, Advance Warning, Business Service, Decision-making	Initial, Developing, Standard, Mature, Leading	Analytic Hierarchy Process; Fuzzy Comprehensive Evaluation

these models have not been dynamically adjusted in accordance with technological advancements, which is not conducive to the continuous improvement of the models and their effective application in the evolving digital ecosystem.

Thirdly, most digital maturity models for enterprise are initially constructed through a combination of literature analysis and expert consultation. While this approach is effective for establishing a conceptual foundation, it often lacks a clear method to quantify the importance of KPAs and indicators. Some models even implicitly assume equal weights for all indicators, which may not reflect their real importance. In addition, the model validation is usually done through simple surveys or interviews, relying on subjective scoring by managers or employees from selected enterprises. These scores are often used directly, without further processing or calibration, which can reduce the objectivity and reliability of the results. However, although most maturity models, particularly those in the domains of FSSC and financial digitalization, have employed appropriate methods to support model validation, they often lack a solid theoretical foundation in the initial development phase, which may hinder the sustainable improvement and application in the future.

2.4 Systems Theory

2.4.1 Concept

This study introduces systems theory to address several of the aforementioned limitations related to the construction of maturity evaluation indicator system, and to enhance the development of maturity models. Systems theory is an interdisciplinary framework for understanding complex entities and their dynamic interactions. It provides a holistic approach to analyzing how different parts of a system function together to produce overall behavior, as well as how systems interact with their external environments (Skyttner, 2005; Luhman et al., 2013). In the field of management, systems theory views organizations as complex and dynamic systems composed of interrelated and interdependent components. It explains how different parts of an organization interact and how changes in one part can influence the entire system. As a result, systems theory can assist managers in designing effective organization structure, fostering a culture of continuous learning and adaptation, formulating informed strategies, and conducting comprehensive assessments of organizational activities and processes (Jackson, 2000; Rice, 2013).

More importantly, the Input-Processing-Output (hereafter referred to as IPO) model, a fundamental concept within systems theory, describes the structure and function of systems by outlining a systematic process that starts with input acquisition, followed by transformation through processing, and concludes with the generation of output (Ilgen et al.,

2005; Subiyakto and Ahlan, 2014). Specifically, inputs such as raw data, user commands, resources, or materials are first collected. These inputs are then transformed through a series of operations or processes such as sorting, filtering, computation, or data analysis into desired outputs, including physical products, reports, services, or information, which are ultimately delivered to end users. Additionally, the IPO model regards organizations as open systems and incorporates external environment as an important factor that exerts a moderating effect on the overall system (Wang et al., 2012; Schneider et al., 2017).

2.4.2 Application

In terms of the application of systems theory, many researchers have adopted the IPO model to identify key factors influencing system quality across various fields, particularly in organizational management and information systems. For instance, Espinosa et al. (2006) developed an IPO-based framework to better understand how global boundaries impact the success of global information systems projects and which mediating processes enhance the likelihood of success. Building upon the IPO model, Wang et al. (2012) found that total quality management positively affects hotel performance with the mediating effect of market orientation and the moderating role of external environmental conditions. Based on the processional and causal models, Subiyakto and Ahlan (2014) proposed an alternative IPO model for evaluating the performance of information systems, which includes project contents and institutional contexts as inputs, project management and product utilization as processing components, and system impacts as outputs. Moreover, Zhang et al. (2022) suggested that the heterogeneity of entrepreneurial team is positively correlated with both team interaction and decision-making performance from the perspective of IPO model.

Beyond its application in organizational management and information systems, systems theory has also been widely utilized to explore digitalization processes and their influencing factors. According to Parviainen et al. (2017), enterprise digitalization can be viewed as a system comprising various interacting elements and their interrelationships, all of which contribute to the realization of digital transformation. Doroshenko et al. (2020) applied systems theory to the field of business process digitalization to investigate ways of enhancing innovation efficiency and enterprise competitiveness. In addition, systems theory has been adopted to analyze the digitalization of small and medium-sized enterprises as well as high-tech enterprises. For example, Viswanathan and Telukdarie (2021) adopted a system dynamics approach to model how digitally enabled smart business solutions deployed via innovation hubs can enhance the productivity, resilience, and strategic decision-making of small and medium-sized enterprises, simulating the impact of skill development and digital investment on enterprise growth, particularly in the context of post-pandemic recovery. Similarly, Barmuta et al. (2022) utilized a systems approach to examine the national

digitalization strategy in Germany, highlighting how interrelated policy pillars collectively support the growth of a digital and innovation-driven economy. This systemic framework allows high-tech enterprises to manage digitalization projects more effectively, thereby improving competitiveness and operational coordination within the context of Industry 4.0. Their findings emphasize the role of systems theory in providing a structured and holistic understanding of digitalization.

Furthermore, the IPO model is frequently used to describe the flow of information or activities within a system, to identify all factors influencing this process, and to improve system outcomes. As a result, it enables researchers to gain a more comprehensive understanding of digitalization. For instance, Deepu and Ravi (2021) developed a conceptual framework based on the IPO model to explain the process of supply chain digitalization. The framework includes organizational and technological factors affecting the digitalization process (input), methods for processing factors through data-information-knowledge-wisdom hierarchy (processing), and value creation and effective decision-making as outcomes (output). Deng et al. (2022) adopted the Delphi method to develop a multidimensional conceptual framework for analyzing the digitalization of healthcare systems. In this framework, healthcare is conceptualized as the core input. The transformation process is driven by five key factors, including community, technology, policy, services, and management, which together constitute the processing stage. The output comprises a set of desirable outcomes such as efficiency, intelligence, sustainability, trustworthiness, safety, health benefits, and economic value. By effectively structuring these elements, the IPO model facilitates the transformation of traditional healthcare into smart healthcare.

Most importantly, systems theory can be further extended to the domain of maturity models. To overcome the inherent limitations of CMM, notably its mechanistic structure and linear progression, as well as the limitations of representative models identified in Section 2.3.3, including the limited applicability to Chinese state-owned enterprises, lack of adaptability to dynamic environments, and constraints on innovation, Pernet and Cano (2014) proposed a systemic maturity model based on the systems theory. This model conceptualizes organizational maturity as an emergent property arising from process alignment and integration, with a particular emphasis on both the external environment and the coordination and interaction among different elements. The proposed systemic maturity model was applied to assess the maturity levels of organizational governance, risk management, and compliance processes in a real-world organization, indicating moderate process cohesion and identifying areas for improvement. Furthermore, Alves et al. (2011) developed a systemic maturity model for Brazilian public software ecosystems. Drawing on systems thinking and structured around learning cycles, this model departs from traditional capability-based metrics and instead emphasizes ecosystem evolution, reflexivity, and institutional adaptation as key

indicators of maturity.

2.5 Research Gap

This chapter begins by reviewing the existing literature on financial shared service, focusing on five key aspects: its origin, objectives, development, influencing factors, and performance evaluation. It also defines FSSC as a unit that delivers centralized and standardized finance-related services within an enterprise to enhance efficiency and consistency. However, existing studies mainly focus on traditional functions and performance evaluation, with limited attention to the impact of digital technologies on FSSC. Secondly, through an examination of the origin, definition, influencing factors, and evaluation systems of digitalization in both enterprise and finance, this chapter introduces the concept of digitalization of FSSC. It mainly defines its core essence as the management of the data value chain through the integration of digital technologies with processes in FSSC. However, there is still a lack of in-depth understanding of the digitalization of FSSC, particularly in identifying the unique factors that influence it and in developing a dedicated evaluation system for assessing its level of development. Thirdly, in order to assess the development levels of both FSSC and its digitalization, this chapter explores the concept of maturity, particularly within the frameworks of the CMM and the digital maturity model. These models provide structured approaches for evaluating and enhancing process capability and digitalization respectively. However, after analyzing existing maturity models for FSSC, enterprise digitalization, and financial digitalization, this chapter summarizes the limitations of these models and finds that current research lacks a generalizable digital maturity model specifically designed to evaluate the development of digitalization of FSSC in Chinese state-owned enterprise. Finally, this chapter introduces systems theory, specifically the IPO model, which has been widely applied in the field of digitalization to better understand the digitalization process, and is also utilized in the domain of maturity modeling to improve traditional maturity models by enhancing their adaptability and structure.

To fill these research gaps, it becomes both necessary and significant to develop a digital maturity model for measuring and improving the development level of digitalization of FSSC in Chinese state-owned enterprise. Building upon the aforementioned maturity models and systems theory, this paper intends to adopt a mixed-methods approach that combines qualitative and quantitative methodologies to develop a comprehensive digital maturity model that integrates both internal and external factors, while also taking into account the latest technologies and applications relevant to Chinese state-owned enterprises.

More specifically, from a model development perspective, the comparative review of representative maturity models related to FSSC and digitalization in Section 2.3, including

the CMM for FSSC as well as digital maturity models for enterprise and enterprise finance, serves two main purposes. First, it provides the theoretical basis for selecting an appropriate strategy for developing a digital maturity model tailored to the digitalization of FSSC in Chinese state-owned enterprise. Second, it helps inform the direction for model optimization. Together, these insights guide the overall development of the proposed digital maturity model, within which the construction of maturity evaluation indicator system and the division of maturity levels constitute two interrelated components.

First, according to Becker et al. (2009), maturity model development typically follows one of four strategies: developing a completely new model, enhancing an existing model, combining multiple existing models into a new one, or transferring structures or contents from existing models to a new application domain. Based on the findings of the literature review, this study adopts the model-combination strategy to develop the digital maturity model for FSSC in Chinese state-owned enterprise.

This choice is driven by the hybrid nature of the digitalization of FSSC, which lies at the intersection of enterprise digitalization and financial digitalization. No single existing maturity model sufficiently captures this dual positioning. In contrast, the three families of maturity models reviewed in Section 2.3 jointly cover the core domains that underpin the digitalization of FSSC, including the operational characteristics of FSSC itself, the digital transformation of enterprise-wide systems, and the digitalization of financial management. By adopting the model-combination strategy, this study is able to integrate complementary perspectives from different maturity models and synthesize their respective strengths. Specifically, the CMM for FSSC provides insights into centralized financial processes and organization structures that characterize shared service operations. Digital maturity models for enterprise contribute perspectives on digital infrastructure, system integration, and broader enterprise transformation. Digital maturity models for enterprise finance include financial and data management, as well as data value creation. The integration of these perspectives enables the development of a digital maturity model that is both comprehensive and context-specific, ensuring that the resulting KPAs and maturity levels are well aligned with the FSSC digitalization context.

Furthermore, in the field of digitalization research, scholars frequently synthesize multiple maturity models to construct new evaluation frameworks, especially when defining KPAs and maturity levels. For example, Schumacher et al. (2016) combined and extended existing readiness and maturity models in manufacturing to propose an Industry 4.0 Maturity Model. Similarly, Ding (2020) integrated maturity models for quality management and manufacturing digitalization to develop a digital maturity model tailored to quality management in the manufacturing sector. Li (2023) also combined financial capability

maturity models with enterprise digitalization maturity models to construct a digital maturity model for enterprise financial management. These studies further support the appropriateness of adopting the model-combination strategy in this research.

Second, the comparative review of existing maturity models also helps identify several structural limitations that constrain their applicability when developing a new digital maturity model in Section 2.3, thereby informing the direction for model optimization in this study. One prominent limitation lies in the rigidity and homogeneity of model structures. Many existing models tend to reuse similar KPAs and maturity level frameworks proposed by professional institutions without sufficient adaptation to specific organizational contexts. Another major limitation concerns the insufficient adaptability of existing models to dynamic environments and technological advancement.

To address these limitations, this study introduces systems theory as the main optimization direction for model development, with particular emphasis on the IPO model. Within the field of digitalization research, the IPO model has been widely applied to conceptualize digitalization as a dynamic open system. From this perspective, digital technologies, infrastructure, strategy, and talent constitute key inputs, which are transformed through digitalized workflows and data transformation. These processes ultimately generate outputs in the form of value creation, performance improvement, and enhanced decision support, while being continuously influenced by the external environment (Wang et al., 2012; Deepu and Ravi, 2021; Barmuta et al., 2022; Deng et al., 2022). In addition, systems theory provides a useful foundation for improving traditional maturity models by moving beyond rigid and linear structures. When informed by systems theory, organizational maturity can be understood as an emergent outcome of process alignment, integration, and interaction among multiple elements, rather than as a simple progression across predefined stages. This perspective allows the systemic maturity model to simultaneously consider internal structures, external environments, and their interdependencies (Pernet and Cano, 2014). As a result, systems theory is particularly well suited to the digitalization of FSSC, as FSSC integrates technologies, processes, data, and organizational coordination while interacting with both internal business units and the external environment.

Taken together, by adopting the model-combination strategy and integrating systems theory, this study establishes a theoretically grounded approach to developing the digital maturity model for FSSC in Chinese state-owned enterprise. This approach mainly involves two interrelated components: the preliminary construction of maturity evaluation indicator system and the initial division of maturity levels.

Chapter 3 Research Methodology

This chapter presents the methodological framework employed in the study. It explains the rationale for adopting Design Science Research Paradigm, Mixed Research Approach and Method, and then establishes the procedure for model design, detailing the specific steps from problem definition to model evaluation.

3.1 Research Paradigm

Research paradigm refers to the philosophical framework that guides the conduct of research, defining how researchers understand and interpret reality, knowledge, and methodologies (Creswell and Creswell, 2017). This study adopts the **Design Science Research Paradigm** informed by pragmatism. According to Saunders et al. (2009), pragmatism recognizes that no single point of view can provide a complete picture of reality, and therefore supports the use of both objective and subjective knowledge, making it especially compatible with mixed methods research. In addition, it emphasizes solving practical problems and applying research findings directly to real-world contexts. Design Science Research (hereafter referred to as DSR) aligns seamlessly with pragmatism. It is a research paradigm commonly applied in the fields of information systems, engineering, and management, focusing on the design, creation, and evaluation of innovative artifacts intended to solve practical problems. Such artifacts typically include models, frameworks, methods, constructs, or instantiated systems designed to effectively address organizational and technological issues (March and Smith, 1995; Hevner et al., 2004). Unlike traditional social science methodologies that primarily seek explanatory or descriptive understanding, DSR emphasizes the practical usefulness of knowledge. It aims at addressing real-world issues through rigorous artifact development, iterative refinement, and comprehensive evaluation processes. As a result, DSR consistently balances rigor in terms of theoretical soundness and relevance in terms of practical utility, bridging the gap between academia and practice (Gregor and Hevner, 2013). Due to its pragmatic orientation, DSR has become particularly influential in fields such as digitalization, maturity modeling, enterprise architecture, and information system design, providing both practical solutions and theoretical contributions. For example, several studies have successfully applied DSR to develop digital maturity models in various organizational contexts, including the Industry 4.0 Maturity Model (Schumacher et al., 2016), and the Multi-attribute Model (Kljajić Borštnar and Pucihar, 2021).

This research aims to develop a digital maturity model specifically for FSSCs in Chinese state-owned enterprises, addressing the need for a structured way to assess and improve the development level of their digitalization, which requires both theoretical rigor and practical

relevance. Therefore, DSR aligns perfectly with this dual requirement, as it is particularly suitable for the following reasons. First, it promotes methodological pluralism, allowing for the integration of both qualitative and quantitative methods to comprehensively address the research questions. This pluralism supports structured model design, which ensures theoretical rigor. Second, it aligns with the iterative nature of the model development process, emphasizing continuous refinement of theories and solutions through real-world application and expert feedback, thereby delivering practical relevance. Third, it recognizes the collaborative participation of stakeholders from academia and industry, ensuring that the outcomes are both theoretically sound and practically valuable. The ontological, epistemological, and methodological assumptions aligned with DSR paradigm in this study are summarized in Table 3.1.

Table 3.1 Ontological, Epistemological and Methodological Assumptions

Assumptions	Descriptions
Ontology	This study is based on the assumption that reality is shaped by purposeful human action and is constructed through the creation and evaluation of designed artifacts, specifically a digital maturity model developed for FSSCs in Chinese state-owned enterprises. It views reality as artificial and problem-oriented, where knowledge emerges from the interaction between the artifact and its use context, particularly within this domain.
Epistemology	Knowledge is generated through the iterative design, construction, and empirical evaluation of artifacts intended to address real-world problems. In this study, knowledge about digital maturity is created through the development and refinement of a digital maturity model grounded in both theoretical insights and practical validation.
Methodology	This study adopts mixed method, combining qualitative and quantitative methods to iteratively construct, improve, and evaluate the digital maturity model. This method ensures both theoretical rigor and practical relevance in addressing the research problem.

3.2 Research Approach

Research approach refers to the general plan for how a researcher goes about answering the research question, including the logic of reasoning and the relationship between theory and data (Creswell and Creswell, 2017). In line with the DSR paradigm, this study adopts a **Mixed Research Approach** that combines induction and deduction, while also integrating

abductive reasoning at the early stages of model development. According to Saunders et al. (2009), a mixed research approach integrates both inductive reasoning, which derives theory from empirical observations, and deductive reasoning, which tests theory through structured analysis. Meanwhile, abductive reasoning seeks the most plausible explanation based on incomplete or surprising observations, and is particularly useful in the early phases of research where new theoretical structures or artifacts are being explored (Paavola et al., 2006). This mixed research approach is particularly suitable for this study. It begins with the observation of practical challenges, using abductive reasoning to propose an initial conceptual model. This is followed by inductive reasoning to identify and structure model components, and finally deductive reasoning to refine and validate the model. This combination enables the development of a digital maturity model that has both theoretical rigor and practical relevance, aligning well with the iterative nature of DSR and the pragmatic emphasis on practical solutions.

The mixed research approach is justified for the following specific reasons. First, abductive reasoning plays a critical role in the early phase of this study by guiding the initial conceptualization of the digital maturity model and laying the foundation for further development. The study begins with the observation of real-world challenges faced by FSSCs in Chinese state-owned enterprises during their digitalization. In response to these context-specific and underexplored issues, abductive reasoning is used to generate plausible explanations and propose an initial framework for the digital maturity model, based on the current conditions and practical demands of the digitalization of FSSC as well as early insights from existing maturity models. Second, inductive reasoning plays an important role in developing the detailed content of the digital maturity model, drawing on expert opinions and findings from a comprehensive literature review. Through systematic comparison and synthesis, the initial framework generated by abduction is expanded into a complete conceptual model. This use of inductive reasoning contributes to the mixed research approach by enabling the systematic development of model content grounded in empirical insights. Third, the mixed research approach supports ongoing refinement and validation through continuous feedback loops between theory and practice. In this study, deductive reasoning is used to refine and test model components against expert feedback and real-world data, enabling structured evaluation of the model's applicability and reliability. Specifically, through iterative cycles between conceptual frameworks and empirical findings, the research continuously refines the model structure and content based on new evidence and expert input. Ultimately, the digital maturity model is tested and validated through real-world implementation, ensuring its theoretical rigor and practical relevance (Tashakkori and Teddlie, 2010; Creswell and Clark, 2017).

3.3 Research Method

Research method refers to the specific techniques and procedures used to collect, analyze, and interpret data in order to answer research questions (Creswell and Creswell, 2017). The choice of research method is guided by the nature of the research problem and the overall methodological approach adopted in the study. This study applies a **Mixed Research Method** in alignment with the DSR paradigm and the mixed research approach. The mixed method involves the combination of qualitative and quantitative techniques to collect and analyze data, allowing for a more comprehensive and iterative development and evaluation of the research artifact: the digital maturity model for FSSC in Chinese state-owned enterprise (Johnson and Onwuegbuzie, 2004; Venkatesh et al., 2016).

In line with the iterative design and evaluation cycle of DSR, qualitative methods are first used to establish the theoretical foundation, construct the initial framework, and incorporate expert knowledge. Specifically, this study conducts a literature analysis to synthesize existing maturity models as well as relevant research on digitalization, FSSC, and financial management. This provides the basis for constructing the initial structure and content of the digital maturity model. In addition, the Delphi method is applied to continuously gather expert insights and iteratively refine the model components. In the evaluation phase, quantitative methods are employed to structure, test, and validate the model. Specifically, this study applies the Analytic Hierarchy Process to quantitatively determine the relative weights of KPAs and indicators within the digital maturity model. Subsequently, a multiple case study, combined with Fuzzy Comprehensive Evaluation is conducted across selected FSSCs in Chinese state-owned enterprises to evaluate the digital maturity model in terms of its reliability, validity, and practical applicability. Additionally, both semi-structured interviews as a qualitative method and structured questionnaires as a quantitative method are used to collect empirical data from experts and practitioners throughout both the development and evaluation stages of the model. Therefore, this mixed-methods integration combines qualitative richness with quantitative precision to develop the digital maturity model that is both theoretically rigorous and practically relevant. The specific procedures and implementation steps for each method are described in the following sections.

3.4 Research Design

Research design can be regarded as a scientific discovery process involving problem identification, literature review, data collection, analysis, and validation. In DSR, research design is understood as a structured yet iterative process that focuses on two core activities: build, which involves the construction of innovative artifacts; and evaluation, which emphasizes assessing the utility, quality, and effectiveness of those artifacts in addressing

real-world problems (Hevner et al., 2004; Gregor and Hevner, 2013). These core activities are elaborated through a structured six-phase process proposed by Peffers et al. (2007), as follows. The first phase, problem identification and motivation, involves identifying a relevant practical problem and establishing its significance within the research context. The second phase, definition of objectives for a solution, focuses on specifying what the artifact is intended to achieve. The third phase, design and development, entails creating the artifact by drawing upon both theoretical foundations and empirical insights. The fourth phase, demonstration, applies the artifact to a specific instance of the problem to illustrate its utility. The fifth phase, evaluation, assesses the effectiveness, efficiency, and generalizability of the artifact through appropriate empirical methods. The final phase, communication, disseminates the research outcomes clearly to both academic and professional communities.

In this study, model design serves as the core activity, reflecting the research aim of developing a digital maturity model tailored to FSSCs in Chinese state-owned enterprises. However, in terms of methodological approaches to maturity model design, many existing models lack a sound theoretical foundation and systematic development process. Although numerous maturity models have been developed and applied across various domains, there is limited research on how to design a maturity model that is theoretically sound, rigorously tested, and widely accepted (García-Mireles et al., 2012; De Carolis et al., 2017). Only in recent years have some scholars begun to propose structured approaches for developing maturity models in a more systematic and theory-driven way. For instance, De Bruin et al. (2005) proposed a generic framework for developing maturity models applicable across various domains such as knowledge management, business process management, information systems, and IT governance. The framework consists of six key phases: first, scope, which defines the purpose, target audience, and boundaries of the model; second, design, which specifies the model architecture and structure; third, populate, which identifies and formulates the model content such as dimensions and indicators; fourth, test, which assesses the reliability, validity, and applicability of the model; fifth, deploy, which applies the model in the target context; finally, maintain, which ensures the model remains relevant and up to date over time. Meanwhile, Becker et al. (2009) proposed a procedure model which provides a comprehensive, systematic, and standardized roadmap for developing maturity models in the field of IT management. This model includes the following key stages: problem definition, comparison of existing maturity models, determination of development strategy, iterative maturity model development, and conception of transfer and evaluation. Based on a comparison of existing development frameworks, García-Mireles et al. (2012) noted that these frameworks follow similar underlying guidelines, and identified five common activities in the development of maturity models, including inception, elaboration, construction, deployment, and maintenance. The inception phase involves identifying the problem, key participants, and setting the scope and objectives. In the elaboration phase, the design strategy

and model architecture are defined. During construction, the maturity assessment tool is built and procedures for its application are established. The deployment phase focuses on validating the model and its assessment tool. Finally, in the maintenance phase, the model is updated and refined as needed.

Furthermore, among the studies reviewed in Chapter 2 that adopt DSR for the development of maturity models, Schumacher et al. (2016) serve as a representative example. In their study on assessing Industry 4.0 readiness and maturity in manufacturing enterprises, the authors combined the structured process of DSR with the step-by-step procedure for the maturity model development proposed by Becker et al. (2009). This dual-framework approach ensured both methodological rigor and practical relevance throughout the model development process. Therefore, building on this integrated methodology, this study establishes its own procedure for model design. Specifically, it synthesizes the DSR research design process with the common elements identified in the maturity model development frameworks discussed above, in order to guide the systematic construction and evaluation of a digital maturity model for FSSC in Chinese state-owned enterprise. The specific design steps, which consist of five key phases, are illustrated in Figure 3.1.

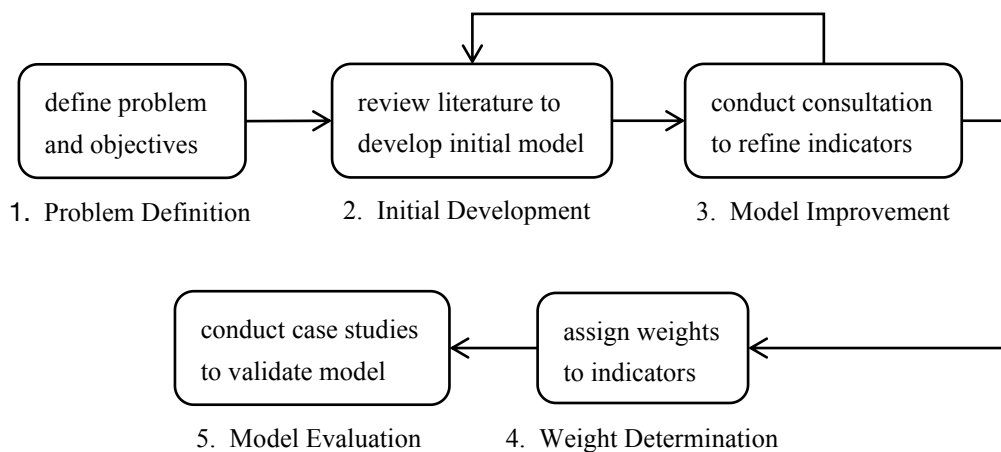


Figure 3.1 Procedure for Model Design

3.4.1 Problem Definition

The first step of the model design procedure begins with problem definition, which is elaborated in Chapter 1. This step entails four key aspects. First, it is essential to identify the drivers that motivate the development and application of the digital maturity model. As outlined in Chapter 1, both internal and external forces have catalyzed the digitalization of FSSCs in Chinese state-owned enterprises. Internally, challenges such as fragmented management structures, inefficient financial processes, and outdated information systems have restricted the effectiveness of FSSC. Externally, the advancement of digital technologies,

supportive government policies, growing regulatory pressure, and increasing market competition have collectively driven the need for digitalization. Second, the problem definition must clarify the targeted domains and stakeholder groups. This study focuses on two primary domains: the digitalization of financial management processes, particularly within FSSC, and the development of maturity models. The main stakeholders include academic researchers interested in financial digitalization, and practitioners, especially FSSC managers, who need a reliable tool to guide and benchmark their digitalization efforts.

Third, the practical relevance of the problem must be explicitly defined. Despite substantial progress in enterprise digitalization, many Chinese state-owned enterprises remain unclear about the current stage of digitalization in their FSSCs and the appropriate strategies for improvement. This ambiguity largely results from the absence of specialized evaluation tools and models tailored to the unique characteristics of digitalization of FSSC. Therefore, this study aims to develop a digital maturity model specifically for FSSCs in Chinese state-owned enterprises, providing a structured framework to evaluate the development level of their digitalization and to support continuous improvement and strategic transformation. Fourth, the type of maturity model to be developed must be determined. According to De Carolis et al. (2017), maturity models can generally be classified into three types based on their objectives: first, descriptive model, which aims to objectively depict the characteristics, status, and progression of a given phenomenon; second, prescriptive model, which focuses on identifying causal relationships between actions and outcomes in order to recommend best practices; third, comparative model, which provides benchmarking tools by comparing maturity levels across different organizations. Given its primary objective to describe the current state and development of digitalization in FSSC, this study adopts a descriptive maturity model. Specifically, the proposed digital maturity model aims to serve as the first systematic evaluation framework for describing the stages, components, and factors involved in digitalization of FSSC in Chinese state-owned enterprise.

3.4.2 Initial Development

The central phase of the model design procedure is the initial development, which is elaborated in detail in Chapters 2 and 4. This phase includes two essential tasks that lay the foundation for the development of the digital maturity model for FSSC in Chinese state-owned enterprise.

First of all, it is necessary to select and compare several representative maturity models related to FSSC or digitalization. These include models such as the CMM for FSSC and digital maturity models for enterprise and finance. The purpose of this comparison is to identify the strengths and limitations of existing models and to propose an optimization

direction. As a result, the comparative analysis of these models supports the selection of an appropriate development strategy. According to Becker et al. (2009), four common strategies include: first, the development of a completely new model; second, the enhancement of an existing model; third, the combination of multiple models into a new one; fourth, the transfer of contents or structures from existing models to new domains. Therefore, this study adopts the third strategy that is model combination, and integrates theoretical support to enhance its effectiveness. Specifically, by combining the CMM for FSSC with digital maturity models for enterprise and finance, and introducing systems theory, this study initiates the development of the digital maturity model for FSSC in Chinese state-owned enterprise, which mainly involves two components: the preliminary construction of the evaluation indicator system for digital maturity, and the initial classification of maturity levels. First, the structure of the evaluation indicator system for digital maturity must be designed, particularly the determination of KPAs. These KPAs are derived from the combination of common elements across existing models, and organized according to systems theory to form a coherent and structured evaluation framework. Second, the maturity levels are preliminarily classified based on the proposed KPAs and widely accepted maturity level structures used in existing models. Finally, once the KPA structure and maturity levels are defined, it is necessary to identify specific indicators under each KPA, thereby ensuring a rigorous and evidence-based construction of the evaluation indicator system for digital maturity. These include both first-level and second-level indicators, which must not only be measurable but also reflect key contributors to the digitalization of FSSC in Chinese state-owned enterprise.

To support these two tasks, literature analysis is applied throughout this phase. In the earlier part of the phase, it informs the selection and comparison of existing maturity models and guides the introduction of systems theory, thereby supporting the formation of KPAs and the classification of maturity levels. In the latter part, literature analysis is used to select appropriate first-level and second-level indicators from relevant literature. According to Snyder (2019), literature analysis refers to the systematic process of collecting, organizing, and analyzing literature to deepen understanding of a research problem. In addition, rich and comprehensive literature provides researchers with essential, objective, and systematic insights, while minimizing the influence of subjective bias on research outcomes. De Bruin et al. (2005) also emphasize that in relatively new research areas, evaluation indicator systems can be constructed based on robust evidence gathered from existing literature. Therefore, this study systematically collects and reviews scientific publications and online resources related to FSSC, digitalization, and maturity from databases such as the University of Reading and Hebei University libraries, EBSCO, ScienceDirect, Web of Science, and Google Scholar. Based on comprehensive literature analysis, the initial development phase results in a preliminary version of the digital maturity model for FSSC in Chinese state-owned enterprise, which includes a structured three-layer evaluation indicator system consisting of KPAs as

well as clearly defined first-level and second-level indicators, and an initial classification of maturity levels that reflect progressive stages in the digitalization of FSSC.

3.4.3 Model Improvement

In the phase following the initial development, the model improvement phase involves refinement to the evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise, as detailed in Chapter 5. This phase primarily addresses two issues. First, literature analysis can only offer a theoretical basis for the preliminary development of the KPAs and the first-level and second-level indicators, which results in an incomplete set of indicators that lack sufficient practical guidance. Second, the preliminary three-layer evaluation indicator system remains insufficiently detailed to fully describe the evaluation object. In particular, the contents of the second-level indicators are not specific enough and require further subdivision. Therefore, based on the refined KPAs and existing indicators, it becomes necessary to introduce a fourth layer by developing the third-level indicators to enhance the operability and practical value of the evaluation indicator system. To achieve this, additional empirical methods are needed. One such method is the Delphi method, which entails gathering expert opinions on a given research issue, summarizing and analyzing responses, and providing feedback in iterative rounds until a consensus is reached (Diamond et al., 2014; Grime and Wright, 2016). This method is especially suitable under the following conditions: first, the problem is complex with multiple influencing factors; second, diverse expert opinions are needed to improve decision-making; third, knowledge is incomplete; finally, empirical evidence is limited. All these conditions apply to the improvement of the digital maturity model for FSSC in Chinese state-owned enterprise. Therefore, this study adopts the Delphi method to refine the KPAs and the first-level and second-level indicators, and to further develop the third-level indicators, thereby constructing a complete four-layer evaluation indicator system for digital maturity.

A panel of 50 experts must be established, comprising professionals and scholars from top universities and major state-owned enterprises in China, all with at least five years of experience in digitalization or FSSC-related fields. The Delphi process includes four rounds of consultation. The first two rounds focus on revising the preliminary KPAs, and first-level and second-level indicators in the three-layer evaluation indicator system. Structured questionnaires using a five-point Likert scale are distributed to the experts, who are asked to assess the representativeness of the KPAs, the relevance of the first-level indicators, and the rationality of the second-level indicators based on their practical experience and professional judgment (Joshi et al., 2015). The collected responses are then analyzed using Excel and SPSS. Based on the critical value method, indicators are deleted, modified, or added according to statistical thresholds and expert suggestions. As a result, once all KPAs and the

first two levels of indicators meet the criteria after the second round, the revisions are finalized and a refined three-layer evaluation indicator system is formally established. For the development of the third-level indicators, semi-structured interviews should be conducted with the same expert panel to gather suggestions on how to further expand the contents of the second-level indicators and what specific sub-indicators could be introduced. These interviews, each lasting two to three hours, are guided by a set of predefined questions but allow for open-ended responses and probing, enabling a deeper understanding of the experts' perspectives (Kallio et al., 2016). The collected data are analyzed to subdivide the second-level indicators, resulting in a preliminary set of third-level indicators that align with the overall evaluation objectives and dimensions. Subsequently, two additional rounds of Delphi consultation should be conducted to revise the third-level indicators. Experts are again asked to evaluate the rationality of the third-level indicators through structured questionnaires with a five-point Likert scale. The same statistical analysis process is followed to apply the critical value method for final revisions. Indicators not meeting the required thresholds are either deleted or modified based on expert feedback. In some cases, overlapping or redundant indicators are consolidated or relocated within the system. By the end of the fourth round, the final version of the third-level indicators is confirmed.

Through this rigorous process, a comprehensive evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise is constructed, comprising four hierarchical layers of refined KPAs, and first-level, second-level and third-level indicators. Therefore, with the complete construction of its evaluation indicator system, the digital maturity model for FSSC in Chinese state-owned enterprise is significantly improved, enhancing its precision, applicability, and practical relevance.

3.4.4 Weight Determination

Following the construction of the complete evaluation indicator system for digital maturity, assigning appropriate weights to each KPA and corresponding indicators is crucial for the effectiveness and applicability of the digital maturity model. The weight determination, as elaborated comprehensively in Chapter 6, enables stakeholders to clearly identify and understand the relative importance of each element within the hierarchical system. According to Saaty (1977), the weight of an indicator represents its relative importance compared to other indicators. In addition, existing methods for weight determination can generally be classified into three categories: subjective weighting, objective weighting, and combination weighting methods (Hwang and Yoon, 1981). As subjective weighting methods primarily rely on expert judgment, a certain degree of subjectivity is inevitable. Nevertheless, such methods often produce weights that closely reflect real-world conditions, especially in contexts where comprehensive empirical data are

lacking. Given the limited prior research on digital maturity models for FSSCs, particularly in the Chinese context, objective data are scarce and difficult to obtain. Furthermore, considering the complexity of the hierarchical structure developed for the evaluation indicator system and the domain expertise of the involved stakeholders, this study adopts the Analytic Hierarchy Process (hereafter referred to as AHP), a well-established subjective weighting method, to systematically determine weights for KPAs and their underlying indicators. The AHP combines qualitative and quantitative analyses, utilizing operational research techniques to assign indicator weights at each hierarchical level (Vaidya and Kumar, 2006). It provides a structured framework for decomposing complex problems, quantifying relationships among elements, and systematically aggregating judgments to determine priorities.

According to Saaty (1977, 2008, 2013), this study implements the following steps to apply AHP. Before commencing the formal steps, 10 assessors are selected from the expert panel that participated in the previous Delphi rounds. These assessors are chosen for their familiarity with the proposed KPAs and indicators as well as their proficiency in applying the AHP method. First, a hierarchical structure model of the evaluation indicator system is established, consisting of clearly defined layers: the goal level, criteria level, and sub-criteria levels. The goal level articulates the ultimate objective. Criteria and sub-criteria levels represent KPAs and detailed measurable indicators, respectively. Second, pairwise comparison matrices are constructed at each hierarchical level. The selected expert assessors perform these comparisons based on their AHP expertise and domain knowledge. Each matrix involves comparing pairs of indicators in terms of their relative importance towards achieving the higher-level objective, using Saaty's standard 1–9 scale. Third, local weights, which reflect the relative significance of each indicator within its hierarchical level, are calculated through the row average method. Fourth, consistency tests are conducted for each pairwise comparison matrix to validate the rationality and reliability of expert judgments. In addition to individual matrix tests, an overall consistency test for the entire hierarchy is performed to ensure that judgments remain consistent across all levels of the hierarchy. Subsequently, scores from multiple expert assessors are aggregated using the geometric mean to construct aggregated pairwise comparison matrices. Local weights are recalculated from these matrices to represent consensus opinions, with additional consistency tests both at the matrix level and for the overall hierarchy performed to confirm the rationality and reliability of the aggregated results. Finally, global weights, indicating the overall importance of indicators across the entire hierarchy, are computed. These are obtained by propagating local weights through the hierarchy, thereby directly reflecting the influence of each indicator on the ultimate objective of digital maturity.

Through this AHP process, reliable and systematic weights for KPAs and indicators in

the four-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise are determined, enhancing both the theoretical rigor and practical relevance of the developed digital maturity model.

3.4.5 Model Evaluation

The model design procedure concludes with the model evaluation phase, which is elaborated in detail in Chapter 7. Specifically, this phase aims to evaluate whether the proposed digital maturity model delivers the expected benefits and provides effective solutions to the problems identified in the initial phase. To this end, the evaluation focuses on three key aspects: the reliability, validity, and practical applicability of the model, particularly with respect to the construction of the evaluation indicator system and the classification of maturity levels. These aspects are assessed through the model's practical application in real-world settings. To achieve this, the multiple case study method is employed, whereby several selected enterprises are invited to adopt and apply the proposed digital maturity model in practice. According to Gerring (2006), case study research entails an in-depth and context-specific examination of one or more cases in real-world settings. A defining feature of this method is its use of evidence derived from individual cases to explore or illuminate broader patterns or phenomena. The multiple case study method is particularly suitable for this study, as it enables cross-case comparison and provides a more robust and generalizable assessment of how the model performs across diverse organizational environments.

However, the final phase also requires a dedicated analytical method to evaluate the digital maturity of FSSCs in the sample enterprises selected through the multiple case study. In this study, the relationships among indicators in the evaluation indicator system for digital maturity are complex and uncertain, as most KPAs and indicators are qualitative in nature and exhibit a certain degree of fuzziness. Moreover, the evaluation process itself is inherently ambiguous, as staff and managers in the selected enterprises may not fully or objectively understand the meaning and implementation of digitalization of FSSC (Karim and Cherkaoui, 2021). The Fuzzy Comprehensive Evaluation (hereafter referred to as FCE) method is adopted to address the inherent ambiguity, complexity, and subjectivity involved in assessing digital maturity, aspects often difficult to quantify precisely. FCE effectively integrates qualitative judgments with quantitative analysis, allowing for comprehensive evaluation of complex hierarchical systems and transforming subjective perceptions into structured and quantifiable results (Zadeh, 1965; Zimmermann, 2012). Therefore, FCE is especially suitable for evaluating the digital maturity of FSSCs in Chinese state-owned enterprises, given the diverse, multi-dimensional, and subjective nature of the evaluation criteria in this study.

The application and validation processes are detailed as follows. First, five prominent

Chinese state-owned enterprises operating FSSCs across different industries are selected as evaluation subjects. These enterprises are specifically chosen due to their influential positions within their respective industries and their active involvement in digitalization of FSSCs. Approximately 20 respondents from each enterprise are selected to complete structured questionnaires, ensuring sufficient data for robust analysis. Respondents are carefully identified based on their roles and direct involvement in FSSC digitalization initiatives, including management and operational staff, to guarantee comprehensive and reliable evaluation. The evaluation questionnaire employs a scoring scale of 1 to 5, directly corresponding to the five defined maturity levels in the developed digital maturity model. Respondents assess each indicator based on their practical experiences and perceptions of their respective FSSC's current level of digital maturity. Furthermore, the collected data are analyzed using FCE, which comprises the following detailed steps (Liang and Wang, 1991; Chen, 2000; Zhu, 2022). First, based on the hierarchical structure of KPAs and indicators developed earlier, a factor set and a maturity grade set are established. The factor set corresponds directly to the complete evaluation indicator system, while the grade set aligns with the five defined digital maturity levels. Second, the indicator weights previously determined through AHP are directly applied in this phase. Third, responses collected from the questionnaires are processed to construct fuzzy membership matrices, quantifying the degree to which respondents perceive their FSSC's digital maturity in relation to each indicator. Fourth, based on the principles of fuzzy mathematics, the indicator weights are combined with the fuzzy membership matrices to compute fuzzy evaluation vectors at each hierarchical level, which are then aggregated to produce a final evaluation vector for each FSSC. Fifth, the aggregated evaluation results are transformed into final numerical scores that reflect the overall digital maturity of each FSSC. These scores are subsequently used to determine the corresponding digital maturity levels, and to rank the five enterprises, thereby facilitating cross-enterprise comparison and digital benchmarking. Finally, the detailed analysis steps, along with the calculated digital maturity scores and levels for each FSSC, are communicated back to approximately 20 participants in each selected enterprise. Participants are asked to assess whether the results accurately reflect their perceived reality of digital maturity, to express their level of satisfaction with the overall model and its evaluation outcomes, and to provide suggestions for further refinement. Through this comprehensive validation process, involving direct stakeholder feedback and final model adjustments, the reliability, validity, and practical applicability of the digital maturity model for FSSC in Chinese state-owned enterprise are confirmed.

Chapter 4 Model Development

This chapter focuses on the initial development, the second phase in the procedure for model design, during which five digital maturity levels are defined and a preliminary three-layer evaluation indicator system for digital maturity, comprising the KPAs, first-level and second-level indicators, is constructed.

4.1 KPA Determination

As a preliminary step, this study constructs the evaluation indicator system for digital maturity by determining KPAs through model combination and structuring the overall framework using systems theory. The KPAs are derived by integrating common elements shared by existing maturity models and are subsequently organized into a coherent and well structured framework suited to the digitalization of FSSC in Chinese state-owned enterprise.

4.1.1 Model Combination

Based on the justification in Chapters 2 and 3, this study uses the model-combination strategy to identify KPAs. This strategy is particularly appropriate given the hybrid nature of the digitalization of FSSC, which spans FSSC operations, enterprise digitalization, and financial digitalization. Accordingly, multiple maturity model types are jointly considered to capture complementary perspectives and to provide a comprehensive basis for KPA determination.

Drawing on the maturity models reviewed in Chapter 2, this study summarizes the typical and common KPAs for each model type. Specifically, KPAs are first identified from CMM for FSSC, which primarily emphasizes process standardization and organizational restructuring. Subsequently, KPAs are identified from enterprise and financial digital maturity models, which introduce essential digitalization dimensions. Accordingly, the key KPAs identified include strategic planning, personnel management, information systems, process management, and operation management in the CMM for FSSC; strategy, culture, personnel, leadership, technology, operation, data, product, service, and customer in the digital maturity model for enterprise; and organization structure, information technology, financial management, data management, and effectiveness and efficiency in the digital maturity model for enterprise finance. More importantly, common KPAs occur in all three types of models, including strategy, culture, personnel and leadership, organization structure, information systems and technology, process and operation management, data management, product and service, customer, and performance and effectiveness.

Furthermore, this study synthesizes these three types of maturity models by combining similar KPAs with commonalities. It should be noted that the combination of KPAs is not simply their mechanical merging, but their substantive integration, which requires not only the elimination of KPAs unrelated to the digitalization of FSSC but also the formulation of new KPAs in accordance with the research objectives. As a result, this study conducts a conceptual consolidation guided by relevance to digitalization of FSSC, non-redundancy, and decision usefulness, as detailed below. First, strategy, culture, personnel, leadership, and organization structure are integrated as Strategy and Organization. Second, information systems and information technology are combined as Infrastructure. Third, operation management and financial management are subsumed under Process Management. Fourth, given its salience in maturity models for both enterprise and financial digitalization, Data Management is retained as an independent area. Finally, service and customer are combined with effectiveness and efficiency as Digital Performance. This yields a preliminary KPA set of five areas: Strategy and Organization, Infrastructure, Process Management, Data Management, and Digital Performance.

To align these areas with the objectives of this research, this study specifies their meanings in the context of the digitalization of FSSCs in Chinese state-owned enterprises. Strategy and Organization refers to the strategic planning for the digitalization of FSSC and the organizational arrangements that enable its effective implementation. Infrastructure denotes the foundational physical and technological infrastructure that supports the digitalization of FSSC. Process Management involves the consolidation of dispersed financial processes across various departments and their standardization, integration, and digitalization within FSSC. Data Management concerns the governance of the end-to-end data value chain, positioning the FSSC as an enterprise-level big data center. Digital Performance represents the achievement and progress attributable to the digitalization of FSSC.

4.1.2 Theory Application

Following the determination of KPAs through model combination, this study applies systems theory to structure the evaluation framework, with the aim of enhancing the development of the digital maturity model. In this study, systems theory serves as an optimization direction, guiding the alignment, integration, and refinement of the model's components so that they operate as a coherent and effective whole. Drawing on the conceptualization of digitalization through the IPO model and the advantages of the systemic maturity model discussed in Chapter 2, the IPO model is first employed to conceptualize the digitalization process of FSSC in Chinese state-owned enterprise in a systematic manner. Subsequently, the systemic maturity model is applied to design the structure of the evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise. In this way,

the resulting digital maturity model goes beyond traditional maturity models by explicitly incorporating internal structures, external environmental influences, and the coordination and interaction among KPAs, thereby capturing the dynamic and multidimensional nature of digitalization in FSSC operations. The specific steps for applying systems theory in this study are presented below.

First, consistent with the IPO model, the digitalization of FSSC in Chinese state-owned enterprise is regarded as an open system in which inputs are transformed through processing into outputs, while interacting continuously with its external environment. Accordingly, External Environment is included as an important and necessary component in the digitalization and is added as the sixth KPA in the evaluation indicator system for digital maturity. It encompasses the broader factors and forces outside FSSC that can affect the inputs, processing, and outputs of its digitalization. To ensure the smooth progress of digitalization, FSSC must adapt to these external environmental changes.

Second, in developing the systemic maturity model, it is essential not only to examine the interrelationships among the determined KPAs, but also to align them with the corresponding stages of the IPO-based digitalization process. Through this alignment, KPAs are positioned within a structured framework that reflects both the sequential flow of digitalization activities from input to output and the systemic interdependencies among different components.

Based on the meanings of the preliminary KPAs proposed in Section 4.1.1, Strategy and Organization, along with Infrastructure, are classified as the “Input” component, as both provide the foundational conditions necessary for transformation. Process Management and Data Management are grouped under the “Processing” component, as they represent the core activities undertaken by FSSC to achieve transformation. Digital Performance is classified as the “Output” component, reflecting the realized outcomes following transformation. External Environment corresponds to the “Environment” component in the IPO model, as external forces can influence every stage of the transformation process.

Therefore, taking into account the external environment, the relationships among internal and external KPAs, and the alignment of these KPAs with the IPO process of digitalization of FSSC, the final six KPAs are determined. On this basis, the complete structure of the evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise is constructed and presented in Figure 4.1.

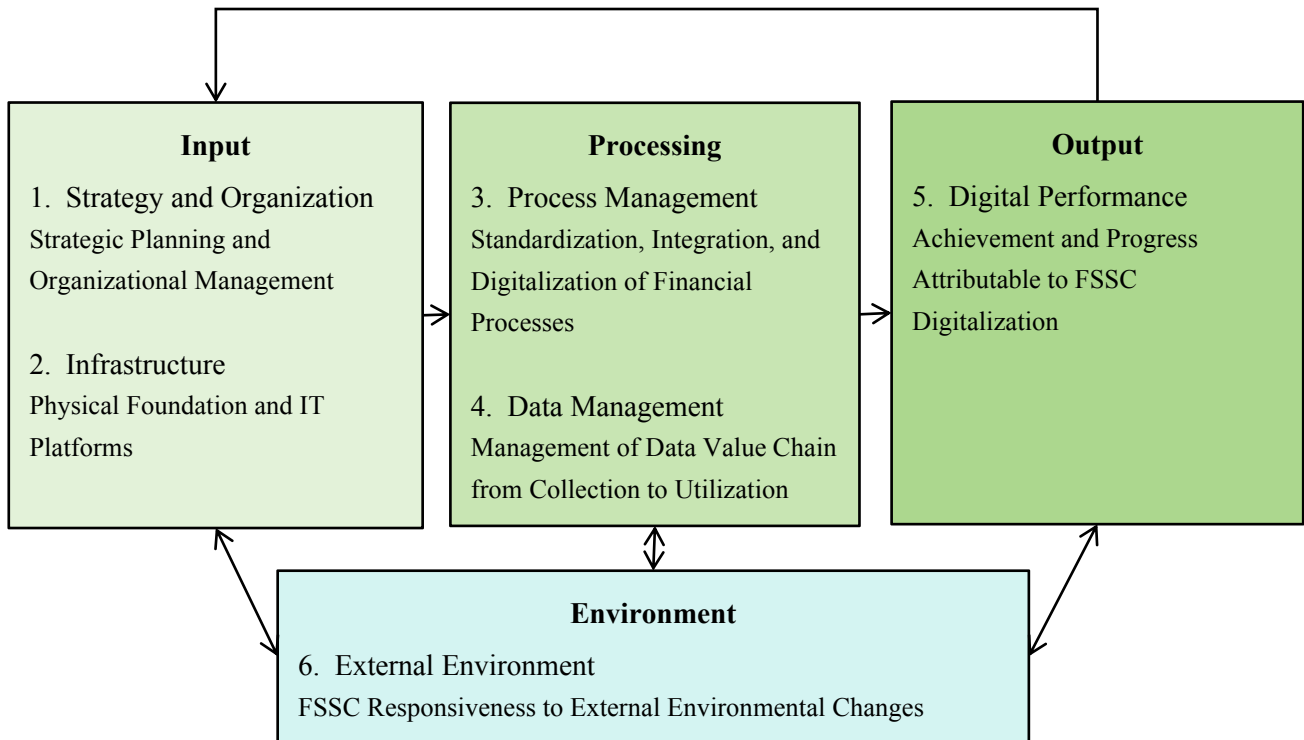


Figure 4.1 Structure of Evaluation Indicator System for Digital Maturity

4.2 Level Division

For the digitalization of FSSC in Chinese state-owned enterprise, breaking down the process into distinct levels is essential to identify its current development level, as the transformation process is inherently gradual and cannot be accomplished at one stroke. In maturity models, the division into different maturity levels is a core component, as it provides the structured stages through which an organization’s capabilities evolve over time. This correspondence makes maturity levels an effective tool for defining the development level of digitalization, thereby forming the digital maturity levels of FSSC in Chinese state-owned enterprise, with higher levels building upon the foundation of lower ones. Accordingly, the digital maturity improves progressively with the increase in its level. As outlined in Chapters 2 and 3, the digital maturity levels in this study are determined using the model-combination strategy, which integrates the CMM for FSSC with digital maturity models for enterprise and finance. Following this strategy, the digital maturity levels are specified in terms of both their number and naming, and their characteristics are then elaborated in relation to the KPAs and key practices. The specific steps are described below.

From the literature review in Chapter 2, three common patterns in maturity level classification can be identified across the maturity models reviewed. First, all three types of models follow a staged, progressive path, moving from an initial, basic, or repeatable stage toward an optimized, leading, or continuously improving stage. Second, although the specific

naming varies, the number of maturity levels typically ranges from three to six, with five levels being the most commonly adopted structure in existing flexible models (Van Steenberg et al., 2010). Third, the maturity levels cover the full evolution of organizational capabilities, encompassing not only technical aspects but also management, processes, and strategic development, thus reflecting the complete lifecycle of digitalization. Based on these shared characteristics, this study adopts five digital maturity levels: **Initial**, **Repeatable**, **Defined**, **Managed**, and **Optimizing**, arranged from the lowest to the highest. This choice inherits the strengths of level divisions in established maturity models and aligns with the maturity structure widely accepted in both academic and industrial contexts, particularly the CMM, which represents a natural progression from basic capability to full optimization. In addition, the selected levels retain the most representative and widely used terms across the reviewed maturity models, while avoiding redundant or overlapping terminology. Afterwards, the descriptions and characteristics of each level are developed by systematically integrating the staged progression patterns identified across the reviewed models. Key practices refer to the specific measures implemented by FSSC to address defined problems and achieve the goals at each digital maturity level, thereby fulfilling the KPAs required for that level (Marx et al., 2012). Subsequently, based on the six identified KPAs and the characteristics of each maturity level, appropriate KPAs and corresponding key practices are assigned to each level.

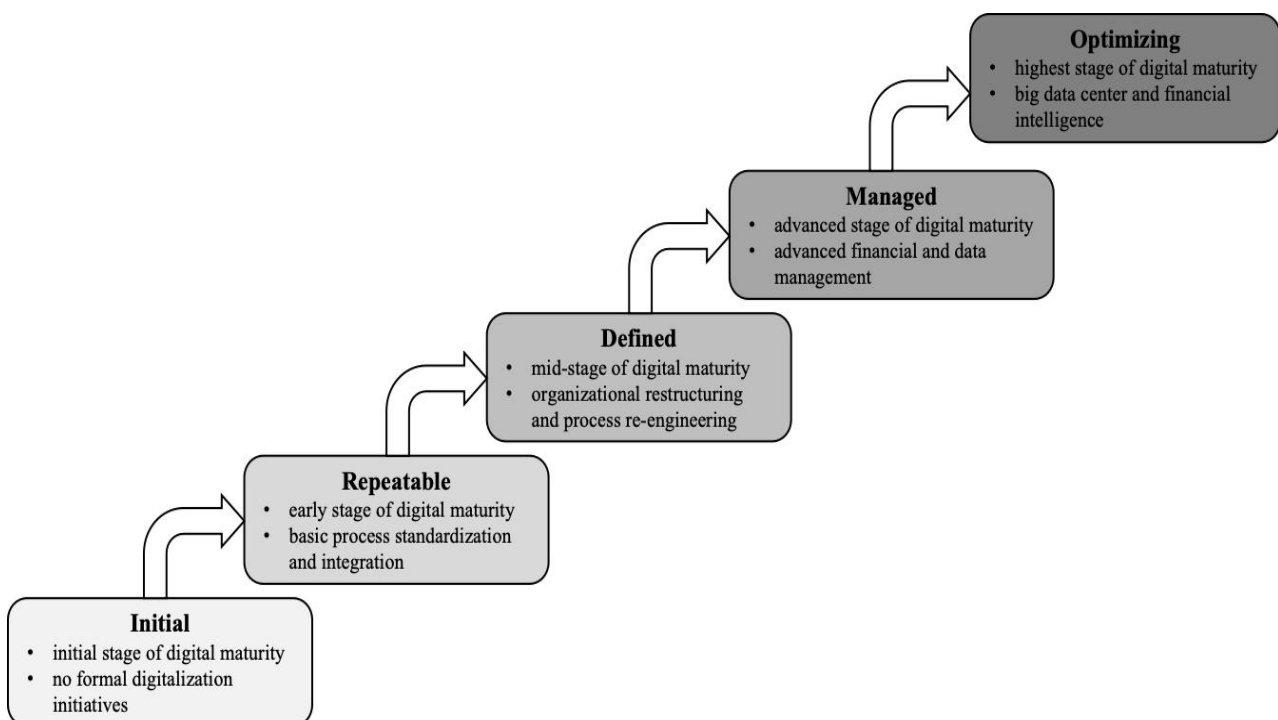


Figure 4.2 Digital Maturity Levels

These details are illustrated in Figure 4.2, which provides an overview of the five digital maturity levels. The subsequent subsections elaborate on each level in detail.

4.2.1 Initial Level

At the Initial level, FSSC in Chinese state-owned enterprise remains at the foundational stage of digital maturity, where no substantive digital initiatives have yet been undertaken. Leadership has limited or no awareness of the strategic importance of digitalization, and there is an absence of formal planning to guide transformation. Financial personnel generally possess limited or outdated technical skills, relying on isolated departmental systems. These systems often lack interoperability, leading to duplicated data entry, inconsistent record-keeping, and prolonged processing times. Moreover, financial processes remain fragmented and predominantly manual, being performed in a traditional manner. Finally, data assets, while potentially valuable, are scattered and underutilized, with no structured framework for ensuring data security and quality. Consequently, there are almost no tangible benefits attributable to digitalization. Transitioning to the Repeatable level requires building basic awareness, establishing initial digital objectives, and creating conditions for process re-engineering. KPAs and specific key practices are not formally defined at this level.

4.2.2 Repeatable Level

At the Repeatable level, FSSC in Chinese state-owned enterprise is in the initial stage of deliberate digitalization. Leadership begins to acknowledge its importance and sets preliminary directions for enhancing future competitiveness and operational performance. Talent development programs start to take shape, but training efforts remain sporadic and lack comprehensive planning. Additionally, investments are made in basic information systems, though these are often limited in scope and may serve only specific functional areas. While basic operations continue to dominate daily work, initial steps toward process standardization and integration are undertaken, typically focusing on consolidating repetitive transactional processes. More importantly, data is increasingly recognized as a valuable asset, leading to the first attempts at building partial data value chains, although these efforts often remain experimental and fragmented. As a result, the benefits realized from digitalization remain modest, and external responsiveness is minimal, as most activities are internally focused. Nonetheless, this level is critical in establishing a repeatable pattern of digital practices, laying the groundwork for broader organizational change, deeper process re-engineering, and more sophisticated technology integration at the Defined level. The specific Key Practices for each KPA at the Repeatable level are summarized in Table 4.1.

Table 4.1 KPAs and Key Practices at Repeatable Level

KPAs	Key Practices
Strategy and Organization	FSSC initiates development of digital strategy and begins cultivating digital talents.

KPAs	Key Practices
Infrastructure	FSSC adopts initial digital technologies and establishes basic information systems.
Process Management	FSSC starts to standardize and integrate basic financial processes across departments.
Data Management	FSSC recognizes data as key asset and begins establishing partial links in data value chain.
Digital Performance	FSSC obtains limited and preliminary benefits from early digitalization efforts.
External Environment	FSSC exhibits minimal capacity to respond to external environmental changes.

4.2.3 Defined Level

At the Defined level, FSSC in Chinese state-owned enterprise enters the mid-stage of digital maturity, where digitalization is not only recognized but systematically structured. Leadership adopts a structured and coordinated approach to digitalization, supported by a clearly defined digital strategy. Talent development shifts from ad hoc training to continuous capacity-building programs, while recruitment strategies target personnel with digital expertise. Organizational restructuring is undertaken to better align functions, processes, and responsibilities with digital objectives. Furthermore, digital technologies are deployed to a broader range of functions, enabling higher degrees of process automation and integration. Specifically, process re-engineering extends beyond basic transactions to encompass end-to-end workflows that connect financial operations with business activities, which in turn strengthens cross-functional collaboration. More importantly, data management becomes more robust, with systematic efforts to improve data quality, completeness, and traceability across the value chain. Although stable and measurable benefits from digitalization such as cost savings and improved service quality are increasingly evident, FSSC remains somewhat vulnerable to environmental or market fluctuations, even as its ability to respond to such changes becomes more flexible. Achieving this level provides the organizational and technical foundation necessary for moving toward the Managed level, where advanced integration and data-driven decision-making become possible. The specific Key Practices for each KPA at the Defined level are summarized in Table 4.2.

Table 4.2 KPAs and Key Practices at Defined Level

KPAs	Key Practices
Strategy and Organization	FSSC executes digital strategy, expands digital talents, and adjusts organization structure.
Infrastructure	FSSC applies various digital technologies across most processes.
Process Management	FSSC automates and integrates most financial and business processes.

KPAs	Key Practices
Data Management	FSSC actively improves data quality and enhances key data value chain.
Digital Performance	FSSC begins to achieve stable and measurable benefits from digitalization.
External Environment	FSSC responds with moderate flexibility to external environmental changes.

4.2.4 Managed Level

At the Managed level, FSSC in Chinese state-owned enterprise enters an advanced stage of digital maturity, in which digitalization is embedded as its core operational and strategic capability. Leadership effectively implements the digital strategy, supported by a dedicated and well-resourced digitalization team, which oversees technology adoption, system upgrades, and continuous process improvement. In addition, the technological infrastructure features advanced, fully integrated information systems. More importantly, all core financial management processes are not only automated but also closely aligned to support business decision-making at both operational and executive levels, thereby dismantling interdepartmental barriers and achieving collaborative workflows. Data management capabilities reach a high standard, with a complete data value chain and strong data security measures, thereby facilitating real-time, seamless data flows across departmental boundaries. Consequently, strategic decision-making is increasingly data-driven, supported by advanced analytical tools and predictive models. Finally, the benefits from digitalization are significant, ranging from improved efficiency and accuracy to enhanced analytical insight and predictive capability. FSSC demonstrates resilience to environmental changes through adaptive strategies and flexible resource allocation, positioning itself as a critical enabler of enterprise transformation. This level sets the stage for the Optimizing level, where innovation and ecosystem integration become the primary focus. The specific Key Practices for each KPA at the Managed level are summarized in Table 4.3.

Table 4.3 KPAs and Key Practices at Managed Level

KPAs	Key Practices
Strategy and Organization	FSSC fully executes digital strategy and maintains large, dedicated digitalization team.
Infrastructure	FSSC employs advanced digital technologies and upgrades and integrates existing systems.
Process Management	FSSC integrates all financial management and provides decision support for business.
Data Management	FSSC establishes complete data value chain and achieves secure data sharing across units.
Digital Performance	FSSC realizes significant and sustained benefits from digitalization.
External Environment	FSSC demonstrates strong adaptability to external environmental changes.

4.2.5 Optimizing Level

At the Optimizing level, FSSC in Chinese state-owned enterprise reaches the highest stage of digital maturity, where it operates as an innovation leader and a central intelligence hub for the enterprise. Digitalization is not only fully institutionalized but also continuously refined, supported by a large team of highly skilled digital experts and a culture of knowledge sharing and process innovation. Additionally, technological capabilities are at the leading edge of the industry, with cutting-edge applications integrated seamlessly into all processes. Most importantly, data management positions FSSC as the enterprise’s big data center and a driver of financial intelligence. Leveraging vast datasets and advanced computing capabilities, FSSC provides rapid, precise, and predictive decision support in areas such as risk management, financial forecasting, and strategic planning. This support extends beyond internal optimization, influencing supply chain coordination, customer engagement, and partnership development. As a result, the entire enterprise has largely completed financial digitalization and continues to evolve toward intelligent financial operations. Externally, FSSC participates in building digital ecosystems, engaging with upstream and downstream stakeholders in the supply chain to co-create value, and offering outsourcing financial services. At this final level, the emphasis shifts from implementation to innovation, ensuring the enterprise’s long-term competitiveness and leadership in financial digitalization within the market. The specific Key Practices for each KPA at the Optimizing level are summarized in Table 4.4.

Table 4.4 KPAs and Key Practices at Optimizing Level

KPAs	Key Practices
Strategy and Organization	FSSC fully aligns digital strategy with organization structure, supported by digital experts.
Infrastructure	FSSC reaches leading level in application of advanced digital technologies.
Process Management	FSSC completely integrates all processes with systems and continuously optimizes them.
Data Management	FSSC operates as big data center and evolves toward financial intelligence.
Digital Performance	Entire enterprise consistently obtains substantial benefits from digitalization.
External Environment	FSSC provides outsourcing services and builds digital ecosystems with stakeholders.

4.3 Indicator Selection

After determining the KPAs and defining the digital maturity levels, the next essential step is to identify the specific indicators under each KPA, as each KPA can be examined

from multiple dimensions. This step is critical for ensuring a rigorous and evidence-based construction of the evaluation indicator system for digital maturity, in which the indicators are not only measurable but also capable of reflecting the key contributors to the digitalization of FSSC in Chinese state-owned enterprise (Fraser et al., 2002; Mettler, 2011).

To this end, this study conducts a systematic review of the relevant literature to determine the dimensions encompassed within each KPA. The reviewed literature covers several closely related areas, including studies on Chinese state-owned enterprises, FSSC development and financial capability models, digital transformation frameworks and financial digitalization, as well as maturity model development and methodological approaches. Through this review, the major dimensions associated with each KPA are identified, and relevant factors are extracted and organized into the corresponding KPAs based on conceptual alignment and functional relevance.

Specifically, the broad dimensions identified in the literature are first extracted and used as first-level indicators, each of which is assigned to the most appropriate KPA. As a result, a total of 19 first-level indicators are identified for the evaluation indicator system for digital maturity, with the corresponding references summarized in Table 4.5. Subsequently, a more detailed analysis of the literature is conducted to identify the underlying factors associated with each first-level indicator. These factors are developed as second-level indicators and systematically arranged under their respective first-level indicators to form a coherent hierarchical structure. The selection and development of the second-level indicators, together with their supporting literature, are discussed in detail in the following sections.

Table 4.5 References for First-level Indicators in Evaluation Indicator System

IPO	KPAs	First-level Indicators	References
Input	Strategy and Organization	Strategy	Janssen and Joha, 2008; He and Zhou, 2013; Matt et al., 2015; Remane et al., 2017; Chanias, et al., 2019; Lam and Law, 2019
		Culture	Herbert and Seal, 2012; Schneider et al., 2013; Berghaus and Back, 2016; Fulton and Parchure, 2018; Martínez-Caro et al., 2020
		Talent	Petrișor and Cozmiuc, 2016; De Carolis et al., 2017; Ivančić et al., 2019; Frankiewicz and Chamorro-Premuzic, 2020
		Structure	Brynjolfsson and Hitt, 2000; Janssen and Joha, 2008; Chanias and Hess, 2016; Colli et al., 2018; Isaev et al., 2018; Li et al., 2018

IPO	KPAs	First-level Indicators	References
	Infrastructure	Technology	Matt et al., 2015; Zilic and Cosic, 2016; Isaev et al., 2018; Chen and Srinivasan, 2023; Du et al., 2023
		Network	Zhang and Lin, 2011; Pagani and Pardo, 2017; Richter, 2020; Bai et al., 2022; Wang, 2023
		Capital	Rudzioniene and Sakalauskiene, 2014; Hu et al., 2023; Bai et al., 2024
Processing	Process Management	Process Re-engineering	Gunn et al., 1993; Reijers and Mansar, 2005; Rigby and Bilodeau, 2005; He and Cao, 2009; Lam and Law, 2019; Buntak et al., 2020
		Process Integration	Keith and Hirschfield, 1996; Reijers and Mansar, 2007; Samaranyake, 2009; Leyh et al., 2016; Taillard et al., 2016; Blatz et al., 2018
		Information Systems	Dubois et al., 2010; Soudani, 2012; Hu et al., 2013; Durward et al., 2016; Fulton and Parchure, 2018; Gofwan, 2022
	Data Management	Data Acquisition	Brewer and Johnson, 2010; Emilio, 2013; Miller and Mork, 2013; Sukumar and Ferrell, 2013; Holm et al., 2014
		Data Analysis	Kandel et al., 2012; Miller and Mork, 2013; Chen et al., 2015; Onggo et al., 2021; Soni et al., 2022; Yang et al., 2023
		Data-driven Decision-making	Mandinach et al., 2006; Provost and Fawcett, 2013; Brynjolfsson and McElheran, 2016; Mosteanu and Faccia, 2020; Chowdhury, 2023
		Data Security	Wang et al., 2020; Yang et al., 2020; Berdik et al., 2021; Liu, 2022
	Output	Digital Performance	Effectiveness
Efficiency			Girdea and Nilsson, 2010; Böhner et al., 2018; Peng and Tao, 2022; Wang, 2023; Wang et al., 2023
Environment	External Environment	Government	Wei and Liu, 2015; Park et al., 2020; Pan et al., 2022; Zhou et al., 2023
		Ecosystem	Weill and Woerner, 2015; Jiang, 2016; Jacobides et al., 2019; Petrova et al., 2021; Iheanachor et al., 2023

IPO	KPAs	First-level Indicators	References
		COVID-19	Almeida et al., 2020; Fitriasaki, 2020; Halina and Magdalena, 2021; Leoni et al., 2022; Yang et al., 2022

4.3.1 Strategy and Organization

In the digitalization of FSSC within Chinese state-owned enterprise, strategy and organization constitute the foundational conditions that determine both the direction and effectiveness of change. A well-defined strategy provides clarity of objectives and ensures the alignment of digital initiatives with the broader goals of the enterprise, while organizational arrangements determine whether these strategies can be effectively implemented. The strategic dimension reflects how enterprises conceptualize digitalization, translate this vision into actionable plans, and allocate resources to achieve transformation. Meanwhile, the organizational dimension captures the cultural, structural, and human-resource aspects that enable or constrain execution. Drawing on these considerations, this KPA is further decomposed into four first-level indicators: strategy, culture, talent, and structure. Together, these indicators provide a comprehensive perspective through which the strategic and organizational readiness of FSSC for digitalization can be evaluated.

The sustainable development of FSSC primarily requires a strategic transformation reflected in the clarity of digital objectives and the feasibility of planning. With the acceleration of enterprise digitalization, FSSC must reassess its strategic positioning and carry out appropriate strategic realignments to effectively implement digitalization and gain competitive advantages. Specifically, such strategic transformation encompasses redefining strategic objectives on digitalization and formulating detailed plans to achieve these objectives (Correani et al., 2020; AlNuaimi et al., 2022). First of all, it is important to clarify the strategic goals, as this clarification enables FSSC to identify a tailored transformation path and enhances the likelihood of successful implementation (Bergeron, 2004; He, 2013). Moreover, these strategic goals should be established based on the current operational context, ensuring alignment with the overall enterprise strategy, thus making digitalization an integral part of the overall strategic framework (Bharadwaj et al., 2013). Additionally, strategic goals must align with the expectations and requirements of all stakeholders, particularly FSSC customers, to maintain their consistency and effectiveness (Taillard et al., 2016). Secondly, effective strategic planning requires the development of specific operational models and phased implementation plans. This includes decisions regarding the timing of initiating digitalization, selection of appropriate transformation models, and strategic resource allocation (Rothwell et al., 2011). Consequently, this paper intends to evaluate the

implementation level of strategy mainly from two aspects: goal of digital strategy and planning of digital strategy.

After establishing the digital strategy, FSSC must foster a transformation-oriented organizational culture that reflects openness to digital thinking and innovation. The success of digitalization depends not solely on the implementation of technology, but more fundamentally on whether FSSC recognizes digitalization as a cultural transformation rather than a technical undertaking (Capgemini Consulting, 2017). It is essential for FSSC to cultivate a culture that promotes data-driven decision-making and innovation, while also demonstrating a tolerance for uncertainty, risk, and potential failure (Di Fabio, 2017; Martínez-Caro et al., 2020; Li et al., 2021). Among various cultural dimensions, two are particularly critical for the digitalization of FSSC. The first is the culture of digital thinking, which motivates employees to actively support digitalization, move away from traditional bookkeeping, adopt digital workflows, and rely on data-driven approaches in both decision-making and management processes (Dubey et al., 2019). The second is the culture of innovation and change, characterized by continuous reform and a willingness to challenge existing norms when necessary (Azeem et al., 2021). Accordingly, this paper intends to divide culture into two categories: culture of digital thinking and culture of innovation and change.

Furthermore, the organizational culture discussed above plays a crucial role in enabling FSSC to identify, cultivate, and retain digital talent, a dimension that emphasizes the availability and development of digitally skilled personnel. Such talent can be categorized into two main groups: first, business talents with substantial experience in the application of digital technologies within business contexts; and second, technical talents who provide essential support for digitalization through their mastery of core technologies (Chen and Ma, 2018). The cultivation of digital talent can enhance the digitalization of FSSC, driving both advanced applications and technological innovation. As a result, it is necessary to not only increase but also sustain the proportion and quality of digital talent within FSSC through comprehensive talent training and robust talent security measures (Liu and Zhang, 2010; Fulton and Parchure, 2018). First of all, due to the continuous adoption of new technologies and the redesign of business processes, FSSC should implement personalized training programs tailored to the different roles within the organization. These programs should be delivered on a regular basis and integrate content related to accounting, business operations, and digital technologies, thereby fostering the development of interdisciplinary talent (Herbert and Seal, 2012; Lam and Law, 2019). Secondly, FSSC must take appropriate measures to enhance talent retention and mitigate brain drain, including improving the talent appraisal system and establishing the talent incentive mechanism (DiRomualdo et al., 2018; Fenech et al., 2019). Accordingly, this paper intends to examine talent from three key

dimensions: proportion and quality of digital talent, talent training, and talent security.

Finally, the successful implementation of digital strategy requires an organization structure within FSSC that emphasizes leadership commitment and structural adaptability. Accordingly, FSSC typically consists of four primary components: first, shared finance, which manages basic financial processes; second, business finance, which provides financial analysis and forecasting for front-end business operations; third, strategic finance, which participates in financial planning and enterprise-level strategic decision-making; finally, IT department, which is mainly responsible for driving the digitalization of FSSC (Li et al., 2020). Given this structure, the advancement of digitalization within FSSC requires both strengthening of digital leadership in the IT department and organizational restructuring of the other three sectors (Zhang et al., 2017; Chen and Xu, 2020). Firstly, the cognition and attitude of digital leader toward digitalization fundamentally determine whether the transformation can be successfully achieved, because effective digitalization demands a clear and compelling vision from leadership regarding how digital technologies can create value (AlNuaimi et al., 2022; Benitez et al., 2022; Chatterjee et al., 2023). Secondly, it is essential to restructure the organizational framework of FSSC, including enhancing the leadership position in the IT department and adopting a more flattened structure across the organization, in order to increase management emphasis on digitalization, enhance adaptability, and facilitate more efficient information flow and responsiveness (Gökalp and Martinez, 2021; Fu et al., 2022). Therefore, this paper intends to categorize structure into two aspects: digital leadership and organizational restructuring.

4.3.2 Infrastructure

Infrastructure serves as the technological and physical backbone for the digitalization of FSSC in Chinese state-owned enterprise, providing the basic conditions under which digital processes can be deployed, scaled, and sustained. Without adequate infrastructure, even well-defined strategies cannot be effectively realized. In this context, infrastructure is not limited to physical assets but encompasses a broad range of technological, network, and financial inputs that enable digitalization. Specifically, it reflects the extent to which FSSC has invested in advanced digital technologies, established robust network connectivity, and mobilized sufficient financial capital to support transformation. Accordingly, this KPA is structured into three first-level indicators: technology, network, and capital. These dimensions together determine whether FSSC possesses the foundational capabilities to support digitalization.

The technology base serves as both a prerequisite and a cornerstone for the application of digital solutions within FSSC, referring to the adoption and integration of core digital

technologies. It specifically refers to the core digital technologies as well as the associated services and facilities that support the digitalization of FSSC (Colli et al., 2018; Li et al., 2018). As a result, the technology base includes not only advanced digital technologies such as the IoT, big data, cloud computing, blockchain, and AI, along with related software systems, but also physical hardware such as computers, mobile devices, and application platforms (Chen and Xu, 2020; Vial, 2021). Accordingly, the technology base can be assessed through two key components: digital technology basis and digital infrastructure. The digital technology basis refers to the types of digital technologies currently adopted by FSSC and the development stage of each technology, which is reflected in the extent to which the technology is applied and integrated into specific business operations (Sambamurthy et al., 2003; Piccoli and Ives, 2005). In contrast, the digital infrastructure refers to the deployment and capability of computers and their systems, typically measured by metrics such as hardware density and degree of equipment digitalization (Wade and Hulland, 2004; Ravichandran et al., 2005). Therefore, this paper intends to select digital technology basis and digital infrastructure as evaluation indicators for the technology base.

Furthermore, the development of digital technologies and infrastructure has the potential to reconfigure the network systems within FSSC, emphasizing the availability and efficiency of internal and external connectivity. FSSC can not only access external resources, information and data by connecting to the Internet, but also build internal networks such as shared service systems and cloud platforms to enable the efficient circulation of internal information across the organization (Sadalia et al., 2017). As a result, the network base emerges as another critical dimension in evaluating infrastructure. It should be distinguished from the technology base, as recognized in previous literature, and examined from two perspectives: construction of Internet connectivity and development of internal network (Wade and Hulland, 2004; Ravichandran et al., 2005). Specifically, all equipment within FSSC must be connected to both the external Internet and internal network to support seamless data exchange (Zhang and Lin, 2011). More importantly, FSSC can establish integrated Internet and internal network platforms that connect intelligent terminals, cloud storage, and grassroots-level systems. These platforms facilitate the rapid collection and preliminary processing of data from different regions and time points, and subsequently deliver refined and actionable information to relevant employees (Poon et al., 2003; Wang, 2023). Therefore, this paper intends to adopt Internet construction and internal network construction as evaluation indicators of the network base.

Moreover, the capital base reflects the sufficiency of financial resources allocated to digital initiatives. It plays a critical role in the digitalization of FSSC, serving as the essential economic foundation for both the preparatory stage of digitalization, including organizational management and infrastructure development, and the subsequent stages of transformation

such as business process redesign and data management (Janssen and Joha, 2008; Khisro, 2020). A defining characteristic of FSSC digitalization is its high capital intensity, as substantial investment is required across multiple areas, including organizational restructuring, software and hardware procurement, information system upgrade and maintenance, and business process re-engineering. These investments are essential for enhancing the overall maturity of digitalization (Zhu, 2017). For example, according to the financial analyses of A-share listed companies in China from 2004 to 2017 (Liu and Liu, 2019), large capital expenditures are necessary to ensure the successful establishment, operation, and digitalization of FSSC. In the short term, such investments often make cost control difficult, resulting in a continuous increase in total costs. Therefore, this paper intends to select digital capital investment as the only indicator to evaluate the capital base.

4.3.3 Process Management

Process management represents the operational core of the digitalization of FSSC in Chinese state-owned enterprise, as it directly involves the redesign, integration, and digitalization of financial processes across the organization. The success of digitalization depends not only on acquiring new technologies but also on embedding them into standardized and streamlined workflows that eliminate redundancy, improve accuracy, and enable value creation. In this regard, process management captures the degree to which financial activities are re-engineered, integrated across departments, and supported by effective information systems. It emphasizes a shift from manual, fragmented practices toward cohesive, technology-enabled processes that are aligned with enterprise-wide objectives. To evaluate this area, three first-level indicators are identified: process re-engineering, process integration, and information systems. Collectively, these indicators provide a robust framework for assessing how well operational processes in FSSC are being transformed to achieve digital maturity.

The re-engineering of financial processes represents efforts to redesign workflows to enhance effectiveness and efficiency, as the success of digitalization ultimately relies on the alignment of financial processes with the digital operating environment. To this end, the traditionally fragmented, repetitive, and manual financial processes distributed across departments must be consolidated within FSSC to enable standardization and digitalization. This integration allows FSSC to leverage the advantages of centralized management and economies of scale to achieve cost-efficient value creation (Gunn et al., 1993; Keith and Hirschfield, 1996; Lam and Law, 2019). Furthermore, the key aspects of this transformation are the continuous monitoring, management, and optimization of financial processes to ensure the realization of process standardization (Ulbrich, 2006; Reijers and Mansar, 2007; Janssen and Joha, 2008). Firstly, system establishment plays an important role in developing

a comprehensive process framework, unifying working standards, standardizing accounting classifications, and consolidating data resources, thereby laying the foundation for effective process management (Xia and Yang, 2019). However, one-off process re-engineering is insufficient to address ongoing management problems, especially given the change in organization structure and the transformation of staff (Triplett and Scheumann, 2000; Wang and Zhou, 2016). FSSC must therefore implement mechanisms for continuous process monitoring, and propose corresponding optimization measures for problems that arise or are hidden in operation. As a result, five core financial processes are typically standardized within FSSC: procurement and accounts payable, sales and accounts receivable, expense reimbursement, asset accounting, and general ledger and reporting (Larsen and Myers, 1997; Zhang et al., 2010). Ultimately, all of these processes should be integrated with information systems through digital technologies such as RPA and smart contracts, to achieve automation and intelligent process management (Van der Aalst et al., 2018; Huang and Vasarhelyi, 2019). Accordingly, this paper intends to examine process re-engineering through five key dimensions: management and monitoring, continuous optimization, standardization, automation and intelligence.

Following process re-engineering, the next critical step is process integration, which measures the extent of cross-departmental coordination. It involves three key dimensions: the integration of financial processes within FSSC, the integration of FSSC with front-end business departments, and the integration of various financial management functions (Park and Kusiak, 2005; Van Steenbergen et al., 2010). First of all, effective coordination among the five core financial processes mentioned earlier enhances the quality and efficiency of financial accounting. It also reduces the time spent by staff on routine accounting tasks, allowing them to focus more on supporting the operational management of front-end business units (Gospel and Sako, 2010; Li et al., 2018; Chen and Xu, 2020). At the same time, the integration between financial and business processes requires not only the automated alignment of financial activities with actual business needs, but also the establishment of end-to-end connections between financial and operational workflows (Gao, 2022; Jia et al., 2022). In addition, FSSC personnel are increasingly capable of providing on-site decision support, operational cost analysis, and other value-added services for business departments (Liu, 2014). Therefore, with digitalization, FSSC is better positioned to fulfill the role of management accounting by moving beyond traditional financial accounting (Seal and Herbert, 2013; Raudla and Tammel, 2015; Harritz, 2018). There are four major areas of financial management that are typically integrated within FSSC: first, fund management, which requires centralized control of enterprise funds; second, budget management, which requires budget formulation, monitoring, and forecasting; third, tax management, which aims to ensure compliance and enable lawful tax optimization; finally, risk management, which involves unified assessment and mitigation of enterprise-level financial risks. Accordingly,

this paper categorizes the indicators for evaluating process integration into three aspects: vertical integration within FSSC, horizontal integration with business units, and management integration.

The final step in process management is the construction of information systems, which represent the technological platforms sustaining automation, interoperability, and process stability, since digitally transformed financial processes must be supported by mature financial shared service systems. The specific components of financial shared systems may vary depending on the type and scale of enterprise, whereas most of them include electronic imaging systems, electronic archiving systems, financial accounting systems, expense reimbursement systems, fund management systems, and bank-enterprise interconnection systems (Granlund, 2003; Fitrios, 2016). First of all, it is essential for FSSC to ensure the stable connection between financial processes and shared systems, and to guarantee the successful execution of those processes within the systems. These measures collectively reflect the process support capability of information systems (Chapman and Kihn, 2009; Zhang et al., 2010). Furthermore, financial shared systems must be updated in a timely manner to maintain consistency in the running versions of all subsystems, and to support effective vertical integration among those subsystems within the shared systems (Weißberger and Angelkort, 2011). In addition to internal coordination, its external integration with other business information systems, particularly enterprise resource planning (hereafter referred to as ERP) systems already in place in most enterprises, should also be considered (Samaranayake, 2009; Grabski et al., 2011; Faccia and Petratos, 2021). Finally, the construction of financial shared service systems must incorporate robust security and protection measures, including real-time background monitoring, firewall construction, and other safeguards, all of which are critical to ensuring system security and operational integrity (Dubois et al., 2010; Berdik et al., 2021; Liu, 2022). Therefore, three indicators for the evaluation of information systems are proposed as follows: process support, system integration, and safety and security.

4.3.4 Data Management

As FSSC in Chinese state-owned enterprise evolves into an enterprise-level data center, data management emerges as a key capability underpinning its digitalization. Data is no longer a passive byproduct of financial transactions but a strategic resource that informs decision-making, risk control, and value creation. Effective data management requires FSSC to establish mechanisms for acquiring, processing, and safeguarding data throughout its lifecycle, thereby ensuring both quality and utility. In this sense, the KPA reflects the ability of FSSC to construct a complete data value chain, from data collection and storage to data processing and analysis, which enables real-time insights, supports predictive analytics, and

generates data value for the enterprise. Ultimately, data becomes the foundation for evidence-based decision-making. This study conceptualizes data management through four first-level indicators: data acquisition, data analysis, data-driven decision-making, and data security. Collectively, these indicators highlight the central role of data in elevating FSSC from a process-oriented unit to an intelligence-driven center of value creation.

First, data acquisition addresses the completeness and reliability of data collection and connection. It requires FSSC to establish service-oriented mechanisms that enable systematic data gathering, connectivity, and dynamic synchronization. The ability to collect, manage, and interlink data in real time has become an urgent requirement from senior management, as it constitutes a fundamental precondition for realizing the value of digitalization (Miller and Mork, 2013). Specifically, FSSC can apply IoT, particularly RFID, to collect asset-related data from various stages of the supply chain (Madakam et al., 2015). However, most enterprises currently lack a unified data sharing platform, which prevents FSSC from accessing accurate and comprehensive data. Meanwhile, much of the information obtained through data extraction, analysis, and visualization is based on post-hoc analysis, making real-time decision-making difficult (Addo-Tenkorang and Helo, 2016). To address these challenges, it is essential for FSSC to establish real-time and stable data connection with external systems such as the supply chain, business travel platforms, and tax sharing centers. For instance, the data about approval, order placement, payment, and invoice management in the entire procurement process can be automatically collected through the integration of financial shared service systems with procurement platforms (Vieira et al., 2020; Buntak et al., 2021). Similarly, business travel platforms can be linked to third-party systems such as Ctrip, JD and Didi to achieve the automated collection of relevant business travel data (Butrico et al., 2000; Grasso, 2017). Moreover, FSSC can develop a sharing platform of tax information, integrating data from internal tax-related activities with information from external tax authorities, thus supporting comprehensive and compliant tax management (Kohlhase and Pierk, 2020). Therefore, this paper intends to classify data acquisition into two categories: IoT data collection and real-time data connection.

Furthermore, data analysis assesses the analytical methods and tools employed to derive insights. It reflects not only the technical capacity of FSSC to process large and complex datasets but also its ability to generate actionable knowledge that supports decision-making. First, FSSC should consider the storage and processing of large volumes and diverse types of data as a fundamental component of digitalization. However, traditional approaches such as the use of conventional hard drives and internal servers are increasingly insufficient to meet the demands of modern operations (Nambiar and Mundra, 2022). To address this limitation, data lake architecture and cloud computing technologies provide strong technical support for data management to improve data analysis capability. Firstly, data lakes can significantly

improve the capacity to store and process vast quantities of heterogeneous data. As repositories for multiple data types, including structured, semi-structured, and unstructured data from both internal and external sources, data lakes can eliminate the need for predefined schemas and allow for flexible storage, transformation, and utilization of information (Fang, 2015; Nargesian et al., 2019). Specifically, data stored in the data lake does not have any predetermined structure, and can be quickly converted into any desired formats for processing, analysis, and transmission (Khine and Wang, 2018; Giebler et al., 2019). Second, FSSC should adopt cloud computing to develop a scalable financial cloud platform, integrating internal information systems and databases within a unified and high-performance infrastructure. The cloud platform architecture typically consists of three service models: IaaS, PaaS, and SaaS. They are not mutually exclusive, as most large enterprises adopt all three simultaneously to meet varying operational and technological needs (Al-Zoubi, 2017; Coman et al., 2022). In addition, financial cloud platforms offer unprecedented computing power, reaching speeds of up to 10 trillion calculations per second, which enables the application of advanced data mining techniques and the construction of predictive models for financial forecasting and decision support (Chen and Metawa, 2020; Cheng, 2022). Therefore, this paper proposes heterogeneous data storage, heterogeneous data processing, and cloud platform architecture as the key indicators to evaluate data analysis.

Most importantly, data-driven decision-making represents the ultimate objective of data management. It evaluates the extent to which managerial and strategic decisions are informed and guided by data, thereby transforming data into a core driver of organizational intelligence. Traditionally, decision-making in FSSC has relied heavily on manual procedures and retrospective analyses of historical data (Brynjolfsson et al., 2011). However, with the advancement of digitalization, FSSC now has access to vast amounts of real-time financial and business data from diverse internal and external sources (Soni et al., 2022). By utilizing this data through advanced analytical techniques, FSSC can provide enterprises with real-time insights into operational performance and support strategic decision-making across multiple functional areas. As a result, this transformation facilitates the application of decision-making support system within FSSC and the evolution of FSSC into a big data center (Sukumar and Ferrell, 2013; Ahmed et al., 2020; Onggo et al., 2021). Moreover, the decision-making support system is progressing toward intelligent decision-making. The intelligent decision support system integrates methods from economics, fuzzy mathematics, data mining, and AI to facilitate interactive human-computer decision-making for semi-structured and unstructured issues in financial management (Chowdhury, 2023; Wen, 2023). It is worth mentioning that the technical core of the system is AI, which can simulate the reasoning and problem-solving capabilities of human experts by applying logical rules and domain-specific knowledge (Zhang et al., 2020; Rabbani et al., 2023). Therefore, this paper intends to identify two key indicators for evaluating data-driven decision-making: the

development of big data center and the implementation of intelligent decision support system.

Lastly, data security concerns the mechanisms and safeguards ensuring confidentiality, integrity, and availability of information. It is a crucial component of data management, as FSSC is responsible for storing and protecting the vast majority of the enterprise's financial and business data. However, protecting data security presents a major challenge, particularly in managing the flow of data along the data value chain. According to Lee and Ahmed (2021), most FSSCs have achieved significant progress in safeguarding data by applying cutting-edge technologies and redesigning data-related processes. On the one hand, the distributed ledger, one of the technologies of blockchain, can protect data from tampering during storage and transmission due to its decentralized and immutable nature (Berdik et al., 2021; Yao and Jin, 2023). On the other hand, FSSC can enhance data security by first establishing a comprehensive data security system, then performing regular backups of critical data, finally conducting regular audits to generate compliance reports in accordance with relevant laws and regulations (Yang et al., 2020; Seth et al., 2022). Therefore, this paper intends to select data security protection as the sole indicator for evaluating data security.

4.3.5 Digital Performance

Digital performance reflects the outcomes and benefits attributable to the digitalization of FSSC in Chinese state-owned enterprise, serving as a direct measure of how effectively digital initiatives translate into tangible results. While strategy, infrastructure, processes, and data management describe the enabling conditions and activities of digitalization, digital performance captures its realized effects in terms of effectiveness and efficiency. From an operational perspective, it indicates whether digitalization has reduced costs and improved service quality. From a strategic perspective, it assesses whether digitalization has contributed to broader organizational objectives such as innovation and competitiveness. Consequently, this KPA is represented by two first-level indicators: effectiveness and efficiency. By linking digitalization inputs and processes with measurable outcomes, digital performance provides a critical benchmark for assessing the digital maturity of FSSC.

Effectiveness refers to the extent to which digital initiatives achieve their intended objectives and generate measurable benefits for FSSC (Ernawatiningsih and Kepramareni, 2019). It encompasses various dimensions, mainly including cost reduction, service quality, customer satisfaction, and social and environmental benefits. One of the primary goals of FSSC digitalization is to reduce costs arising from manual operations, redundant tasks, and inefficient workflows. By automating repetitive tasks, optimizing resource allocation, and utilizing cloud-based technologies, FSSC can achieve significant cost savings in labor, operations, and management. These improvements contribute to enhanced financial

performance, including increased profitability, stronger solvency, and long-term sustainable growth (Tammel, 2017; Liu, 2021; Wang, 2023). Secondly, the digital services provided by FSSC, particularly in financial reporting and analysis, require high levels of information transparency and data completeness. In addition, ensuring the accuracy and reliability of accounting information can improve the quality of financial analysis and support more informed decision-making (Liu et al., 2022; Zhang, 2024). Thirdly, the adoption of digital technologies allows FSSC to improve service delivery, responsiveness, and accessibility, thereby enhancing customer satisfaction and loyalty (Amin, 2016). For instance, the use of digital channels for communication and interaction, one of the customer-centric strategies, can further strengthen the relationship between FSSC and its internal or external customers (Sujud and Hachem, 2019). Finally, digitalization contributes to the fulfillment of corporate social responsibilities, including energy conservation, emissions reduction, and environmental protection. These efforts are particularly important for FSSC in supporting the broader commitment of enterprise to carbon neutrality and sustainable development (Wen et al., 2021; Huong and Thanh, 2022). Therefore, this paper proposes four criteria for evaluating effectiveness: financial performance, service quality, customer satisfaction, and social and environmental benefits.

Efficiency refers to the optimal use of resources through improvements in utilization, time reduction, and operational accuracy. Under the traditional financial processing model, the basic financial operations in each subsidiary are managed independently by their respective departments. This fragmented approach creates information barriers within the enterprise, weakens connections among subsidiaries, and causes great difficulties in communications, ultimately affecting the efficiency of operation, management and decision-making, and information transfer (Volkoff et al., 2004; Hsu et al., 2007). First of all, digitalization aims to streamline financial processes, automate routine tasks, and minimize manual errors, thereby increasing the operational efficiency of the five core financial processes previously discussed. These improvements also enable FSSC to manage higher transaction volumes with greater speed, flexibility, and scalability (Madanhire and Mbohwa, 2016; Liu, 2021). Secondly, in terms of management and decision-making, digitalization enables FSSC to make data-driven decisions aligned with enterprise digital strategies. Through the adoption of predictive modeling and scenario analysis, decision-making efficiency can be significantly improved across key functions such as fund management, budgeting, tax avoidance, and risk control (Onggo et al., 2021; Tang and Yang, 2023). Furthermore, the organization structure of FSSC is gradually becoming more flattened due to the reduction in management hierarchy of FSSC, which can lead to the improvement in efficiency of information communication within FSSC (Behrendt and Richter, 2015; Sova et al., 2022). In addition, the financial business process integration with the integrated information systems can enhance the communication and coordination between FSSC and

front-end business departments, while also improving the efficiency of data aggregation and updating (Bendoly et al., 2009; Peng and Tao, 2022). Therefore, this paper proposes three key metrics for evaluating efficiency: operational efficiency, management and decision efficiency, and information transfer efficiency.

4.3.6 External Environment

The external environment forms an indispensable component of the digitalization of FSSC in Chinese state-owned enterprise, as transformation is shaped not only by internal strategies and resources but also by the broader institutional, economic, and societal context in which FSSC operates. External pressures and drivers such as government policies, industry ecosystems, and unforeseen disruptions directly influence the pace and direction of digitalization. Particularly in the Chinese state-owned enterprise context, strong policy orientation, dynamic digital ecosystems, and global shocks like COVID-19 present both opportunities and challenges that FSSC must navigate. Accordingly, this KPA is conceptualized through three first-level indicators: government, ecosystem, and COVID-19. These dimensions highlight that digital maturity of FSSC is not only internally driven but also externally conditioned.

Government, which captures the influence of regulations, incentives, and policy directives, plays a decisive role in shaping the digitalization of FSSC. Accordingly, the digitalization of FSSC relies on the introduction of targeted policy incentives and appropriate financial assistance from the government (Park et al., 2020). However, to date, the Chinese government has yet to issue a comprehensive regulatory framework specific to financial shared service and its digitalization. Only a few provisions related to supporting the development of financial shared service can be found in documents issued by the government such as the “Norms for Enterprise Accounting Informatization Work” (Ma, 2023). Given this regulatory gap, FSSC must proactively perceive, access, and understand information regarding government policies and subsidy programs in the future, in order to assist in its digitalization (Peña-López, 2010; Zhou et al., 2023). For instance, FSSC may establish dedicated departments responsible for monitoring government announcements, interpreting new policy directives, and maintaining constructive government relations (Lu and Pan, 2016). Moreover, to ensure the sustainability of digitalization, FSSC must also be capable of attracting government funding. This requires FSSC to effectively demonstrate to the government that its digitalization has social and economic value, as well as the potential to contribute to long-term sustainable development (Doh and Kim, 2014; Pan et al., 2022). Therefore, this paper intends to evaluate the maturity of government from two categories: policy support and financial support.

Ecosystem reflects the collaborative networks and partnerships that shape digital capabilities. As the scopes of competition and cooperation among enterprises continue to expand, exploring the strategic value of digital ecosystem for financial shared service has emerged as a key trend in the current era of digitalization (Jacobides et al., 2019). A digital ecosystem for financial shared service refers to a digitally enabled alliance of interests formed between FSSC and external stakeholders, including upstream and downstream partners in the supply chain, through the application of digital technologies (Jiang, 2016; Buntak et al., 2021). A well-functioning digital ecosystem depends not only on the ability of FSSC to fully leverage the capabilities of external stakeholders to improve its own digital maturity, but also on its capacity for coordination and ecosystem management to support the implementation of digital ecosystem (Iheanachor et al., 2023). To this end, FSSC should take the lead in building shared databases and cloud platforms within the digital ecosystem. These databases and platforms serve as collaborative infrastructures through which FSSC can integrate and co-develop digital resources such as data, technology and knowledge with upstream and downstream partners in the supply chain and even competitors, thereby promoting the joint digitalization (Addo-Tenkorang and Helo, 2016; Vieira et al., 2020; Peng et al., 2023). Moreover, in cases where internal resources are insufficient to support digitalization, FSSC may actively seek external support from universities, research institutions, and consulting firms to bridge gaps and accelerate transformation (Perkmann and Walsh, 2007). Therefore, this paper intends to examine ecosystem from the perspective of digital ecosystem construction.

COVID-19 reflects the role of crisis-driven adaptation in accelerating digitalization. The COVID-19 pandemic has significantly impacted the operations and management of FSSC, bringing new challenges to the digitalization of FSSC. During the outbreak, FSSC faced increased difficulties in managing budgets and anti-epidemic materials, which in turn weakened the operational capability of FSSC, particularly in terms of capital turnover (Fitriasari, 2020; Yang and Di, 2022). In response, FSSC must conduct effective risk management and make reasonable work arrangement. Firstly, the management systems for budget and material should be strengthened to enhance emergency management capabilities, and the early warning mechanisms should be established to identify potential capital risks in advance (Yang et al., 2022; Berger et al., 2023). Furthermore, the widespread adoption of remote working in the post-pandemic era has become a major catalyst for accelerating digitalization in FSSC (Arunprasad et al., 2022). Remote work refers to a working mode where staff in FSSC can fulfill their responsibilities outside of traditional office environments, typically from their homes or other remote locations. This arrangement allows nearly all financial operations to be completed through online platforms, highlighting the importance of robust digital infrastructure. Therefore, this paper summarizes two aspects for evaluating COVID-19, including epidemic risk management and work arrangement.

4.4 Summary

When initially developing the digital maturity model for FSSC in Chinese state-owned enterprise, this study first designs a structured three-layer evaluation indicator system. By applying the model-combination strategy integrated with systems theory, six KPAs are determined to capture the core dimensions of digitalization, and the digital maturity is divided into five levels ranging from Initial to Optimizing. On this basis, a comprehensive literature analysis is further employed to develop 19 first-level indicators and 44 second-level indicators under the KPAs. In addition, each KPA and indicator is marked with its corresponding label to facilitate subsequent analysis. Therefore, the preliminary three-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise is constructed, as presented in Table 4.6. Together, this evaluation indicator system for digital maturity and the five digital maturity levels jointly constitute the preliminary version of the digital maturity model.

Table 4.6 Preliminary Three-layer Evaluation Indicator System for Digital Maturity of FSSC in Chinese State-owned Enterprise

IPO	KPAs	First-level Indicators	Second-level Indicators
Input	A1 Strategy and Organization	B1 Strategy	C1 Digital Strategy Goal
			C2 Digital Strategy Planning
		B2 Culture	C3 Digital Thinking
			C4 Innovation and Change
		B3 Talent	C5 Digital Talent
			C6 Talent Training
			C7 Talent Security
		B4 Structure	C8 Digital Leadership
	C9 Organizational Restructuring		
	A2 Infrastructure	B5 Technology	C10 Digital Technology Basis
			C11 Digital Infrastructure
		B6 Network	C12 Internet Construction
			C13 Internal Network Construction
		B7 Capital	C14 Digital Capital Investment
Processing	A3 Process Management	B8 Process Re-engineering	C15 Management and Monitoring
			C16 Continuous Optimization
			C17 Standardization
			C18 Automation and Intelligence
	B9 Process Integration	C19 Vertical Integration	
		C20 Horizontal Integration	

IPO	KPAs	First-level Indicators	Second-level Indicators	
		B10 Information Systems	C21 Management Integration	
			C22 Process Support	
			C23 System Integration	
			C24 Safety and Security	
	A4 Data Management	B11 Data Acquisition	C25 IoT Data Collection	
			C26 Real-time Data Connection	
		B12 Data Analysis	C27 Heterogeneous Data Storage	
			C28 Heterogeneous Data Processing	
			C29 Cloud Platform Architecture	
		B13 Data-driven Decision-making	C30 Big Data Center	
	C31 Intelligent Decision Support System			
	B14 Data Security	C32 Data Security Protection		
	Output	A5 Digital Performance	B15 Effectiveness	C33 Financial Performance
				C34 Service Quality
C35 Customer Satisfaction				
C36 Social and Environmental Benefits				
B16 Efficiency			C37 Operational Efficiency	
			C38 Management and Decision Efficiency	
			C39 Information Transfer Efficiency	
Environment	A6 External Environment	B17 Government	C40 Policy Support	
			C41 Financial Support	
		B18 Ecosystem	C42 Digital Ecosystem Construction	
		B19 COVID-19	C43 Epidemic Risk Management	
C44 Work Arrangement				

Chapter 5 Model Improvement

This chapter presents the model improvement, the third phase in the procedure for model design, during which the preliminary evaluation indicator system is first refined, followed by the formulation and revision of third-level indicators, and finally the construction of a complete four-layer evaluation indicator system.

5.1 Preliminary System Refinement

In order to ensure the comprehensiveness and validity of the Delphi consultation, this study established a panel of 50 experts, evenly drawn from academia and industry. Specifically, 26 experts were selected from leading universities across Beijing, Fujian, Guangdong, Hebei, Jiangsu, and Zhejiang, including associate professors and professors with extensive research experience in digitalization and financial management. Meanwhile, 24 experts were selected from FSSCs of major state-owned enterprises located in Beijing, Guangdong, Hebei, Liaoning, and Tianjin, comprising both middle and top managers with over five years of practical experience in FSSC operation and digital transformation. This balanced composition of experts from both academia and industry ensured that the Delphi consultation reflected both theoretical rigor and practical relevance, in line with the dual objectives of DSR. Tables 5.1 and 5.2 respectively present the composition of the expert panel, including the affiliations and professional roles of experts from universities and state-owned enterprises' FSSCs.

The first two rounds of the Delphi consultation focused on revising the preliminary KPAs, first-level indicators, and second-level indicators in the three-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise. Structured questionnaires using a five-point Likert scale were distributed to the experts, who were asked to assess the representativeness of the KPAs, the relevance of the first-level indicators, and the rationality of the second-level indicators. The template of the first-round questionnaire, which included Section 1, an investigation into the basic information of experts, and Sections 2–4, an evaluation of KPAs and first-level and second-level indicators, is presented in Appendix 1. In the second round, the basic information section was removed, since the same panel of experts participated in both rounds, and the revised questionnaire was redesigned to reflect the deleted, modified, or added indicators based on the results of the first-round consultation, while maintaining the same overall structure.

The first-round consultation was conducted between September and October 2023, with all 50 experts participating. The researcher adopted a one-on-one mode of administration, assisting each expert in completing the questionnaire either via telephone or through video

conference, thereby ensuring the accuracy and integrity of responses. After collecting the questionnaires, the data were summarized and analyzed using Excel and SPSS, and the preliminary evaluation indicator system was refined accordingly. The second round was carried out in November 2023 with the same group of experts, using the revised questionnaire. The collected responses were again processed through Excel and SPSS, and the analysis results confirmed that the deletions, modifications, and additions of indicators made after the first round were appropriate. These two rounds of consultation thus produced a refined evaluation indicator system, which laid the foundation for the subsequent enrichment and improvement of the digital maturity model. The following sections elaborate on the specific processes of data analysis.

Table 5.1 Expert Panel Composition: Universities

Sources		Positions		Total
Provinces	Universities	Associate Professors	Professors	
Beijing	Capital University of Economics and Business	1	2	3
	Renmin University of China	2	–	2
Fujian	Xiamen University	3	1	4
Guangdong	Sun Yat-sen University	1	2	3
Hebei	Hebei University	2	3	5
	North China Electric Power University	1	2	3
Jiangsu	Nanjing University	2	2	4
Zhejiang	Zhejiang University	2	–	2
Total		14	12	26

Table 5.2 Expert Panel Composition: State-owned Enterprises' FSSCs

Sources		Positions		Total
Provinces	State-owned Enterprises' FSSCs	Middle Managers	Top Managers	
Beijing	China Post Group	1	1	2
	Sinopec Group	1	–	1
Guangdong	China Southern Power Grid	2	2	4
Hebei	Baoding Tianwei Group	3	2	5
	Baoding Transportation Development Group	2	3	5
Liaoning	Ansteel Group	1	2	3
Tianjin	Tianjin TEDA Group	3	1	4
Total		13	11	24

5.1.1 Expert Evaluation

First of all, it is essential to examine the basic information of the experts and to evaluate their responses in each round of the Delphi consultation in terms of positivity and authority, as well as the concentration and coordination of expert opinions. Such an evaluation ensures the reliability and validity of the questionnaire results (Okoli and Pawlowski, 2004; Diamond et al., 2014).

Positivity and Authority

The positivity of experts, reflected in the 100% response rate, was demonstrated in the first two rounds. Each round of consultation achieved full participation owing to the one-on-one administration of the survey. This indicates a high degree of expert positivity, as all 50 experts actively participated in both rounds of the Delphi consultation.

Table 5.3 Experts’ Familiarity with Evaluation Content in First Two Rounds

Familiarity	Very Familiar	Familiar	Neither	Unfamiliar	Very Unfamiliar
Number	16	20	14	0	0
Assignment	1	0.8	0.5	0.2	0

Table 5.4 Basis for Experts’ Evaluation in First Two Rounds

Basis for Evaluation	Large Dependence		Medium Dependence		Small Dependence	
	Number	Assignment	Number	Assignment	Number	Assignment
Theoretical Analysis	26	0.3	22	0.2	2	0.1
Practical Experience	30	0.5	17	0.4	3	0.3
Domestic and Foreign Counterparts	24	0.1	20	0.1	6	0.1
Intuition	20	0.1	22	0.1	8	0.1

As shown in Tables 5.3 and 5.4, the authority of experts can be assessed based on their self-evaluations of familiarity with the evaluation content and the basis for their judgments (Okoli and Pawlowski, 2004; Diamond et al., 2014). Each response option was assigned a numerical value in order to quantify qualitative judgments. For familiarity, higher levels of familiarity were assigned higher values, ranging from 1 for “Very Familiar” to 0 for “Very Unfamiliar”. This reflects the strength of the experts’ self-reported knowledge. For the basis for evaluation, larger dependence on rigorous sources such as theoretical analysis or practical experience was assigned higher values, for example 0.5 for large dependence on practice, while weaker bases such as intuition were consistently given lower weights, such as 0.1. This assignment scheme provides a sound basis for deriving the coefficients of expert authority.

Accordingly, three coefficients are calculated to measure expert authority. The familiarity coefficient (hereafter referred to as C_s) reflects the extent to which experts report familiarity with the evaluation content, and is computed as:

$$C_s = \Sigma(n_i \times a_i) / N$$

where n_i denotes the number of experts selecting each level of familiarity, a_i represents the numerical value assigned to that level, and N is the total number of experts. The judgment coefficient (hereafter referred to as C_a) reflects the soundness of the bases on which experts make their evaluations, and is calculated as:

$$C_a = \Sigma(n_{ij} \times a_{ij}) / N$$

where n_{ij} denotes the number of experts at a given level of dependence on a particular judgment basis, a_{ij} is the numerical value assigned to that level, and N is the total number of experts. The authority coefficient (hereafter referred to as C_r) is then derived as the arithmetic mean of C_s and C_a :

$$C_r = (C_s + C_a) / 2$$

Based on the results of the first two rounds, C_s and C_a were calculated in Excel as 0.780 and 0.902, respectively, indicating that the experts reported a high level of familiarity with the evaluation content and relied on well-grounded bases in forming their judgments. C_r , computed as the average of the two, is 0.841. According to established Delphi research practice, a C_r value greater than 0.7 is generally recognized as indicating a high level of authority (Okoli and Pawlowski, 2004; Diamond et al., 2014). Therefore, the results demonstrate that the 50 experts in this study possessed a high degree of authority when participating in the first two rounds of the Delphi consultation.

Concentration and Coordination

Table 5.5 Concentration and Coordination of Expert Opinions in First Round

Evaluation Content	Range of Average Score	Frequency Range of Full Score	Range of CV	Kendall's W
Representativeness of KPAs	3.940–4.920	0.180–0.920	0.060–0.113	0.521
Relevance of First-level Indicators	3.600–4.860	0.040–0.860	0.075–0.179	0.361
Rationality of Second-level Indicators	3.560–4.720	0.000–0.780	0.090–0.220	0.202

Table 5.6 Concentration and Coordination of Expert Opinions in Second Round

Evaluation Content	Range of Average Score	Frequency Range of Full Score	Range of <i>CV</i>	Kendall's <i>W</i>
Representativeness of KPAs	–	–	–	–
Relevance of First-level Indicators	4.120–4.940	0.220–0.960	0.066–0.135	0.423
Rationality of Second-level Indicators	3.880–4.900	0.100–0.880	0.071–0.158	0.384

The concentration of expert opinions reflects the reliability of the scoring results in each round. As shown in Tables 5.5 and 5.6, the degree of concentration is measured by the average score and the frequency of full score, both of which were calculated using SPSS (Okoli and Pawlowski, 2004). The average score represents the mean value of expert ratings, while the frequency of full score indicates the proportion of experts assigning the maximum score. A higher average score and a higher frequency of full score suggest greater importance attributed to the corresponding KPA or indicator. In the first round, the average scores ranged from 3.560 to 4.920, while the frequencies of full score ranged from 0.000 to 0.920. In the second round, these ranges improved to 3.880–4.940 and 0.100–0.960, respectively. These results demonstrate that the degree of concentration of expert opinions increased after the second round of the Delphi consultation.

The coordination of expert opinions reflects the consistency of evaluations across KPAs and indicators. As shown in Tables 5.5 and 5.6, the degree of coordination is represented by the coefficient of variation (hereafter referred to as *CV*) and Kendall's coefficient of concordance (hereafter referred to as Kendall's *W*), both of which were also computed using SPSS (Okoli and Pawlowski, 2004). The *CV* measures the degree of dispersion in expert scores and is calculated as the standard deviation of the scores divided by the average score. According to established Delphi research practice, a *CV* less than 0.25 is generally regarded as indicating acceptable consistency, with smaller values reflecting stronger coordination. Kendall's *W* measures the consistency of rankings among multiple experts. It is obtained by comparing the observed level of consistency in the experts' rankings of KPAs and indicators with the level of agreement that would be expected by chance. Kendall's *W* ranges between 0 and 1, with larger values indicating stronger consistency. In Delphi studies, values between 0.3 and 0.5 are generally considered to reflect acceptable consistency, and values above 0.5 indicate strong coordination of expert opinions. In addition to the magnitude of Kendall's *W*, its statistical significance must also be verified through the chi-square test, as only significant values provide valid evidence of expert consensus (Okoli and Pawlowski, 2004; Diamond et al., 2014).

In the first round, *CV* values ranged from 0.060 to 0.220, and Kendall's *W* values were 0.521 for the representativeness of the KPAs, 0.361 for the relevance of the first-level indicators, and 0.202 for the rationality of the second-level indicators, all statistically significant at the 1% level with p-values less than 0.01. These results indicate strong coordination on KPAs, moderate coordination on first-level indicators, and low coordination on second-level indicators, thus necessitating a second round of consultation, which focused primarily on improving the coordination of expert ratings on the first-level and second-level indicators. In the second round, *CV* values decreased to 0.066–0.135 for first-level indicators and 0.071–0.158 for second-level indicators, while Kendall's *W* values increased to 0.423 and 0.384, respectively, both statistically significant at the 1% level with p-values less than 0.01. Compared with the first round, these improvements demonstrate a higher degree of coordination of expert opinions. Consequently, after two rounds of the Delphi consultation, expert judgments tended to converge, and no further round was required for revising the preliminary KPAs, first-level indicators, and second-level indicators in the three-layer evaluation indicator system for digital maturity.

5.1.2 Revision

This study adopted the critical value method to revise the KPAs as well as the first-level and second-level indicators in the preliminary three-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise. In this context, each evaluation objective refers respectively to the representativeness of each KPA, the relevance of each first-level indicator, and the rationality of each second-level indicator, which have already been assessed in terms of their average score, frequency of full score, and *CV* during the analysis of concentration and coordination of expert opinions. As shown in Tables 5.5 and 5.6, these statistics were calculated for both the first and second rounds of consultation, except for KPAs in the second round, since no further consultation on KPAs was conducted for reasons explained later.

The procedure of the critical value method is as follows. First, the average score, frequency of full score, and *CV* of each evaluation objective are calculated, along with their overall means and standard deviations. The critical value of average score and frequency of full score is defined as their mean minus one standard deviation, while the critical value of *CV* is defined as its mean plus one standard deviation. A KPA or indicator is considered important and should be retained if either its average score or frequency of full score exceeds the respective critical value, or if its *CV* is lower than the critical value of *CV*. To avoid the unintended elimination of important KPAs or indicators, the method further stipulates that only those failing to meet all three criteria simultaneously are eliminated. In addition, expert suggestions are fully considered when deciding whether to retain or delete KPAs or

indicators that meet only one or two of the criteria (Joshi et al., 2015; Grime and Wright, 2016). The specific steps of the revision process for KPAs, first-level indicators, and second-level indicators are introduced below.

KPA

Table 5.7 Critical Values for KPAs

	First Round		
	Average Score	Frequency of Full Score	<i>CV</i>
Mean	4.464	0.504	0.098
Standard Deviation	0.331	0.262	0.020
Critical Value	4.133	0.242	0.118

According to Table 5.7, which presents the critical values of the average score, frequency of full score, and *CV* for the representativeness of KPAs in the first round, none of the KPAs failed to meet the criteria proposed by the critical value method. At the same time, experts did not propose to add new KPAs. They unanimously emphasized that the existing six KPAs already provided comprehensive coverage of the essential dimensions of the digital maturity of FSSC. These domains not only reflect the theoretical framework derived from model combination and systems theory but also align with the actual drivers of digital transformation in Chinese state-owned enterprises. Therefore, as the first round was already sufficient to establish their validity, it was deemed unnecessary to carry out a second round of consultation on KPAs, and the six KPAs were finalized.

First-level Indicator

Table 5.8 Critical Values for First-level Indicators

	First Round			Second Round		
	Average Score	Frequency of Full Score	<i>CV</i>	Average Score	Frequency of Full Score	<i>CV</i>
Mean	4.308	0.426	0.132	4.435	0.485	0.114
Standard Deviation	0.358	0.253	0.030	0.255	0.227	0.021
Critical Value	3.951	0.173	0.162	4.180	0.258	0.136

According to Table 5.8, which presents the critical values of the average score, frequency of full score, and *CV* for the relevance of first-level indicators in the first two rounds, two indicators did not meet all three criteria simultaneously in the first round: **B12 Data Analysis** and **B19 COVID-19**.

Experts recommended that **B12 Data Analysis** be modified to **B12 Data Application**. They explained that data analysis represents only one step in the broader process of data application, whereas the ability of FSSCs to transform analysis results into actionable insights for business and financial decision-making is the true reflection of digital maturity. By reframing the indicator as “data application”, the model captures the entire value chain from data collection, processing, and visualization to its actual integration into strategic and operational management, thereby making the indicator more comprehensive and aligned with practice. Experts also suggested that **B19 COVID-19** be modified to **B19 External Disaster**. They argued that limiting the indicator to a single event such as the COVID-19 pandemic would narrow its long-term applicability, as FSSCs in Chinese state-owned enterprises face a variety of external shocks, including natural disasters and technological risks. By broadening the scope to “external disaster”, the model gains greater universality and resilience, ensuring its relevance across different contexts of disruption.

As a result, the above suggestions were accepted, and the consultation on first-level indicators was continued. In the second round of the Delphi consultation, both **B12 Data Application** and **B19 External Disaster**, along with all other first-level indicators, met the criteria of the critical value method. Meanwhile, no further deletions, modifications, and additions were proposed by experts. Therefore, the study finally identified 19 first-level indicators.

Second-level Indicator

Table 5.9 Critical Values for Second-level Indicators

	First Round			Second Round		
	Average Score	Frequency of Full Score	<i>CV</i>	Average Score	Frequency of Full Score	<i>CV</i>
Mean	4.308	0.435	0.141	4.358	0.460	0.122
Standard Deviation	0.271	0.167	0.032	0.230	0.157	0.019
Critical Value	4.038	0.268	0.173	4.128	0.303	0.142

According to Table 5.9, which presents the critical values of the average score, frequency of full score, and *CV* for the rationality of second-level indicators in the first two rounds, several indicators required deletion or modification in the first round. First, three indicators did not meet all three criteria simultaneously in the first round. Experts recommended deleting **C30 Big Data Center**, reasoning that the scope of a big data center is overly broad and typically falls under enterprise-wide digital strategies rather than FSSC-specific practices.

Including it would reduce clarity and operability in evaluating the digital maturity of FSSCs. Similarly, they advised deleting **C36 Social and Environmental Benefits**, explaining that although social and environmental benefits are essential in broader corporate governance, they are rarely integrated into the performance evaluation of FSSCs in Chinese state-owned enterprises. Retaining this indicator would add little analytical value to the digital maturity model. In addition, experts advised that **C32 Data Security Protection** should be subdivided into **C33 Data Encryption** and **C34 Data Assurance**. Their reasoning was that data security involves both technical measures such as encryption of data storage and transmission, and organizational safeguards such as backup, recovery, and audit mechanisms. By splitting this indicator into two, the model gains greater specificity and depth, ensuring that both technological and managerial aspects of data protection are captured.

Second, experts proposed modifications to four indicators that only met one or two of the criteria in the first round. They suggested changing **C15 Management and Monitoring** to **C15 System Establishment**, because the concept of management and monitoring was considered too vague and lacked measurable criteria, whereas system establishment directly reflects the establishment of institutional frameworks within FSSCs and serves as the foundation for process re-engineering. They also recommended modifying **C18 Automation and Intelligence** to **C18 Automation and Digitalization**, noting that most FSSCs in Chinese state-owned enterprises remain at the stage of automating financial processes and building digital systems, and that “intelligence” would therefore be premature. The modification to “automation and digitalization” better matches the current development stage while still allowing space for future progression toward intelligent systems. Likewise, **C29 Cloud Platform Architecture** was replaced with **C29 Data Analysis on Financial Cloud**, since the former term can only be regarded as one of the important components of the financial cloud, as it mainly focuses on the specific construction of internal cloud systems rather than serving as a comprehensive indicator on its own. By contrast, the latter highlights the actual role of cloud-based analytics in supporting financial forecasting, monitoring, and reporting. Finally, experts suggested broadening **C43 Epidemic Risk Management** to **C46 Disaster Risk Management**, as FSSCs must prepare not only for epidemics but also for a wide range of other risks, including natural disasters and cyberattacks. This broader framing ensures greater applicability and rationality for long-term evaluation.

Lastly, experts suggested adding four second-level indicators to enhance the comprehensiveness of the model. They recommended including **C30 Data Visualization** under **B12 Data Application**, because data visualization represents the final and crucial step in data application, enabling complex analytical results to be communicated clearly and applied effectively in management decision-making. They also proposed adding **C31 Decision-making Support System** under **B13 Data-driven Decision-making**, noting that

such systems serve as the prerequisite and foundation for more advanced intelligent decision support. In addition, **C38 External Service Performance** and **C44 Market Adaptation** were added under **B15 Effectiveness** and **B18 Ecosystem**, respectively, reflecting the fact that digitally mature FSSCs in Chinese state-owned enterprises increasingly extend their functions beyond internal financial management to provide outsourcing and other market-oriented services. Evaluating their performance in serving external clients and their ability to adapt to competitive market conditions therefore became necessary.

As a result, the above suggestions were accepted, and the consultation on second-level indicators was continued. In the second round of the Delphi consultation, all modified and newly added indicators, along with all other second-level indicators, met the criteria of the critical value method. Meanwhile, no further deletions, modifications, and additions were proposed by experts. Therefore, the study finally identified 47 second-level indicators.

5.1.3 Summary

After revising the KPAs as well as the first-level and second-level indicators in the preliminary evaluation indicator system, and ensuring that all of them satisfied the criteria through two rounds of the Delphi consultation, this study finalized a refined three-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise. The system consists of six KPAs, 19 first-level indicators, and 47 second-level indicators, as presented in Table 5.10. In addition, the alphabetical labels assigned to each KPA or indicator were retained from the preliminary version. However, due to the deletions and additions made during the consultation, the numbering of subsequent indicators has been adjusted accordingly.

Table 5.10 Refined Three-layer Evaluation Indicator System for Digital Maturity of FSSC in Chinese State-owned Enterprise

IPO	KPAs	First-level Indicators	Second-level Indicators
Input	A1 Strategy and Organization	B1 Strategy	C1 Digital Strategy Goal
			C2 Digital Strategy Planning
		B2 Culture	C3 Digital Thinking
			C4 Innovation and Change
		B3 Talent	C5 Digital Talent
			C6 Talent Training
			C7 Talent Security
		B4 Structure	C8 Digital Leadership
			C9 Organizational Restructuring

IPO	KPAs	First-level Indicators	Second-level Indicators
Processing	A2 Infrastructure	B5 Technology	C10 Digital Technology Basis
			C11 Digital Infrastructure
		B6 Network	C12 Internet Construction
	C13 Internal Network Construction		
	B7 Capital	C14 Digital Capital Investment	
	A3 Process Management	B8 Process Re-engineering	C15 System Establishment
			C16 Continuous Optimization
			C17 Standardization
			C18 Automation and Digitalization
B9 Process Integration		C19 Vertical Integration	
		C20 Horizontal Integration	
		C21 Management Integration	
B10 Information Systems		C22 Process Support	
		C23 System Integration	
		C24 Safety and Security	
A4 Data Management		B11 Data Acquisition	C25 IoT Data Collection
			C26 Real-time Data Connection
	B12 Data Application	C27 Heterogeneous Data Storage	
		C28 Heterogeneous Data Processing	
		C29 Data Analysis on Financial Cloud	
		C30 Data Visualization	
	B13 Data-driven Decision-making	C31 Decision-making Support System	
		C32 Intelligent Decision Support System	
	B14 Data Security	C33 Data Encryption	
		C34 Data Assurance	
Output	A5 Digital Performance	B15 Effectiveness	C35 Financial Performance
			C36 Service Quality
			C37 Customer Satisfaction
			C38 External Service Performance
	B16 Efficiency	C39 Operational Efficiency	
		C40 Management and Decision Efficiency	
C41 Information Transfer Efficiency			
Environment	A6 External Environment	B17 Government	C42 Policy Support
			C43 Financial Support
	B18 Ecosystem	C44 Market Adaptation	
		C45 Digital Ecosystem Construction	

IPO	KPAs	First-level Indicators	Second-level Indicators
		B19 External Disaster	C46 Disaster Risk Management
			C47 Work Arrangement

5.2 Indicator Extension

After completing the refinement of the preliminary three-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise, this study proceeded to further enrich the system by developing a preliminary set of third-level indicators. This step aimed to transform the refined three-layer structure into a more comprehensive four-layer evaluation framework. In line with the model design outlined in Chapter 3, semi-structured interviews were conducted with the same panel of 50 experts who had participated in the two rounds of the Delphi consultation. The interviews were designed to collect in-depth expert insights regarding the subdivision and enrichment of second-level indicators. Specifically, the semi-structured interview protocol consisted of two parts: predefined questions and open-ended discussions (Kallio et al., 2016). The full set of predefined questions and open-ended items is provided in Appendix 2.

The predefined questions focused on asking experts how each second-level indicator could be further subdivided into more concrete dimensions, what new factors should be introduced as third-level indicators, and the rationale behind these subdivisions or introductions. For example, experts were asked to specify whether a second-level indicator such as “data encryption” should be further decomposed into more concrete aspects, including encryption of data storage and transmission. They were also invited to explain why such distinctions are necessary, for instance, differentiating protection of stored financial data from secure transmission across systems, in order to more accurately evaluate the digital maturity. The second part of the interviews emphasized open-ended discussions. Experts were encouraged to propose additional third-level indicators that had not been covered in the predefined questions, to provide concrete examples from their own academic research or managerial practice, and to comment on the applicability of previously suggested indicators. This design allowed the interviews to not only validate the necessity of the proposed subdivisions, but also to capture new perspectives and emerging practices in the digitalization.

The interviews were carried out between December 2023 and February 2024, using one-on-one video conferences to ensure depth and reliability of responses. Each interview lasted approximately two to three hours. During the process, the researcher first asked each

expert the same set of predefined questions in a consistent order, and then adjusted follow-up questions flexibly according to the expert's responses. This approach ensured both comparability across interviews and flexibility for exploration of novel insights. With the consent of all participants, detailed notes and audio recordings were taken during the interviews and subsequently transcribed for analysis. After transcription, the responses were systematically organized and summarized to extract potential third-level indicators. These indicators were then compared and consolidated to form a preliminary set of third-level indicators. Each third-level indicator was assigned a unique label to facilitate subsequent reference and analysis. As a result, the refined three-layer evaluation indicator system was extended into a four-layer structure, consisting of six KPAs, 19 first-level indicators, 47 second-level indicators, and 140 third-level indicators.

It is important to emphasize that these third-level indicators do not yet represent the final version of the evaluation indicator system for digital maturity. Instead, they serve as a preliminary and structured set of indicators developed through the integration of expert knowledge.

To avoid overloading the main text with excessive descriptive detail, the preliminary set of 140 third-level indicators, together with the rationale for their selection, the underlying meanings they represent, and the typical measurement approaches adopted in practice, is presented in Appendix 3 for reference.

5.3 Final System Refinement

After developing a preliminary set of 140 third-level indicators through semi-structured interviews, which aligned with the overall evaluation objectives and dimensions of the model, it remained necessary to further revise this preliminary version in order to enhance its operability and practical value. To achieve this, two additional rounds of Delphi consultation were conducted with the same panel of 50 experts.

The third questionnaire was designed with two parts: Section 1 investigated the basic information of experts, while Section 2–7 evaluated the rationality of the third-level indicators under each KPA. A template of this questionnaire is provided in Appendix 4. Between March and April 2024, the third round of consultation was conducted, and all experts completed the questionnaire either by telephone or through video conference. The collected responses were summarized and analyzed using Excel and SPSS, and the results, together with expert feedback, were used to refine the evaluation indicator system by deleting, modifying, or adding third-level indicators as necessary, and to prepare the fourth questionnaire.

In the fourth round, conducted in May 2024, the basic information section was removed, since the same panel of experts participated in both rounds, and the revised questionnaire was adjusted to reflect the deletions, modifications, and additions made after the third round. Although the final questionnaire is not provided in the appendices, it followed the same structure and process. The collected data were again summarized and analyzed using Excel and SPSS, and the analysis confirmed the rationality of the revisions. As a result, a complete four-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise was finally established. The specific processes of data analysis are introduced in the following sections.

5.3.1 Expert Evaluation

First of all, it is essential to examine the basic information of the experts and to evaluate their responses in the last two rounds of the Delphi consultation in terms of positivity and authority, as well as the concentration and coordination of expert opinions. Such an evaluation ensures the reliability and validity of the questionnaire results.

Positivity and Authority

The positivity of experts, reflected in the 100% response rate, was demonstrated in these rounds as well. Each consultation achieved full participation owing to the one-on-one administration of the survey. This indicates a high degree of expert positivity, as all 50 experts actively participated in both the third and fourth rounds of the Delphi consultation.

Table 5.11 Experts' Familiarity with Evaluation Content in Last Two Rounds

Familiarity	Very Familiar	Familiar	Neither	Unfamiliar	Very Unfamiliar
Number	18	22	10	0	0
Assignment	1	0.8	0.5	0.2	0

Table 5.12 Basis for Experts' Evaluation in Last Two Rounds

Basis for Evaluation	Large Dependence		Medium Dependence		Small Dependence	
	Number	Assignment	Number	Assignment	Number	Assignment
Theoretical Analysis	28	0.3	21	0.2	1	0.1
Practical Experience	30	0.5	18	0.4	2	0.3
Domestic and Foreign Counterparts	22	0.1	20	0.1	8	0.1
Intuition	20	0.1	20	0.1	10	0.1

As shown in Tables 5.11 and 5.12, the authority of experts can be assessed based on their self-evaluations of familiarity with the evaluation content and the basis for their judgments. According to the results of the last two rounds, C_s and C_a calculated in Excel were 0.812 and 0.910, respectively, indicating that the experts reported a high level of familiarity with the evaluation content and relied on well-grounded bases in forming their judgments. C_r , obtained as the arithmetic mean of C_s and C_a , was 0.861. This value, being greater than 0.841 from the first two rounds, demonstrates that the degree of experts' authority in the last two rounds of the Delphi consultation was even higher, thereby ensuring strong reliability of the evaluation results.

Concentration and Coordination

Table 5.13 Concentration and Coordination of Expert Opinions in Third Round

Evaluation Content	Range of Average Score	Frequency Range of Full Score	Range of CV	Kendall's W
Rationality of Third-level Indicators	3.680–4.700	0.060–0.760	0.103–0.225	0.190

Table 5.14 Concentration and Coordination of Expert Opinions in Fourth Round

Evaluation Content	Range of Average Score	Frequency Range of Full Score	Range of CV	Kendall's W
Rationality of Third-level Indicators	3.900–4.920	0.120–0.940	0.074–0.161	0.376

The concentration of expert opinions reflects the reliability of the scoring results in each round. As shown in Tables 5.13 and 5.14, the average scores and the frequencies of full score, both calculated using SPSS, show clear improvement across the two rounds. In the third round, the average scores for the rationality of third-level indicators ranged from 3.680 to 4.700, with the frequencies of full score ranging from 0.060 to 0.760. In the fourth round, these ranges improved to 3.900–4.920 and 0.120–0.940, respectively. These results demonstrate that the degree of concentration of expert opinions on the rationality of third-level indicators increased after the last two rounds of the Delphi consultation.

The coordination of expert opinions reflects the consistency of evaluations across indicators. As shown in Tables 5.13 and 5.14, the CV values and Kendall's W , also computed using SPSS, further confirm the refinement of expert consensus. In the third round, CV values ranged from 0.103 to 0.225, while Kendall's W was 0.190 and statistically significant at the 1% level with p-value less than 0.01. These results indicate relatively low coordination on third-level indicators, thus necessitating a further round of consultation. In the fourth and

final round, *CV* values decreased to 0.074–0.161, and Kendall's *W* increased to 0.376, also statistically significant at the 1% level with *p*-value less than 0.01. Compared with the third round, these results clearly show an improvement in the degree of coordination of expert opinions, indicating that expert judgments became more consistent. Therefore, after the additional two rounds of the Delphi consultation, sufficient convergence was achieved, and no further round was required for revising the preliminary third-level indicators in the four-layer evaluation indicator system for digital maturity.

5.3.2 Revision

At this stage, the critical value method was again applied to revise the preliminary set of third-level indicators in the four-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise. The rationality of these indicators was assessed using the same criteria as in Section 5.1.2, namely average score, frequency of full score, and *CV*, with the statistical ranges across the two rounds of consultation summarized in Tables 5.13 and 5.14. Since the principles and procedures of this method have already been explained earlier, this section focuses only on the revision results.

Third-level Indicator

Table 5.15 Critical Values for Third-level Indicators

	Third Round			Fourth Round		
	Average Score	Frequency of Full Score	<i>CV</i>	Average Score	Frequency of Full Score	<i>CV</i>
Mean	4.342	0.449	0.161	4.453	0.534	0.124
Standard Deviation	0.225	0.157	0.034	0.268	0.224	0.026
Critical Value	4.117	0.293	0.195	4.184	0.309	0.150

According to Table 5.15, which presents the critical values of the average score, frequency of full score, and *CV* for the rationality of third-level indicators in the last two rounds, several deletions were identified in the preliminary set of indicators during the third round of consultation, the rationale for which is explained in detail below.

Seven indicators, namely **D9 R&D Investment**, **D24 Leadership Experience**, **D66 Process Risk Control**, **D67 Problematic Document Ratio**, **D92 Decision-making Timeliness**, **D99 Data Security System Establishment**, and **D109 Customer Complaint Handling**, failed to meet all three critical value criteria. Specifically, their average scores and

frequencies of full score fell below the threshold, while their *CV* exceeded the acceptable value. More importantly, experts noted that these indicators overlapped significantly with other indicators already retained in the system, thereby diminishing their independent explanatory value. For example, **D9 R&D Investment** was considered redundant because its scope largely coincided with **D38 Software and Hardware Investment**, which already encompasses financial and technical inputs relevant to research and development. Since FSSCs are not primary centers of technological research but rather focus on financial and data processes, retaining this indicator would dilute the specificity of the model. Similarly, **D24 Leadership Experience** was found to overlap conceptually with **C1 Digital Strategy Goal**, **C2 Digital Strategy Planning**, and **D13 Digital Application Proficiency**. The practical influence of leadership experience is already indirectly reflected in the formulation of digital strategies and in the capacity of leaders to guide digital application. Hence, its independent measurement would introduce redundancy and ambiguity regarding evaluation boundaries.

The case of **D66 Process Risk Control** further illustrates this issue. This indicator largely duplicates the content of **D62 Unified Risk Management**, which provides a comprehensive framework for risk monitoring across processes. Retaining both would blur conceptual clarity and result in double-counting of risk-related measures. Likewise, **D67 Problematic Document Ratio** was deemed to replicate the evaluation objective of **D65 Successful Process Execution**. The frequency of problematic documents represents only the inverse of process execution success, and maintaining both indicators would not provide new insights but rather create unnecessary complexity. For **D92 Decision-making Timeliness**, experts emphasized that its conceptual boundary strongly overlaps with **D123 Decision Execution Efficiency**, as the latter already encompasses both the speed of decision formulation within FSSC and the responsiveness of enterprise in implementing those decisions. Since timeliness is inherently embedded within execution efficiency, attempting to separate the two would be difficult in practice and may blur the distinction between these closely related phenomena. **D99 Data Security System Establishment** also displayed redundancy. Although not identical to the three indicators under **C15 System Establishment**, its scope overlaps substantially with the combined coverage of **C15** and **B14 Data Security**. Specifically, while **C15** provides the institutional frameworks for process governance and **B14** addresses data protection through encryption and assurance, **D99** merely reiterates these dimensions without offering independent explanatory value. Finally, **D109 Customer Complaint Handling** was considered too narrow, as it merely reflects reactive responses to unmet needs, whereas **D110 Customer Requirement Fulfillment** provides a more comprehensive and proactive assessment of customer orientation. For these reasons, the seven indicators were suggested to be removed from the system.

Beyond these cases of redundancy, two further indicators, namely **D11 Patent Grant Rate** and **D70 System Update Cycle**, were suggested to be deleted due to limited applicability, even though their *CV* fell within acceptable ranges. Experts highlighted that the patent grant rate is not a meaningful measure in the context of FSSCs, since these centers are seldom involved in technological invention or intellectual property management. Their role is primarily operational and financial, and thus patent applications rarely occur in practice. Similarly, the system update cycle was regarded as a basic technical condition rather than a meaningful independent dimension of maturity. Updating and upgrading cycles are already implicitly included within broader system integration and maintenance activities, including both the integration of internal systems within FSSC and the interfaces between financial shared systems and other business systems. As a result, both **D11** and **D70** were suggested to be removed from the system.

In addition to deletions, experts proposed modifications to improve conceptual clarity and practical relevance. **D112 Customer Development** was considered too broad, as it failed to distinguish between internal users such as subsidiaries or departments of the enterprise, and external customers in the emerging outsourcing market. Given that the adaptation of FSSCs to competitive external environments increasingly depends on their ability to attract and serve external clients, this indicator was redefined as **D121 External Customer Development** and reassigned from **C37 Customer Satisfaction** to **C44 Market Adaptation**. This modification ensures that the system explicitly reflects the growing strategic importance of market-oriented service provision as a critical dimension of digital maturity.

As a result, the above suggestions were accepted, and a fourth and final round of consultation was conducted. The results confirmed that all retained and modified third-level indicators, including **D121 External Customer Development**, satisfied the criteria of the critical value method. Meanwhile, no further suggestions for deletion, modification, or addition were proposed at this stage. Consequently, this study identified 131 third-level indicators.

5.3.3 Summary

After revising the third-level indicators, and confirming that all of them satisfied the established criteria through two additional rounds of the Delphi consultation, this study finalized a comprehensive four-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise. The complete system consists of six KPAs, 19 first-level indicators, 47 second-level indicators, and 131 third-level indicators, as presented in Table 5.16. The alphabetical labels assigned to each third-level indicator were retained from the preliminary version, while the numbering of subsequent indicators was adjusted to reflect the

deletions, modifications, and additions made during the consultation process. This refined structure ensures that the model is both comprehensive and concise. It eliminates redundancy, strengthens conceptual clarity, and emphasizes indicators that are distinctive, applicable, and capable of capturing the specific pathways through which FSSCs in Chinese state-owned enterprises achieve digital transformation. Through the entire Delphi process of multiple rounds of consultation and expert interviews, a complete evaluation indicator system has been established, the construction of which represents the realization of model improvement and significantly enhances the overall digital maturity model.

Table 5.16 Final Four-layer Evaluation Indicator System for Digital Maturity of FSSC in Chinese State-owned Enterprise

IPO	KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators
Input	A1 Strategy and Organization	B1 Strategy	C1 Digital Strategy Goal	D1 Actual Situation Alignment
				D2 Business Strategy Alignment
				D3 Customer Value Maximization
			C2 Digital Strategy Planning	D4 Long Term Strategic Development
				D5 Transformation Model Selection
				D6 Resource Allocation Plan
		B2 Culture	C3 Digital Thinking	D7 Data-driven Culture Construction
				C4 Innovation and Change
			D9 Innovative Idea Implementation	
		B3 Talent	C5 Digital Talent	D10 Digital Talent Ratio
				D11 Digital Application Proficiency
				D12 Adaptation and Adjustment
			C6 Talent Training	D13 Accounting Training
				D14 Business Training
				D15 Digital Technology Training
			C7 Talent Security	D16 Talent Appraisal System Establishment
				D17 Promotion Channel Provision
				D18 Talent Incentive Mechanism Construction
		D19 Job Rotation Implementation		
		B4 Structure	C8 Digital Leadership	D20 Leadership Position
				D21 Leadership Engagement
			C9 Organizational Restructuring	D22 Role and Responsibility
				D23 Flat Organization

IPO	KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators
	A2 Infrastructure	B5 Technology	C10 Digital Technology Basis	D24 Decentralized Functional Structure
				D25 IoT Application
				D26 Big Data Application
				D27 Cloud Computing Application
				D28 Blockchain Application
		D29 AI Application		
		C11 Digital Infrastructure	D30 Equipment Digitalization	
		B6 Network	C12 Internet Construction	D31 Internet Access
				D32 Internet Performance
			C13 Internal Network Construction	D33 Internal Network Access
		D34 Internal Network Performance		
	B7 Capital	C14 Digital Capital Investment	D35 Software and Hardware Investment	
			D36 System Upgrade and Maintenance Investment	
			D37 Digital Talent Training Investment	
			D38 Organizational Restructuring Investment	
			D39 Process Re-engineering Investment	
	Processing	A3 Process Management	B8 Process Re-engineering	C15 System Establishment
D41 Efficiency Supervision System				
D42 Operation Management System				
C16 Continuous Optimization				D43 Feedback Mechanism
				D44 Process–Operation Alignment
C17 Standardization				D45 Procurement and A/P Standardization
			D46 Sales and A/R Standardization	
			D47 Expense Reimbursement Standardization	

IPO	KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators
			C18 Automation and Digitalization	D48 General Ledger and Reporting Standardization
				D49 Procurement and A/P Automation
				D50 Sales and A/R Automation
				D51 Expense Reimbursement Automation
				D52 General Ledger and Reporting Automation
		B9 Process Integration	C19 Vertical Integration	D53 Financial Process Coordination
				D54 Financial–Business Process Alignment
			C20 Horizontal Integration	D55 Business Operation Support
				D56 Centralized Fund Management
			C21 Management Integration	D57 Comprehensive Budget Management
				D58 Integrated Tax Management
		B10 Information Systems	C22 Process Support	D59 Unified Risk Management
				D60 Connection Stability
				D61 User-friendly Operation
			C23 System Integration	D62 Successful Process Execution
				D63 FSSC System Integration
			C24 Safety and Security	D64 FSSC–Business System Integration
				D65 Access Control
				D66 Firewall Installation and Update
	D67 Vulnerability Scan and Report			
	A4 Data Management	B11 Data Acquisition	C25 IoT Data Collection	D68 Fault Restoration
D69 System Maintenance				
D70 RFID Asset Identification Integrity				
D71 RFID Data Entry Accuracy				

IPO	KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators
			C26 Real-time Data Connection	D72 Supply Chain Connection
				D73 Business Travel Platform Connection
				D74 Tax Sharing Center Connection
		B12 Data Application	C27 Heterogeneous Data Storage	D75 Data Storage Capacity
				D76 Data Storage Performance
			C28 Heterogeneous Data Processing	D77 Data Processing Timeliness
				D78 Data Processing Quality
			C29 Data Analysis on Financial Cloud	D79 Cloud Platform Architecture
				D80 Computing Speed
				D81 Data Mining Breadth and Depth
				D82 Model Establishment and Prediction
			C30 Data Visualization	D83 Usage Frequency
				D84 Clarity and Conciseness
		D85 Adaptability		
		B13 Data-driven Decision-making	C31 Decision-making Support System	D86 Decision-making Compliance
				D87 Decision-making Effectiveness
			C32 Intelligent Decision Support System	D88 Human–Computer Interaction
		B14 Data Security	C33 Data Encryption	D89 Decision-making Intelligence
				D90 Data Storage Encryption
			C34 Data Assurance	D91 Data Transmission Encryption
D92 Data Backup and Recovery				
Output	A5 Digital Performance	B15 Effectiveness	C35 Financial Performance	D93 Audit and Report
				D94 Cost Benefit Ratio
				D95 Net Profit Growth Rate

IPO	KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	
			C36 Service Quality	D96 Current Ratio	
				D97 Accounting Information Transparency	
				D98 Financial Report Integrity	
				D99 Financial Analysis Validity	
			C37 Customer Satisfaction	D100 Service Agreement Fulfillment	
				D101 Customer Requirement Fulfillment	
				D102 Customer Loyalty	
			C38 External Service Performance	D103 Market Share	
				D104 External Income Ratio	
			B16 Efficiency	C39 Operational Efficiency	D105 Payment Efficiency
					D106 Collection Efficiency
					D107 Reimbursement Review Efficiency
		D108 Report Preparation Efficiency			
		C40 Management and Decision Efficiency		D109 Fund Management Efficiency	
				D110 Budget Management Efficiency	
				D111 Tax Management Efficiency	
				D112 Risk Management Efficiency	
C41 Information Transfer Efficiency	D113 Decision Execution Efficiency				
	D114 FSSC Communication Efficiency				
	D115 FSSC–Business Unit Communication Efficiency				
	D116 Data Summarization Efficiency				
D117 Data Update Efficiency					
Environment	A6 External Environment	B17 Government	C42 Policy Support	D118 Access to Policy Information	
			C43 Financial Support	D119 Government Funding Acquisition	

IPO	KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	
		B18 Ecosystem	C44 Market Adaptation	D120 Market Demand Awareness	
					D121 External Customer Development
					D122 Competitor Monitoring
			C45 Digital Ecosystem Construction	D123 Supply Chain Digital Resource Integration	
					D124 Digital Resource Complementarity with Competitors
					D125 Industry–University–Research Cooperation
				D126 Shared Database Creation	
		B19 External Disaster	C46 Disaster Risk Management	D127 Budget Emergency Management	
					D128 Capital Risk Early Warning
				D129 Material Control	
		C47 Work Arrangement		D130 Emergency Support Team Establishment	
				D131 Remote Work Implementation	

Chapter 6 Weight Determination

This chapter presents the weight determination, the fourth phase in the procedure for model design, during which AHP is applied to construct pairwise comparison matrices, calculate and validate local weights, aggregate expert judgments, and finally derive global weights to provide a reliable weighting foundation for the evaluation indicator system.

6.1 Assessor Selection

In this study, 10 assessors were selected from the expert panel that had previously participated in the Delphi rounds. These expert assessors were chosen for their familiarity with the proposed KPAs and indicators, as well as their proficiency in applying the AHP method. The panel was evenly composed of five scholars from leading universities and five senior practitioners from FSSCs of major state-owned enterprises, ensuring a balance between theoretical expertise and practical experience. Detailed information on these assessors is provided in Table 6.1.

The questionnaire was distributed to the assessors between August and September 2024. The researcher used a one-on-one administration approach, assisting each assessor in completing the questionnaire either via telephone, video conference, or email. This ensured that the assessors had a clear understanding of the questions and could resolve any uncertainties they encountered during the process. Assessors were encouraged to reach out at any time with questions, ensuring the accuracy and integrity of their responses. Once completed, the full set of 10 questionnaires was collected within this two-month period. It should be noted that the specific content and design of the structured questionnaire, which involves the specific steps of AHP, will be discussed later.

Table 6.1 Detailed Information of Expert Assessors

No.	Age	Affiliation	Years of Experience	Position
1	52	Nanjing University	18	Professor
2	38	Renmin University of China	7	Associate Professor
3	48	Sun Yat-sen University	15	Professor
4	36	Xiamen University	6	Associate Professor
5	40	Zhejiang University	9	Associate Professor
6	51	Ansteel Group	24	Top Manager
7	41	China Post Group	17	Top Manager
8	49	China Southern Power Grid	20	Top Manager
9	47	Sinopec Group	21	Middle Manager
10	53	Tianjin TEDA Group	25	Middle Manager

6.2 Hierarchy Establishment

The first step in AHP is to organize the defined problem into a hierarchical structure according to the established evaluation indicator system. According to Saaty (1977, 2008), the hierarchy typically consists of three levels, including goal level, criteria level, and sub-criteria level. The goal level represents the highest level and reflects the ultimate objective that the defined problem aims to achieve. The criteria level contains a series of distinct evaluation criteria that can directly influence the ultimate objective and can be further divided into sub-criteria. At the sub-criteria level, specific and measurable indicators are set based on the criteria to facilitate a more detailed evaluation. It should be emphasized that additional sub-criteria levels can be added depending on the number of levels in the established evaluation indicator system.

Based on the final four-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise, presented in Table 5.16, this study established a hierarchical structure model for digital maturity evaluation, as shown in Table 6.2. In this model, the goal level is defined as the digital maturity of FSSC in Chinese state-owned enterprise (**A**), representing the ultimate objective of this study: determining and improving the development level of digitalization of FSSC in Chinese state-owned enterprise. The criteria level consists of six KPAs (**A1** to **A6**), which directly influence various aspects of digital maturity and reflect the maturity level across different domains. At the sub-criteria level, the first-level indicators (**B1** to **B19**) are defined, followed by the second-level indicators (**C1** to **C47**) and the third-level indicators (**D1** to **D131**), which provide a more detailed and measurable framework for evaluation. The first-level and second-level indicators together form the first sub-criteria level and the second sub-criteria level, respectively. Moving further down the hierarchy, the third-level indicators are introduced, forming the final layer of the hierarchy and falling under the third sub-criteria level. This hierarchical structure model enables a systematic and tiered evaluation of the various key factors in the digitalization process, with each level of indicators building upon the previous one. It provides a clear and actionable assessment of digital maturity, along with practical recommendations for improvement.

Table 6.2 Hierarchical Structure Model

Level	Description
Goal Level	Digital Maturity (A)
Criteria Level	KPAs (A1 to A6)
Sub-criteria Level (1st)	First-level Indicators (B1 to B19)
Sub-criteria Level (2nd)	Second-level Indicators (C1 to C47)
Sub-criteria Level (3rd)	Third-level Indicators (D1 to D131)

6.3 Pairwise Comparison Matrix Construction

The second step in AHP is to construct multiple pairwise comparison matrices at each level of the hierarchy. As shown in Table 6.3, the pairwise comparison matrix A is a square matrix in which elements (A_i and A_j) at the same level are compared pairwise with respect to their impact on the parent element (B_k) at the level above (Saaty, 1977). These comparisons are used to derive scores (a_{ij}) that reflect the relative importance of element A_i over element A_j based on Saaty's 1–9 scale. It is always adopted as the score scale in AHP to represent the intensity of importance between two elements. The detailed definition and explanation of Saaty's 1–9 scale is provided in Table 6.4 (Saaty, 2001).

Based on the established hierarchical structure model, a structured questionnaire was designed to collect expert judgments. The first part of the questionnaire introduced the evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise. This section explained the hierarchical structure and outlined the reference standards for importance ratings according to Table 6.4. The second part of the questionnaire contained the pairwise comparison matrices at different levels of the hierarchy, requiring assessors to evaluate the relative importance of KPAs or indicators by assigning scores according to Saaty's 1–9 scale. The assessors performed these comparisons based on their AHP expertise and domain knowledge.

A total of 67 pairwise comparison matrices were constructed. At the goal level, one matrix was designed to compare the relative importance of the KPAs with respect to the ultimate objective. At the criteria level, six matrices were developed, each corresponding to one of the KPAs. Each matrix compares the relative importance of the first-level indicators with respect to the corresponding KPA. At the sub-criteria levels, 18 matrices were created to compare the relative importance of the second-level indicators with respect to the first-level indicators, and 42 matrices were developed to compare the relative importance of the third-level indicators with respect to the second-level indicators. It should be noted that the number of matrices does not directly correspond to the number of indicators because some indicators, such as **B7 Capital**, only have a single corresponding indicator, such as **C14 Digital Capital Investment**, which does not require a pairwise comparison matrix. This results in 18 matrices for the 19 first-level indicators. Additionally, no pairwise comparison matrices were constructed for the third-level indicators, as they form the final layer of the hierarchy and are not further subdivided. The full questionnaire template used in this study is provided in Appendix 5.

Table 6.3 N-order Pairwise Comparison Matrix $A(a_{ij})_{n \times n}$

B_k	A_1	A_2	...	A_j	...	A_n
A_1	a_{11}	a_{12}	...	a_{1j}	...	a_{1n}
A_2	a_{21}	a_{22}	...	a_{2j}	...	a_{2n}
...
A_j	a_{j1}	a_{j2}	...	a_{jj}	...	a_{jn}
...
A_n	a_{n1}	a_{n2}	...	a_{nj}	...	a_{nn}

Table 6.4 Definition and Explanation of Saaty's 1–9 Scale

Score	Definition	Explanation
1	Equal Importance	Both elements are equally important.
3	Moderate Importance	One element is slightly more important than the other.
5	Strong Importance	One element is strongly more important than the other.
7	Very Strong Importance	One element is significantly more important than the other.
9	Extreme Importance	One element is absolutely more important than the other.
2, 4, 6, 8	Intermediate Values	Used for comparisons that fall between two adjacent judgments.
Reciprocals 1/X (1/3, 1/5, etc.)	Reverse Comparison	If element A_i is X times more important than element A_j , then element A_j is 1/X times as important as element A_i .

6.4 Local Weight Calculation and Validation

Once all the data are collected via questionnaires, the results of the pairwise comparisons from each assessor are analyzed. This analysis first involves calculating the local weights for each element at every level and conducting a consistency test to ensure the rationality and reliability of the expert judgments. To illustrate the process, the results from individual assessors are examined in detail, followed by the aggregation of judgments from all assessors to generate aggregated matrices. The local weights are then recalculated based on these aggregated matrices, and consistency tests are conducted again. Through this stepwise analysis, both the individual and aggregated judgments are validated to be rational and reliable. The procedure for local weight calculation and consistency validation is detailed in the following subsection.

6.4.1 Calculation Procedure

Local weight, which represents the relative importance of each element within its group, synthesized from all pairwise scores (a_{ij}) in the comparison matrix, reflects the overall significance of the element under the same parent element at the same hierarchical level. The local weights for all elements within a group are normalized so that their sum equals one. After the completion of pairwise comparison matrix A , the local weight for element A_i , that is, its relative importance within B_k as aggregated from all pairwise comparisons, is derived as the components of the priority vector. In this study, the row average method is employed to calculate the priority vector, and the procedure is as follows (Saaty, 1977, 2008).

First, the pairwise comparison matrix A is normalized by dividing each score by its respective column sum.

$$\tilde{a}_{ij} = \frac{a_{ij}}{\sum_{i=1}^n a_{ij}} \quad (i, j = 1, 2, \dots, n)$$

Second, the normalized values in each row are summed.

$$\widetilde{W}_i = \sum_{j=1}^n \tilde{a}_{ij} \quad (i, j = 1, 2, \dots, n)$$

Third, the priority vector $W = (W_1, W_2, \dots, W_n)^T$ of the pairwise comparison matrix A , in which W_i represents the local weight for element A_i , is obtained by dividing each row sum by the matrix order (n).

$$W_i = \frac{\widetilde{W}_i}{n} \quad (i = 1, 2, \dots, n)$$

Since the completion of pairwise comparison matrix A relies on subjective judgments by assessors, the consistency test must first be conducted on each completed matrix at every hierarchical level to ensure rational and logical comparisons. This involves calculating the consistency ratio (hereafter referred to as CR) of each matrix, with the detailed procedure described below (Saaty, 1977, 2013).

First, the principal eigenvalue (λ_{\max}) of the matrix A is derived according to the formula shown below. In an ideal case, where the matrix is perfectly consistent, its principal eigenvalue should be equal to the matrix order (n). In practice, λ_{\max} is slightly larger than n

due to the inconsistency in human judgment. The closer λ_{\max} is to n , the more consistent the matrix is.

$$\lambda_{\max} = \frac{1}{n} \sum_{i=1}^n \frac{AW_i}{W_i} \quad (i=1,2,\dots,n)$$

Second, the consistency index (hereafter referred to as CI) is obtained once λ_{\max} is derived.

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

Third, the random consistency index (hereafter referred to as RI) needs to be determined. The value of RI depends on the order of the matrix (n) and is obtained from a standard table developed by Saaty in 1977. Table 6.5 shows RI for matrices of n from 1 to 10.

Table 6.5 Random Consistency Index

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Lastly, CR is calculated by dividing CI by RI . If CR is less than 0.1, matrix A is considered consistent, the comparisons are rational and logical, and the local weight for element A_i is reliable. Otherwise, if CR is greater than or equal to 0.1, matrix A lacks consistency, the comparisons are irrational and illogical, and the judgments which are the scores (a_{ij}) in matrix A should be reviewed and revised.

$$CR = \frac{CI}{RI}$$

Furthermore, since the local weights for elements at each level contribute to the final weight determination, the inconsistencies in intermediate levels can propagate and ultimately lead to unreliable results. Therefore, the consistency test must be performed not only for each pairwise comparison matrix but also for the entire hierarchy. This step ensures that the final weights assigned to the indicators are reliable and consistent with the judgments made at different levels of the hierarchy. Meanwhile, an approximate overall consistency test has been proposed, based on the calculation of the overall consistency ratio (hereafter referred to as CR_{total}) of the pairwise comparison matrices at the final level where such matrices can be

constructed. Assuming matrix A is located at this level, the formula is shown below, in which w_k is the local weight for B_k , and CI_k and RI_k are the consistency index and random consistency index of matrix A for B_k , while m denotes the number of pairwise comparison matrices at this level. If CR_{total} is less than 0.1, the entire hierarchy is considered reasonably consistent and the final results are reliable. Otherwise, if CR_{total} is greater than or equal to 0.1, the judgments made at all levels should be reviewed and revised.

$$CR_{total} = \frac{\sum_{k=1}^m w_k CI_k}{\sum_{k=1}^m w_k RI_k} \quad (k = 1, 2, \dots, m)$$

After all pairwise comparison matrices at all levels completed by each assessor together with the corresponding final results, have passed the consistency test, the judgments made by all assessors can be considered rational and reliable.

6.4.2 Application to Expert Judgments

To demonstrate the application of these procedures, the results from Assessor 1 are used as an illustrative example. Tables 6.6 to 6.9 present one representative pairwise comparison matrix from Assessor 1 at the goal level, criteria level, first sub-criteria level, and second sub-criteria level. Each matrix was analyzed using Excel to calculate the local weights for the KPAs or indicators and conduct consistency tests.

Table 6.6 Pairwise Comparison Matrix for A at Goal Level (Assessor 1)

A Digital Maturity	A1 Strategy and Organization	A2 Infrastructure	A3 Process Management	A4 Data Management	A5 Digital Performance	A6 External Environment
A1 Strategy and Organization	1	4	2	1/3	4	5
A2 Infrastructure	1/4	1	1/2	1/6	1	1
A3 Process Management	1/2	2	1	1/4	2	3
A4 Data Management	3	6	4	1	6	7
A5 Digital Performance	1/4	1	1/2	1/6	1	1
A6 External Environment	1/5	1	1/3	1/7	1	1

Table 6.6 presents the pairwise comparison matrix for **A** with its six KPAs at the goal level. The priority vector W is calculated as (0.234, 0.063, 0.128, 0.455, 0.063, 0.056). The λ_{\max} is 6.075, the CI is 0.015, the RI is 1.24, and the CR is 0.012. Since the CR is less than 0.1, the matrix satisfies the consistency requirement, and the local weights for the six KPAs are considered reliable.

Table 6.7 Pairwise Comparison Matrix for A1 at Criteria Level (Assessor 1)

A1 Strategy and Organization	B1 Strategy	B2 Culture	B3 Talent	B4 Structure
B1 Strategy	1	3	1/2	4
B2 Culture	1/3	1	1/5	2
B3 Talent	2	5	1	7
B4 Structure	1/4	1/2	1/7	1

Table 6.7 displays the pairwise comparison matrix for **A1** with its four first-level indicators at the criteria level. The priority vector W is calculated as (0.288, 0.112, 0.532, 0.068). The λ_{\max} is 4.022, the CI is 0.007, the RI is 0.90, and the CR is 0.008. As the CR is less than 0.1, this matrix meets the consistency requirement, and the local weights for **B1**, **B2**, **B3**, and **B4** are considered reliable. By applying the same procedure, the priority vectors and consistency test results for the other five matrices at the criteria level are obtained, as summarized in Table 6.10.

Table 6.8 Pairwise Comparison Matrix for B1 at First Sub-criteria Level (Assessor 1)

B1 Strategy	C1 Digital Strategy Goal	C2 Digital Strategy Planning
C1 Digital Strategy Goal	1	3
C2 Digital Strategy Planning	1/3	1

Table 6.8 shows the pairwise comparison matrix for **B1** with its two second-level indicators at the first sub-criteria level. The priority vector W is calculated as (0.750, 0.250). The λ_{\max} is 2.000, the CI is 0.000, and the RI is 0.00. In this case, the CR is not applicable because the RI is zero for a two-element matrix. However, such matrices are by definition always consistent, and therefore the local weights for **C1** and **C2** are considered reliable. Similarly, the priority vectors and consistency test results for the other 17 matrices at the first sub-criteria level are computed and reported in Table 6.10.

Table 6.9 presents the pairwise comparison matrix for **C1** with its three third-level indicators at the second sub-criteria level. The priority vector W is calculated as (0.123, 0.320, 0.557). The λ_{\max} is 3.018, the CI is 0.009, the RI is 0.58, and the CR is 0.016. Since the CR is less than 0.1, the matrix satisfies the consistency requirement, and the local weights for **D1**,

D2, and **D3** are considered reliable. By the same method, the priority vectors and consistency test results for the other 41 matrices at the second sub-criteria level are derived and summarized in Table 6.10.

Table 6.9 Pairwise Comparison Matrix for C1 at Second Sub-criteria Level (Assessor 1)

C1 Digital Strategy Goal	D1 Actual Situation Alignment	D2 Business Strategy Alignment	D3 Customer Value Maximization
D1 Actual Situation Alignment	1	1/3	1/4
D2 Business Strategy Alignment	3	1	1/2
D3 Customer Value Maximization	4	2	1

Table 6.10 Priority Vectors and Consistency Test Results (Assessor 1)

Matrix	Priority Vector W	λ_{\max}	CI	RI	CR	Consistency Test Result
A	(0.234, 0.063, 0.128, 0.455, 0.063, 0.056)	6.075	0.015	1.24	0.012	Pass
A1	(0.288, 0.112, 0.532, 0.068)	4.022	0.007	0.90	0.008	Pass
A2	(0.309, 0.110, 0.581)	3.004	0.002	0.58	0.003	Pass
A3	(0.164, 0.539, 0.297)	3.009	0.005	0.58	0.008	Pass
A4	(0.138, 0.274, 0.059, 0.530)	4.050	0.017	0.90	0.019	Pass
A5	(0.250, 0.750)	2.000	0.000	0.00	null	Pass
A6	(0.230, 0.648, 0.122)	3.004	0.002	0.58	0.003	Pass
B1	(0.750, 0.250)	2.000	0.000	0.00	null	Pass
B2	(0.750, 0.250)	2.000	0.000	0.00	null	Pass
B3	(0.309, 0.110, 0.581)	3.004	0.002	0.58	0.003	Pass
B4	(0.750, 0.250)	2.000	0.000	0.00	null	Pass
B5	(0.667, 0.333)	2.000	0.000	0.00	null	Pass
B6	(0.667, 0.333)	2.000	0.000	0.00	null	Pass
B8	(0.423, 0.123, 0.227, 0.227)	4.010	0.004	0.90	0.004	Pass
B9	(0.309, 0.581, 0.110)	3.004	0.002	0.58	0.003	Pass
B10	(0.429, 0.143, 0.429)	3.000	0.000	0.58	0.000	Pass
B11	(0.500, 0.500)	2.000	0.000	0.00	null	Pass
B12	(0.162, 0.489, 0.288, 0.060)	4.019	0.006	0.90	0.007	Pass
B13	(0.250, 0.750)	2.000	0.000	0.00	null	Pass
B14	(0.500, 0.500)	2.000	0.000	0.00	null	Pass
B15	(0.117, 0.254, 0.544, 0.086)	4.108	0.036	0.90	0.040	Pass
B16	(0.275, 0.657, 0.068)	3.044	0.022	0.58	0.038	Pass
B17	(0.750, 0.250)	2.000	0.000	0.00	null	Pass
B18	(0.667, 0.333)	2.000	0.000	0.00	null	Pass
B19	(0.667, 0.333)	2.000	0.000	0.00	null	Pass
C1	(0.123, 0.320, 0.557)	3.018	0.009	0.58	0.016	Pass
C2	(0.309, 0.110, 0.581)	3.004	0.002	0.58	0.003	Pass

Matrix	Priority Vector W	λ_{\max}	CI	RI	CR	Consistency Test Result
C4	(0.250, 0.750)	2.000	0.000	0.00	null	Pass
C5	(0.143, 0.571, 0.286)	3.000	0.000	0.58	0.000	Pass
C6	(0.164, 0.539, 0.297)	3.009	0.005	0.58	0.008	Pass
C7	(0.237, 0.131, 0.578, 0.054)	4.054	0.018	0.90	0.020	Pass
C8	(0.250, 0.750)	2.000	0.000	0.00	null	Pass
C9	(0.309, 0.110, 0.581)	3.004	0.002	0.58	0.003	Pass
C10	(0.119, 0.344, 0.062, 0.357, 0.119)	5.004	0.001	1.12	0.001	Pass
C12	(0.200, 0.800)	2.000	0.000	0.00	null	Pass
C13	(0.667, 0.333)	2.000	0.000	0.00	null	Pass
C14	(0.158, 0.433, 0.280, 0.047, 0.082)	5.049	0.012	1.12	0.011	Pass
C15	(0.110, 0.309, 0.581)	3.004	0.002	0.58	0.003	Pass
C16	(0.800, 0.200)	2.000	0.000	0.00	null	Pass
C17	(0.150, 0.284, 0.063, 0.502)	4.049	0.016	0.90	0.018	Pass
C18	(0.129, 0.052, 0.247, 0.573)	4.069	0.023	0.90	0.026	Pass
C20	(0.500, 0.500)	2.000	0.000	0.00	null	Pass
C21	(0.088, 0.272, 0.158, 0.482)	4.015	0.005	0.90	0.005	Pass
C22	(0.648, 0.122, 0.230)	3.004	0.002	0.58	0.003	Pass
C23	(0.750, 0.250)	2.000	0.000	0.00	null	Pass
C24	(0.123, 0.046, 0.072, 0.300, 0.459)	5.062	0.016	1.12	0.014	Pass
C25	(0.250, 0.750)	2.000	0.000	0.00	null	Pass
C26	(0.292, 0.093, 0.615)	3.003	0.001	0.58	0.002	Pass
C27	(0.200, 0.800)	2.000	0.000	0.00	null	Pass
C28	(0.750, 0.250)	2.000	0.000	0.00	null	Pass
C29	(0.171, 0.066, 0.171, 0.593)	4.037	0.012	0.90	0.014	Pass
C30	(0.143, 0.286, 0.571)	3.000	0.000	0.58	0.000	Pass
C31	(0.833, 0.167)	2.000	0.000	0.00	null	Pass
C32	(0.250, 0.750)	2.000	0.000	0.00	null	Pass
C33	(0.200, 0.800)	2.000	0.000	0.00	null	Pass
C34	(0.333, 0.667)	2.000	0.000	0.00	null	Pass
C35	(0.539, 0.164, 0.297)	3.009	0.005	0.58	0.008	Pass
C36	(0.595, 0.129, 0.277)	3.006	0.003	0.58	0.005	Pass
C37	(0.682, 0.216, 0.103)	3.003	0.001	0.58	0.002	Pass
C38	(0.750, 0.250)	2.000	0.000	0.00	null	Pass
C39	(0.290, 0.535, 0.081, 0.095)	4.016	0.005	0.90	0.006	Pass
C40	(0.158, 0.047, 0.433, 0.082, 0.280)	5.049	0.012	1.12	0.011	Pass
C41	(0.267, 0.104, 0.121, 0.509)	4.016	0.005	0.90	0.006	Pass
C44	(0.659, 0.185, 0.156)	3.029	0.015	0.58	0.025	Pass
C45	(0.188, 0.067, 0.176, 0.568)	4.027	0.009	0.90	0.010	Pass
C46	(0.292, 0.615, 0.093)	3.003	0.001	0.58	0.002	Pass

Matrix	Priority Vector W	λ_{\max}	CI	RI	CR	Consistency Test Result
C47	(0.750, 0.250)	2.000	0.000	0.00	null	Pass

Table 6.10 summarizes the priority vectors and consistency test results for all matrices at different levels, based on the responses of Assessor 1. The results indicate that every pairwise comparison matrix constructed by Assessor 1 at each level of the hierarchy, a total of 67 matrices, passes the consistency test. Accordingly, the local weights derived from these matrices for all KPAs and indicators are considered reliable. Furthermore, by applying the formula for the approximate overall consistency test, which is based on the calculation of the CR_{total} of the pairwise comparison matrices at the second sub-criteria level, the CR_{total} is obtained using Excel. The result is 0.010, which is less than 0.1. This confirms that the entire hierarchy is reasonably consistent and that the final results are reliable and consistent with the judgments made across the different levels of the hierarchy.

The same procedure was subsequently applied to the remaining nine assessors, and in the process of consistency testing, any pairwise comparison matrices that failed to meet the requirement were adjusted and revised until they satisfied the criterion. The results show that all pairwise comparison matrices completed by the 10 assessors, as well as the entire hierarchy, ultimately pass the consistency test. Together, these findings indicate that the judgments provided by all 10 assessors can be regarded as rational and reliable, which provides a solid foundation for the subsequent aggregation and weight determination.

6.4.3 Aggregation of Expert Judgments

Due to multiple assessors making pairwise comparisons of elements simultaneously, AHP always requires the aggregation of scores in matrices provided by each assessor to generate the aggregated matrices that integrate the judgments of all assessors. The geometric average method is used to calculate the average scores in the aggregated matrices, which are then used to compute local weights and conduct consistency tests (Forman and Peniwati, 1998; Saaty, 2008). Moreover, following the procedures described above, the local weights for all elements must be recalculated using the average scores in the aggregated matrices. These weights are considered the final local weights, as they are derived from the integrated judgments of all assessors instead of a single assessor, and they will subsequently be used for the computation of global weights and the application of the established evaluation indicator system. At the same time, both the consistency test for each aggregated matrix and the overall consistency test need to be conducted again according to the procedures described above to ensure that all judgments in the aggregated matrices are consistent and that the final global weights for all indicators, which will be calculated in the next step, are reliable.

In this study, after all pairwise comparison matrices completed by the 10 assessors passed both the consistency tests and the overall consistency test, the geometric average method was also applied to aggregate their judgments. Specifically, for each element in the same matrix, 10 assessors provided 10 scores, and the geometric mean of these scores was calculated. In this way, a new set of aggregated pairwise comparison matrices was generated, in which every entry represents the geometric mean of the judgments given by the 10 assessors. As a result, a total of 67 aggregated matrices were obtained for subsequent analysis. Based on these aggregated matrices, the local weights for each KPA or indicator were recalculated using Excel, and consistency tests were conducted again for each matrix, followed by the overall consistency test. To illustrate the procedure, one aggregated matrix at the goal level is first presented and analyzed in detail.

Table 6.11 Aggregated Pairwise Comparison Matrix for A at Goal Level

A Digital Maturity	A1 Strategy and Organization	A2 Infrastructure	A3 Process Management	A4 Data Management	A5 Digital Performance	A6 External Environment
A1 Strategy and Organization	1	1.320	0.978	0.315	1.644	1.661
A2 Infrastructure	0.758	1	0.675	0.314	1.159	1.188
A3 Process Management	1.023	1.482	1	0.381	1.625	1.732
A4 Data Management	3.178	3.185	2.625	1	4.217	4.225
A5 Digital Performance	0.608	0.863	0.616	0.237	1	1.054
A6 External Environment	0.602	0.842	0.577	0.237	0.949	1

Table 6.11 presents the aggregated pairwise comparison matrix for A with its six KPAs at the goal level. The priority vector W is calculated as (0.146, 0.112, 0.156, 0.401, 0.094, 0.091). The λ_{\max} is 6.008, the CI is 0.002, the RI is 1.24, and the CR is 0.001. Since the CR is less than 0.1, the aggregated matrix satisfies the consistency requirement, and the final local weights for the six KPAs are considered reliable. Furthermore, similar analyses were conducted for the aggregated matrices at the criteria, first sub-criteria, and second sub-criteria levels. To avoid redundancy, the detailed results for each matrix are not presented individually. Instead, the priority vectors and consistency test results for all 67 aggregated matrices across the hierarchy are summarized in Table 6.12 to provide a comprehensive overview.

Table 6.12 Priority Vectors and Consistency Test Results (Aggregated Matrices)

Matrix	Priority Vector W	λ_{\max}	CI	RI	CR	Consistency Test Result
A	(0.146, 0.112, 0.156, 0.401, 0.094, 0.091)	6.008	0.002	1.24	0.001	Pass
A1	(0.235, 0.184, 0.471, 0.111)	4.004	0.001	0.90	0.001	Pass
A2	(0.312, 0.215, 0.473)	3.000	0.000	0.58	0.000	Pass
A3	(0.227, 0.384, 0.389)	3.005	0.002	0.58	0.004	Pass
A4	(0.186, 0.178, 0.244, 0.393)	4.002	0.001	0.90	0.001	Pass
A5	(0.473, 0.527)	2.000	0.000	0.00	null	Pass
A6	(0.301, 0.413, 0.287)	3.001	0.000	0.58	0.001	Pass
B1	(0.527, 0.473)	2.000	0.000	0.00	null	Pass
B2	(0.503, 0.497)	2.000	0.000	0.00	null	Pass
B3	(0.311, 0.199, 0.490)	3.000	0.000	0.58	0.000	Pass
B4	(0.517, 0.483)	2.000	0.000	0.00	null	Pass
B5	(0.448, 0.552)	2.000	0.000	0.00	null	Pass
B6	(0.414, 0.586)	2.000	0.000	0.00	null	Pass
B8	(0.312, 0.184, 0.335, 0.169)	4.001	0.000	0.90	0.000	Pass
B9	(0.305, 0.449, 0.246)	3.001	0.000	0.58	0.001	Pass
B10	(0.282, 0.245, 0.473)	3.000	0.000	0.58	0.000	Pass
B11	(0.438, 0.562)	2.000	0.000	0.00	null	Pass
B12	(0.233, 0.300, 0.372, 0.095)	4.010	0.003	0.90	0.004	Pass
B13	(0.344, 0.656)	2.000	0.000	0.00	null	Pass
B14	(0.468, 0.532)	2.000	0.000	0.00	null	Pass
B15	(0.126, 0.316, 0.432, 0.125)	4.016	0.005	0.90	0.006	Pass
B16	(0.287, 0.420, 0.292)	3.000	0.000	0.58	0.000	Pass
B17	(0.567, 0.433)	2.000	0.000	0.00	null	Pass
B18	(0.500, 0.500)	2.000	0.000	0.00	null	Pass
B19	(0.490, 0.510)	2.000	0.000	0.00	null	Pass
C1	(0.163, 0.419, 0.418)	3.000	0.000	0.58	0.000	Pass
C2	(0.440, 0.333, 0.227)	3.001	0.001	0.58	0.001	Pass
C4	(0.353, 0.647)	2.000	0.000	0.00	null	Pass
C5	(0.152, 0.384, 0.464)	3.001	0.000	0.58	0.001	Pass
C6	(0.175, 0.562, 0.264)	3.001	0.000	0.58	0.001	Pass
C7	(0.166, 0.260, 0.453, 0.121)	4.004	0.001	0.90	0.002	Pass
C8	(0.339, 0.661)	2.000	0.000	0.00	null	Pass
C9	(0.251, 0.217, 0.531)	3.002	0.001	0.58	0.002	Pass
C10	(0.183, 0.297, 0.204, 0.150, 0.165)	5.002	0.001	1.12	0.001	Pass
C12	(0.326, 0.674)	2.000	0.000	0.00	null	Pass
C13	(0.326, 0.674)	2.000	0.000	0.00	null	Pass
C14	(0.147, 0.164, 0.235, 0.154, 0.299)	5.004	0.001	1.12	0.001	Pass
C15	(0.304, 0.262, 0.434)	3.001	0.000	0.58	0.001	Pass

Matrix	Priority Vector W	λ_{\max}	CI	RI	CR	Consistency Test Result
C16	(0.562, 0.438)	2.000	0.000	0.00	null	Pass
C17	(0.168, 0.198, 0.198, 0.437)	4.003	0.001	0.90	0.001	Pass
C18	(0.168, 0.105, 0.307, 0.420)	4.005	0.002	0.90	0.002	Pass
C20	(0.399, 0.601)	2.000	0.000	0.00	null	Pass
C21	(0.147, 0.213, 0.239, 0.401)	4.001	0.000	0.90	0.000	Pass
C22	(0.314, 0.138, 0.549)	3.003	0.002	0.58	0.003	Pass
C23	(0.433, 0.567)	2.000	0.000	0.00	null	Pass
C24	(0.155, 0.127, 0.091, 0.349, 0.278)	5.010	0.002	1.12	0.002	Pass
C25	(0.308, 0.692)	2.000	0.000	0.00	null	Pass
C26	(0.288, 0.114, 0.598)	3.006	0.003	0.58	0.005	Pass
C27	(0.271, 0.729)	2.000	0.000	0.00	null	Pass
C28	(0.381, 0.619)	2.000	0.000	0.00	null	Pass
C29	(0.160, 0.146, 0.287, 0.408)	4.001	0.000	0.90	0.000	Pass
C30	(0.150, 0.307, 0.543)	3.000	0.000	0.58	0.000	Pass
C31	(0.464, 0.536)	2.000	0.000	0.00	null	Pass
C32	(0.341, 0.659)	2.000	0.000	0.00	null	Pass
C33	(0.506, 0.494)	2.000	0.000	0.00	null	Pass
C34	(0.328, 0.672)	2.000	0.000	0.00	null	Pass
C35	(0.373, 0.387, 0.240)	3.002	0.001	0.58	0.001	Pass
C36	(0.324, 0.258, 0.418)	3.000	0.000	0.58	0.000	Pass
C37	(0.283, 0.441, 0.276)	3.000	0.000	0.58	0.000	Pass
C38	(0.564, 0.436)	2.000	0.000	0.00	null	Pass
C39	(0.264, 0.265, 0.282, 0.189)	4.005	0.002	0.90	0.002	Pass
C40	(0.145, 0.136, 0.274, 0.342, 0.103)	5.003	0.001	1.12	0.001	Pass
C41	(0.250, 0.230, 0.147, 0.373)	4.000	0.000	0.90	0.000	Pass
C44	(0.487, 0.327, 0.186)	3.000	0.000	0.58	0.000	Pass
C45	(0.292, 0.188, 0.125, 0.395)	4.002	0.001	0.90	0.001	Pass
C46	(0.348, 0.516, 0.136)	3.000	0.000	0.58	0.000	Pass
C47	(0.744, 0.256)	2.000	0.000	0.00	null	Pass

The results from Table 6.12 indicate that every aggregated pairwise comparison matrix passes the consistency test. Accordingly, the final local weights derived from these aggregated matrices for all KPAs and indicators are considered reliable. Furthermore, by applying the formula for the approximate overall consistency test, which is based on the calculation of the CR_{total} of the aggregated pairwise comparison matrices at the second sub-criteria level, the CR_{total} is obtained using Excel. The result is 0.001, which is less than 0.1. This confirms that the entire aggregated hierarchy is reasonably consistent and that the final global weights assigned to all indicators are reliable and consistent with the aggregated

judgments made across the different levels of the hierarchy. Together, these findings indicate that the judgments aggregated from the 10 assessors can be regarded as rational and reliable, and provide a solid foundation for the final global weight determination.

6.5 Global Weight Determination

The final step in AHP is to determine the global weights for elements at the final sub-criteria level. Global weight represents the overall priority or significance of an element within the entire hierarchical structure, taking into account both its local weight within the same level and the influence of all its parent elements at higher levels. More importantly, the global weight for an element reflects its direct contribution to the ultimate objective defined at the goal level. Additionally, the sum of global weights across all elements at the same level always equals one, thereby ensuring consistency and comparability across the hierarchy. As shown in the following formula, the global weight for each element is obtained by multiplying its local weight by the global weight for its parent, and this multiplication process is repeated through all levels of the hierarchy until the goal level is reached (Saaty, 1977, 2008, 2013).

$$GW_i = LW_i \times LW_{p1} \times LW_{p2} \times \cdots \times LW_k$$

where GW_i denotes the global weight for element A_i , LW_i is its local weight at the lowest sub-criteria level, and LW_{p1} , LW_{p2} , \cdots , LW_k represents the local weights for its parent elements across successive higher levels.

It should be emphasized that in practice, the calculation and presentation of global weights focus only on the elements at the final sub-criteria level rather than those at higher levels. This is because the final-level elements are the most specific and measurable constructs in the hierarchy, directly capturing the phenomena under study. By contrast, the upper-level elements such as KPAs and intermediate indicators primarily serve as structural categories to organize and guide the evaluation process. Their relative weights are already embedded in the computation of the final-level global weights, making it unnecessary and potentially redundant to present them again (Saaty, 1977).

In this study, this procedure is applied to the 131 elements located at the third sub-criteria level, corresponding to the third-level indicators in the established evaluation indicator system. The global weight for each third-level indicator is thus derived by multiplying its local weight by the local weight for its parent at the second sub-criteria level, then multiplying again by the local weight for its parent at the first sub-criteria level, and finally multiplying by the local weight for its parent KPA at the criteria level. All local weights used

in this calculation are obtained from the aggregated pairwise comparison matrices, rather than from the judgments of individual assessors, and are presented for each level because they are essential for applying the model in real FSSCs to compute digital maturity. Through this process, the global significance of every third-level indicator is obtained. The results, including the local and global weights for all 131 third-level indicators together with the local weights for KPAs, first-level indicators, and second-level indicators, are presented in Table 6.13. Therefore, with the passed consistency tests, both local weights and global weights are assigned to KPAs and indicators at all levels and to indicators at the final level respectively, becoming the important components of the comprehensive four-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise.

Through the four phases of the procedure for model design, the digital maturity model for determining and improving the development level of digitalization of FSSC in Chinese state-owned enterprise has been fully developed. The model comprises two integral components. First, a complete evaluation indicator system for digital maturity, which consists of a four-layer hierarchical structure covering six KPAs, 19 first-level indicators, 47 second-level indicators, and 131 third-level indicators, each assigned both local and global weights to ensure their relative importance is rigorously established. Second, a set of five digital maturity levels previously defined, which provides a progressive framework for assessing the level of digitalization across FSSCs. Together, the evaluation indicator system and the maturity levels form a comprehensive and operational model that enables both the diagnosis of current digital maturity and the identification of specific pathways for continuous improvement.

Table 6.13 Comprehensive Results of Local and Global Weights across Hierarchical Structure Model

Goal Level	Criteria Level		Sub-criteria Level (1st)		Sub-criteria Level (2nd)		Sub-criteria Level (3rd)		
	KPAs	Local Weights	First-level Indicators	Local Weights	Second-level Indicators	Local Weights	Third-level Indicators	Local Weights	Global Weights
Digital Maturity of FSSC in Chinese State-owned Enterprise	A1 Strategy and Organization	0.146	B1 Strategy	0.235	C1 Digital Strategy Goal	0.527	D1 Actual Situation Alignment	0.163	0.003
							D2 Business Strategy Alignment	0.419	0.008
							D3 Customer Value Maximization	0.418	0.008
					C2 Digital Strategy Planning	0.473	D4 Long Term Strategic Development	0.440	0.007
							D5 Transformation Model Selection	0.333	0.005
							D6 Resource Allocation Plan	0.227	0.004
			B2 Culture	0.184	C3 Digital Thinking	0.503	D7 Data-driven Culture Construction	1.000	0.013
							C4 Innovation and Change	0.497	D8 Risk Appetite
					D9 Innovative Idea Implementation	0.647			0.009
			B3 Talent	0.471	C5 Digital Talent	0.311	D10 Digital Talent Ratio	0.152	0.003
							D11 Digital Application Proficiency	0.384	0.008
							D12 Adaptation and Adjustment	0.464	0.010
					C6 Talent Training	0.199	D13 Accounting Training	0.175	0.002
							D14 Business Training	0.562	0.008
							D15 Digital Technology Training	0.264	0.004
					C7 Talent Security	0.490	D16 Talent Appraisal System Establishment	0.166	0.006
							D17 Promotion Channel Provision	0.260	0.009
							D18 Talent Incentive Mechanism Construction	0.453	0.015
			B4 Structure	0.111	C8 Digital Leadership	0.517	D19 Job Rotation Implementation	0.121	0.004
							D20 Leadership Position	0.339	0.003
					C9 Organizational	0.483	D21 Leadership Engagement	0.661	0.006
							D22 Role and Responsibility	0.251	0.002

Goal Level	Criteria Level		Sub-criteria Level (1st)		Sub-criteria Level (2nd)		Sub-criteria Level (3rd)				
	KPAs	Local Weights	First-level Indicators	Local Weights	Second-level Indicators	Local Weights	Third-level Indicators	Local Weights	Global Weights		
	A2 Infrastructure	0.112	B5 Technology	0.312	Restructuring		D23 Flat Organization	0.217	0.002		
							D24 Decentralized Functional Structure	0.531	0.004		
			B6 Network	0.215	C10 Digital Technology Basis	0.448	D25 IoT Application		D26 Big Data Application	0.183	0.003
							D27 Cloud Computing Application		0.297	0.005	
							D28 Blockchain Application		0.204	0.003	
							D29 AI Application		0.150	0.002	
									0.165	0.003	
									1.000	0.019	
			B7 Capital	0.473	C11 Digital Infrastructure	0.552	D30 Equipment Digitalization		D31 Internet Access	0.326	0.003
							D32 Internet Performance		0.674	0.007	
							D33 Internal Network Access		0.326	0.005	
							D34 Internal Network Performance		0.674	0.009	
			B8 Process Re-engineering	0.227	C12 Internet Construction	0.414	D35 Software and Hardware Investment		D36 System Upgrade and Maintenance Investment	0.147	0.008
							D37 Digital Talent Training Investment		0.164	0.009	
							D38 Organizational Restructuring Investment		0.235	0.012	
							D39 Process Re-engineering Investment		0.154	0.008	
									0.299	0.016	
			A3 Process Management	0.156	C13 Internal Network Construction	0.586	D40 Quality Assessment System		D41 Efficiency Supervision System	0.304	0.003
							D42 Operation Management System		0.262	0.003	
							D43 Feedback Mechanism		0.434	0.005	
D44 Process-Operation Alignment	0.562	0.004									
	0.184	0.004									
						0.438	0.003				

Goal Level	Criteria Level		Sub-criteria Level (1st)		Sub-criteria Level (2nd)		Sub-criteria Level (3rd)		
	KPAs	Local Weights	First-level Indicators	Local Weights	Second-level Indicators	Local Weights	Third-level Indicators	Local Weights	Global Weights
					C17 Standardization	0.335	D45 Procurement and A/P Standardization	0.168	0.002
							D46 Sales and A/R Standardization	0.198	0.002
							D47 Expense Reimbursement Standardization	0.198	0.002
							D48 General Ledger and Reporting Standardization	0.437	0.005
					C18 Automation and Digitalization	0.169	D49 Procurement and A/P Automation	0.168	0.001
							D50 Sales and A/R Automation	0.105	0.001
							D51 Expense Reimbursement Automation	0.307	0.002
							D52 General Ledger and Reporting Automation	0.420	0.003
			B9 Process Integration	0.384	C19 Vertical Integration	0.305	D53 Financial Process Coordination	1.000	0.018
							C20 Horizontal Integration	0.449	D54 Financial–Business Process Alignment
					D55 Business Operation Support	0.601			0.016
					C21 Management Integration	0.246			D56 Centralized Fund Management
							D57 Comprehensive Budget Management	0.213	0.003
			B10 Information Systems	0.389	C22 Process Support	0.282	D58 Integrated Tax Management	0.239	0.004
							D59 Unified Risk Management	0.401	0.006
							D60 Connection Stability	0.314	0.005
C23 System Integration	0.245	D61 User-friendly Operation			0.138	0.002			
		D62 Successful Process Execution			0.549	0.009			
		D63 FSSC System Integration			0.433	0.006			
C24 Safety and Security	0.473	D64 FSSC–Business System Integration	0.567	0.008					
		D65 Access Control	0.155	0.004					
						D66 Firewall Installation and Update	0.127	0.004	

Goal Level	Criteria Level		Sub-criteria Level (1st)		Sub-criteria Level (2nd)		Sub-criteria Level (3rd)		
	KPAs	Local Weights	First-level Indicators	Local Weights	Second-level Indicators	Local Weights	Third-level Indicators	Local Weights	Global Weights
		0.401					D67 Vulnerability Scan and Report	0.091	0.003
							D68 Fault Restoration	0.349	0.010
							D69 System Maintenance	0.278	0.008
			B11 Data Acquisition	0.186	C25 IoT Data Collection	0.438	D70 RFID Asset Identification Integrity	0.308	0.010
							D71 RFID Data Entry Accuracy	0.692	0.023
					C26 Real-time Data Connection	0.562	D72 Supply Chain Connection	0.288	0.012
							D73 Business Travel Platform Connection	0.114	0.005
			B12 Data Application	0.178	C27 Heterogeneous Data Storage	0.233	D74 Tax Sharing Center Connection	0.598	0.025
							D75 Data Storage Capacity	0.271	0.005
					C28 Heterogeneous Data Processing	0.300	D76 Data Storage Performance	0.729	0.012
							D77 Data Processing Timeliness	0.381	0.008
					C29 Data Analysis on Financial Cloud	0.372	D78 Data Processing Quality	0.619	0.013
							D79 Cloud Platform Architecture	0.160	0.004
							D80 Computing Speed	0.146	0.004
					C30 Data Visualization	0.095	D81 Data Mining Breadth and Depth	0.287	0.008
							D82 Model Establishment and Prediction	0.408	0.011
			D83 Usage Frequency	0.150			0.001		
			D84 Clarity and Conciseness	0.307			0.002		
B13 Data-driven Decision-making	0.244	C31 Decision-making Support System	0.344	D85 Adaptability	0.543	0.004			
				D86 Decision-making Compliance	0.464	0.016			
		C32 Intelligent Decision Support System	0.656	D87 Decision-making Effectiveness	0.536	0.018			
				D88 Human-Computer Interaction	0.341	0.022			
				D89 Decision-making Intelligence	0.659	0.042			

Goal Level	Criteria Level		Sub-criteria Level (1st)		Sub-criteria Level (2nd)		Sub-criteria Level (3rd)		
	KPAs	Local Weights	First-level Indicators	Local Weights	Second-level Indicators	Local Weights	Third-level Indicators	Local Weights	Global Weights
			B14 Data Security	0.393	C33 Data Encryption	0.468	D90 Data Storage Encryption	0.506	0.037
							D91 Data Transmission Encryption	0.494	0.036
					C34 Data Assurance	0.532	D92 Data Backup and Recovery	0.328	0.027
							D93 Audit and Report	0.672	0.056
					C35 Financial Performance	0.126	D94 Cost Benefit Ratio	0.373	0.002
							D95 Net Profit Growth Rate	0.387	0.002
	D96 Current Ratio	0.240	0.001						
	C36 Service Quality	0.316	D97 Accounting Information Transparency	0.324	0.005				
			D98 Financial Report Integrity	0.258	0.004				
			D99 Financial Analysis Validity	0.418	0.006				
	C37 Customer Satisfaction	0.432	D100 Service Agreement Fulfillment	0.283	0.005				
			D101 Customer Requirement Fulfillment	0.441	0.009				
			D102 Customer Loyalty	0.276	0.005				
	C38 External Service Performance	0.125	D103 Market Share	0.564	0.003				
			D104 External Income Ratio	0.436	0.002				
	A5 Digital Performance	0.094	B15 Effectiveness	0.473	C39 Operational Efficiency	0.287	D105 Payment Efficiency	0.264	0.004
							D106 Collection Efficiency	0.265	0.004
							D107 Reimbursement Review Efficiency	0.282	0.004
D108 Report Preparation Efficiency							0.189	0.003	
C40 Management and Decision Efficiency					0.420	D109 Fund Management Efficiency	0.145	0.003	
						D110 Budget Management Efficiency	0.136	0.003	
B16 Efficiency	0.527	C40 Management and Decision Efficiency	0.420	D111 Tax Management Efficiency	0.274	0.006			
				D112 Risk Management Efficiency	0.342	0.007			
				D113 Decision Execution Efficiency	0.103	0.002			

Goal Level	Criteria Level		Sub-criteria Level (1st)		Sub-criteria Level (2nd)		Sub-criteria Level (3rd)					
	KPAs	Local Weights	First-level Indicators	Local Weights	Second-level Indicators	Local Weights	Third-level Indicators	Local Weights	Global Weights			
		0.091			C41 Information Transfer Efficiency	0.292	D114 FSSC Communication Efficiency	0.250	0.004			
							D115 FSSC–Business Unit Communication Efficiency	0.230	0.003			
							D116 Data Summarization Efficiency	0.147	0.002			
							D117 Data Update Efficiency	0.373	0.005			
			A6 External Environment		0.091	B17 Government	0.301	C42 Policy Support	0.567	D118 Access to Policy Information	1.000	0.016
								C43 Financial Support	0.433	D119 Government Funding Acquisition	1.000	0.012
						B18 Ecosystem	0.413	C44 Market Adaptation	0.500	D120 Market Demand Awareness	0.487	0.009
										D121 External Customer Development	0.327	0.006
										D122 Competitor Monitoring	0.186	0.004
								C45 Digital Ecosystem Construction	0.500	D123 Supply Chain Digital Resource Integration	0.292	0.006
										D124 Digital Resource Complementarity with Competitors	0.188	0.004
										D125 Industry–University–Research Cooperation	0.125	0.002
						D126 Shared Database Creation	0.395			0.007		
						B19 External Disaster	0.287	C46 Disaster Risk Management	0.490	D127 Budget Emergency Management	0.348	0.004
										D128 Capital Risk Early Warning	0.516	0.007
										D129 Material Control	0.136	0.002
								C47 Work Arrangement	0.510	D130 Emergency Support Team Establishment	0.744	0.010
D131 Remote Work Implementation	0.256	0.003										

Chapter 7 Model Evaluation

This chapter presents the model evaluation, the final phase in the procedure for model design, during which the developed digital maturity model is applied to multiple case studies of FSSCs in Chinese state-owned enterprises. Using the FCE method, the study integrates weights and survey data to derive digital maturity scores, thereby testing the model's reliability, validity, and practical applicability.

7.1 Sample Selection

In the evaluation phase of this study, the multiple case study method was adopted to apply and validate the proposed digital maturity model for FSSC in Chinese state-owned enterprise. The purpose of employing multiple case studies is to examine the model in real-world contexts, thereby assessing its reliability, validity, and practical applicability. By applying the model to a group of representative FSSCs in Chinese state-owned enterprises, it becomes possible to generate empirical insights into its effectiveness, while also identifying potential areas for refinement and improvement.

A total of five FSSCs from Chinese state-owned enterprises—namely, Ansteel Group, Baoding Transportation Development Group, China FAW Group, Lubei Group, and Tianjin TEDA Group—were ultimately selected for this initial validation. The decision to limit the number of cases to five was driven by two considerations. First, this phase of the research is intended as a preliminary validation of the model rather than a large-scale application. Conducting in-depth evaluation with a smaller sample allows for careful observation of the model's explanatory power and practical utility, while ensuring that sufficient detail can be captured for each case. This approach facilitates an assessment of the model's reliability, validity, and applicability within the constraints of the doctoral research timeframe. Second, given the comprehensive structure of the model and the complexity of the evaluation process, a focused set of five cases provides a feasible balance between scope and depth, with the expectation that further large-scale application can be undertaken in subsequent studies after this initial validation.

The selection of these five FSSCs was based on both subjective and objective considerations. Subjectively, three of them—Ansteel Group, Baoding Transportation Development Group, and Tianjin TEDA Group—were chosen because their middle and top managers had previously participated in the Delphi consultation and semi-structured interviews during the third phase of this study. Their familiarity with the model's content and digitalization concepts helped to ensure smoother cooperation and more reliable responses in the evaluation process. Objectively, the five enterprises represent diverse industries,

including steel manufacturing, transportation, automobile manufacturing, chemicals, and financial investment. Their FSSCs manage heterogeneous financial and business processes, face distinct digitalization challenges, and operate under varying external environments. Applying the model across such industries thus enabled a more comprehensive test of its cross-sector adaptability and robustness. In addition, the feasibility of access, facilitated through the support of academic supervisors and professional contacts, played a critical role in securing the participation of these five state-owned enterprises' FSSCs. Furthermore, the digitalization background of each enterprise and its FSSC will be briefly introduced in the subsequent analysis to provide necessary context for interpreting their evaluation results.

In implementing the proposed digital maturity model within these five FSSCs, this study employed the FCE method. The FCE requires the collection of structured empirical data from respondents within each case, typically through the distribution of questionnaires designed to capture perceptions of digital maturity across multiple indicators (Zadeh, 1965; Chen and Hwang, 1992). In line with this requirement, and taking into account the specific circumstances of each enterprise, approximately 20 managers and staff members directly or indirectly involved in the daily operation or digitalization of each FSSC were invited to participate. Specifically, 24 valid responses were collected from Ansteel Group, 20 from Baoding Transportation Development Group, 21 from China FAW Group, 21 from Lubei Group, and 21 from Tianjin TEDA Group, resulting in a total of 107 completed questionnaires. The survey was conducted between October 2024 and January 2025, and all 107 questionnaires were successfully retrieved, yielding a response rate of 100%. The distribution of participants in terms of their roles and the proportion directly engaged in digitalization will be indicated in the subsequent analysis of the digital maturity of FSSC in each enterprise. The questionnaire format and scoring procedure, which serve as the foundation for the FCE application, are detailed in the following sections of this chapter.

7.2 Model Application

Having introduced the selection of the five cases and the process of data collection, this section presents the application of the developed digital maturity model within the selected FSSCs through the use of the FCE method. FCE is particularly suitable for this study because it integrates qualitative judgments with quantitative analysis, thereby addressing the inherent fuzziness and subjectivity associated with evaluating digital maturity. To ensure methodological rigor, the evaluation process follows a structured procedure that provides a systematic pathway for transforming the hierarchical evaluation indicator system into empirical results, enabling a rigorous and comprehensive assessment of the digital maturity levels of the participating FSSCs.

7.2.1 Factor Set Establishment

The first step in FCE is to establish the factor set, which is a collection of the factors to be evaluated. Each element of the set represents one evaluation factor. This step lays the foundation of the model by ensuring that all relevant criteria are comprehensively defined and systematically represented:

$$U = \{u_1, u_2, \dots, u_n\}$$

where $u_i (i = 1, 2, \dots, n)$ denotes each evaluation factor (Zimmermann, 2012).

In this study, based on the final four-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise presented in Chapter 5, the factor set is defined as the set of indicators across four hierarchical levels: criteria level, first sub-criteria level, second sub-criteria level, and third sub-criteria level. The complete structure covers six KPAs, 19 first-level indicators, 47 second-level indicators, and 131 third-level indicators. To maintain clarity, the factor sets of criteria level and first sub-criteria level are fully presented below, while the second and third sub-criteria levels are illustrated by a representative example in the main text, with the full lists already provided in Table 5.16.

Factor Set of Criteria Level:

$$U = \{A1 \text{ Strategy and Organization, A2 Infrastructure, A3 Process Management, A4 Data Management, A5 Digital Performance, A6 External Environment}\}$$

Factor Set of First Sub-criteria Level:

$$U_1 = \{B1 \text{ Strategy, B2 Culture, B3 Talent, B4 Structure}\}$$

$$U_2 = \{B5 \text{ Technology, B6 Network, B7 Capital}\}$$

$$U_3 = \{B8 \text{ Process Re-engineering, B9 Process Integration, B10 Information Systems}\}$$

$$U_4 = \{B11 \text{ Data Acquisition, B12 Data Application, B13 Data-driven Decision-making, B14 Data Security}\}$$

$$U_5 = \{B15 \text{ Effectiveness, B16 Efficiency}\}$$

$$U_6 = \{B17 \text{ Government, B18 Ecosystem, B19 External Disaster}\}$$

Illustrative Examples of Factor Sets of Second and Third Sub-criteria Levels:

$$U_{11} = \{C1 \text{ Digital Strategy Goal, C2 Digital Strategy Planning}\}, \text{ under B1 Strategy}$$

$$U_{111} = \{D1 \text{ Actual Situation Alignment, D2 Business Strategy Alignment, D3 Customer Value Maximization}\}, \text{ under C1 Digital Strategy Goal}$$

These examples demonstrate how the factor sets are organized hierarchically from the criteria

level down to the third sub-criteria level.

7.2.2 Evaluation Set Establishment

The second step is to establish the evaluation set, which represents the possible outcomes or grades assigned to the evaluated object. Each grade corresponds to a fuzzy subset, reflecting qualitative judgments such as “very good”, “good”, “average”, or “poor”. This step transforms vague linguistic assessments into structured categories that can be quantified:

$$V = \{v_1, v_2, \dots, v_m\}$$

where $v_j (j = 1, 2, \dots, m)$ denotes each evaluation grade (Zhu, 2022).

In this study, the evaluation set corresponds to the maturity grade set, which aligns with the five defined digital maturity levels. Following the framework established in Chapter 4, the maturity grade set is thus expressed as $V = \{\text{Initial, Repeatable, Defined, Managed, Optimizing}\}$ arranged from the lowest to the highest level. To facilitate quantification in the FCE process, these five maturity levels are further assigned numerical scores from 1 to 5, such that Initial corresponds to 1, Repeatable to 2, Defined to 3, Managed to 4, and Optimizing to 5. Accordingly, the score intervals are defined as 0–1 for the Initial level, 1–2 for the Repeatable level, 2–3 for the Defined level, 3–4 for the Managed level, and 4–5 for the Optimizing level. This classification ensures that qualitative maturity assessments can be systematically transformed into quantitative evaluation outcomes, thereby providing a standardized scale for model evaluation.

7.2.3 Weight Vector Determination

To reflect the relative importance of each evaluation factor, a weight vector is determined. Weights can be derived through methods such as AHP, expert scoring, or equal assignment when no prior information is available (Karim and Cherkaoui, 2021). The weight vector ensures that different indicators contribute proportionally to the overall evaluation, with the sum of weights normalized to one:

$$W = (w_1, w_2, \dots, w_n), \text{ with } w_i \geq 0 \text{ and } \sum w_i = 1$$

In this study, the weight vector is derived from the results of the AHP procedure conducted in Chapter 6. Specifically, Table 6.12 reports the priority vectors obtained from the pairwise comparison matrices at the goal level, criteria level, and the first and second sub-criteria levels. Building upon these results, Table 6.13 presents the local and global

weights for all KPAs and indicators across the criteria level, first sub-criteria level, second sub-criteria level, and third sub-criteria level. Since the local weights represent the relative importance of each indicator within its hierarchical group, and the global weights synthesize these relative importances across levels, they serve as the weight vectors required in the FCE framework. Accordingly, the local and global weights derived through AHP are directly applied in this chapter as the weight vectors, forming the quantitative basis for subsequent fuzzy evaluation and analysis. For example, at the criteria level, the weight vector is given as $W = (0.146, 0.112, 0.156, 0.401, 0.094, 0.091)$ representing the relative importance of the six KPAs. The complete set of local and global weights for all indicators has already been provided in Table 6.13.

7.2.4 Fuzzy Membership Matrix Construction

Next, a fuzzy membership matrix is constructed to quantify the degree of membership of each evaluation factor with respect to each evaluation grade. This matrix is obtained through single-factor fuzzy evaluation, typically based on expert scoring. Each row corresponds to an evaluation factor, while each column represents the membership degree of that factor to a particular evaluation grade:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix}$$

where r_{ij} denotes the membership degree of factor u_i to grade v_j (Zadeh, 1965; Zimmermann, 2012).

In this study, the rows of the fuzzy membership matrices correspond to the 131 third-level indicators in the factor set of the third sub-criteria level, which represent the most specific and measurable dimensions of digital maturity. The columns correspond to the five grades in the maturity grade set, numerically valued as 1 to 5, which represent the levels of Initial, Repeatable, Defined, Managed, and Optimizing, respectively. Since the 131 third-level indicators are grouped under 47 second-level indicators in the factor set of the second sub-criteria level, each second-level indicator forms the basis of one fuzzy membership matrix. In other words, for each second-level indicator, a fuzzy membership matrix is constructed, with its rows representing the associated third-level indicators and its columns representing the five levels. Consequently, a total of 47 fuzzy membership matrices are initially established.

To populate these matrices, structured questionnaires were distributed to respondents. The questionnaire consisted of two sections: the first part collected demographic and organizational information of the respondents, while the second part required them to evaluate each of the 131 third-level indicators. Respondents were asked to assign a score ranging from 1 to 5, each corresponding to one of the five maturity levels, by checking the option that best reflected the digital maturity level of the given indicator. The questionnaire template is provided in Appendix 6.

Based on the collected data, the fuzzy membership matrices were constructed separately for each enterprise. As described earlier, this study selected five prominent Chinese state-owned enterprises operating FSSCs, with approximately 20 respondents from each enterprise participating in the survey, yielding around 100 valid responses in total. Taking one enterprise as an illustrative example, the number of respondents assigning scores 1 through 5 to a specific third-level indicator was first counted and then divided by the total number of respondents. The resulting proportions represent the membership degrees of that indicator to the five maturity levels, thereby filling the entries of the fuzzy membership matrix. Repeating this procedure for all third-level indicators under each second-level indicator yields 47 complete fuzzy membership matrices for the enterprise. By following the same procedure, five sets of fuzzy membership matrices, one for each enterprise, were eventually obtained and used for subsequent fuzzy evaluation and analysis.

7.2.5 Fuzzy Comprehensive Evaluation

The fuzzy comprehensive evaluation is carried out by combining the weight vector with the fuzzy membership matrix using appropriate fuzzy operators. This process generates a fuzzy evaluation vector, which represents the degree of membership of the evaluated object across all defined evaluation grades:

$$C = W \circ R = (w_1, w_2, \dots, w_n) \circ [r_{ij}]_{n \times m} = (c_1, c_2, \dots, c_m)$$

where c_j denotes the overall membership degree to evaluation grade v_j . Common fuzzy operators include weighted average, max–min, and max–product methods, selected according to the evaluation context. Among these, the weighted average method is the most widely used and recognized in fuzzy comprehensive evaluation. Furthermore, the resulting fuzzy evaluation vector is normalized to ensure comparability, and the membership degrees are analyzed to interpret the evaluation outcome. The principle of maximum membership is often applied to determine the grade most representative of the evaluated object. Finally, a comprehensive score is computed by multiplying each normalized membership degree by its corresponding grade value and summing the results:

$$\text{Score} = \sum(b_j \times v_j)$$

where b_j is the normalized membership degree for grade v_j , and v_j is the numerical value assigned to that grade. This score provides a precise, quantitative representation of the evaluation outcome, enabling cross-comparisons between different objects or systems (Liang and Wang, 1991; Chen, 2000; Zhu, 2022).

While the above procedure describes a single round of fuzzy comprehensive evaluation, this study requires a multi-level evaluation process, consistent with the hierarchical structure of the four-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise. Therefore, the weight vectors are combined with the fuzzy membership matrices to compute fuzzy evaluation vectors at each hierarchical level, which are then aggregated step by step to produce a final fuzzy evaluation vector for each FSSC. Taking one enterprise as an illustrative example, the process is as follows:

First, based on the 47 fuzzy membership matrices established in Section 7.2.4 for the 47 second-level indicators in the factor set of the second sub-criteria level, each matrix is combined with the local weights for its associated third-level indicators. This produces 47 fuzzy evaluation vectors, each representing one second-level indicator. Second, 19 fuzzy membership matrices are constructed, corresponding to the 19 first-level indicators in the factor set of the first sub-criteria level. In each matrix, the rows represent the second-level indicators, the columns represent the five maturity levels, and the entries are the membership degrees of a second-level indicator to a specific maturity level, which are derived from the 47 fuzzy evaluation vectors obtained in the previous step. By combining each matrix with the local weights for its second-level indicators, 19 fuzzy evaluation vectors are generated, each representing one first-level indicator. Following the same principle, the 19 fuzzy evaluation vectors are aggregated into six fuzzy evaluation vectors, each corresponding to a KPA in the factor set of the criteria level. Finally, these six fuzzy evaluation vectors are synthesized into one final fuzzy evaluation vector representing the overall digital maturity of the enterprise's FSSC.

At each stage of aggregation, the resulting fuzzy evaluation vectors are normalized such that the five membership degrees sum to one. In addition, each fuzzy evaluation vector can be transformed into a comprehensive score using the formula above. This score indicates the digital maturity level of the corresponding indicator, KPA, or the overall FSSC, with the score intervals determining its final classification, as defined in Section 7.2.2. Through this multi-level fuzzy comprehensive evaluation process, the hierarchical evaluation indicator system is systematically integrated into a single, interpretable outcome that reflects the overall digital maturity level of each FSSC.

To illustrate the application of the fuzzy comprehensive evaluation process, this study takes Ansteel Group as a representative case among the five selected Chinese state-owned enterprises operating FSSCs. A total of 24 structured questionnaires were distributed to managers and staff directly or indirectly involved in the daily operation or digitalization of Ansteel Group FSSC, and all 24 valid responses were collected. The data obtained were processed in Excel to calculate the proportions of respondents selecting each maturity level from 1 to 5 for every third-level indicator. These proportions constitute the membership degrees of the indicators to the five maturity levels, which in turn form the fuzzy membership matrices. Therefore, the factor set, maturity grade set, and membership degrees of the third-level indicators are presented in Tables 7.1–7.6, providing the empirical basis for the fuzzy comprehensive evaluation of Ansteel Group FSSC. In this evaluation, the process is organized by KPA and divided into six parts. For each KPA, fuzzy evaluation vectors are calculated step by step from the lowest to the highest level, leading to its comprehensive score. These six KPA-level vectors are then aggregated to produce the final fuzzy evaluation vector and comprehensive score representing the digital maturity of Ansteel Group FSSC. For clarity, only the detailed calculation steps for **A1 Strategy and Organization** are presented, while for the remaining KPAs, only their fuzzy evaluation vectors and comprehensive scores are reported.

Table 7.1 Membership Degrees of Third-level Indicators under A1

Factor Sets				Maturity Grade Set				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
A1 Strategy and Organization	B1 Strategy	C1 Digital Strategy Goal	D1 Actual Situation Alignment	0.000	0.208	0.125	0.333	0.333
			D2 Business Strategy Alignment	0.042	0.042	0.333	0.292	0.292
			D3 Customer Value Maximization	0.042	0.125	0.167	0.500	0.167
		C2 Digital Strategy Planning	D4 Long Term Strategic Development	0.042	0.208	0.208	0.292	0.250
			D5 Transformation Model Selection	0.042	0.208	0.125	0.375	0.250
			D6 Resource Allocation Plan	0.083	0.208	0.167	0.250	0.292
	B2 Culture	C3 Digital Thinking	D7 Data-driven Culture Construction	0.042	0.125	0.292	0.250	0.292
			C4 Innovation and Change	D8 Risk Appetite	0.042	0.042	0.333	0.292
		D9 Innovative Idea Implementation		0.042	0.167	0.208	0.250	0.333
	B3 Talent	C5 Digital Talent	D10 Digital Talent Ratio	0.042	0.083	0.250	0.292	0.333

Factor Sets				Maturity Grade Set					
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5	
			D11 Digital Application Proficiency	0.042	0.125	0.167	0.375	0.292	
			D12 Adaptation and Adjustment	0.083	0.125	0.250	0.208	0.333	
		C6 Talent Training	D13 Accounting Training	0.083	0.208	0.208	0.167	0.333	
			D14 Business Training	0.042	0.167	0.250	0.208	0.333	
			D15 Digital Technology Training	0.042	0.083	0.208	0.417	0.250	
		C7 Talent Security	D16 Talent Appraisal System Establishment	0.083	0.125	0.250	0.208	0.333	
			D17 Promotion Channel Provision	0.000	0.125	0.250	0.417	0.208	
			D18 Talent Incentive Mechanism Construction	0.125	0.125	0.292	0.292	0.167	
			D19 Job Rotation Implementation	0.042	0.208	0.208	0.208	0.333	
		B4 Structure	C8 Digital Leadership	D20 Leadership Position	0.042	0.208	0.167	0.417	0.167
				D21 Leadership Engagement	0.000	0.125	0.375	0.208	0.292
			C9 Organizational Restructuring	D22 Role and Responsibility	0.000	0.083	0.292	0.292	0.333
	D23 Flat Organization			0.125	0.125	0.208	0.250	0.292	
	D24 Decentralized Functional Structure			0.125	0.125	0.250	0.292	0.208	

Based on the membership degrees of the third-level indicators under **A1 Strategy and Organization** shown in Table 7.1, and the corresponding local weights for these indicators reported in Tables 6.13, nine fuzzy evaluation vectors can be calculated. The computation was carried out in SPSS by combining the local weights with the nine fuzzy membership matrices formed from the above membership degrees through the weighted average operator. These fuzzy evaluation vectors represent the membership degrees of the nine second-level indicators under **A1 Strategy and Organization** to the five maturity levels. The specific calculation process is as follows.

$$\begin{aligned}
C_{111} &= W_{111} \circ R_{111} \\
&= (0.163, 0.419, 0.418) \circ \begin{pmatrix} 0.000 & 0.208 & 0.125 & 0.333 & 0.333 \\ 0.042 & 0.042 & 0.333 & 0.292 & 0.292 \\ 0.042 & 0.125 & 0.167 & 0.500 & 0.167 \end{pmatrix} \\
&= (0.035, 0.104, 0.230, 0.386, 0.246)
\end{aligned}$$

$$\begin{aligned}
C_{112} &= W_{112} \circ R_{112} \\
&= (0.440, 0.333, 0.227) \circ \begin{pmatrix} 0.042 & 0.208 & 0.208 & 0.292 & 0.250 \\ 0.042 & 0.208 & 0.125 & 0.375 & 0.250 \\ 0.083 & 0.208 & 0.167 & 0.250 & 0.292 \end{pmatrix} \\
&= (0.051, 0.208, 0.171, 0.310, 0.259)
\end{aligned}$$

$$\begin{aligned}
C_{121} &= W_{121} \circ R_{121} = (1.000) \circ (0.042 \ 0.125 \ 0.292 \ 0.250 \ 0.292) \\
&= (0.042, 0.125, 0.292, 0.250, 0.292)
\end{aligned}$$

$$\begin{aligned}
C_{122} &= W_{122} \circ R_{122} = (0.353, 0.647) \circ \begin{pmatrix} 0.042 & 0.042 & 0.333 & 0.292 & 0.292 \\ 0.042 & 0.167 & 0.208 & 0.250 & 0.333 \end{pmatrix} \\
&= (0.042, 0.123, 0.252, 0.265, 0.319)
\end{aligned}$$

$$\begin{aligned}
C_{131} &= W_{131} \circ R_{131} \\
&= (0.152, 0.384, 0.464) \circ \begin{pmatrix} 0.042 & 0.083 & 0.250 & 0.292 & 0.333 \\ 0.042 & 0.125 & 0.167 & 0.375 & 0.292 \\ 0.083 & 0.125 & 0.250 & 0.208 & 0.333 \end{pmatrix} \\
&= (0.061, 0.119, 0.218, 0.285, 0.317)
\end{aligned}$$

$$\begin{aligned}
C_{132} &= W_{132} \circ R_{132} \\
&= (0.175, 0.562, 0.264) \circ \begin{pmatrix} 0.083 & 0.208 & 0.208 & 0.167 & 0.333 \\ 0.042 & 0.167 & 0.250 & 0.208 & 0.333 \\ 0.042 & 0.083 & 0.208 & 0.417 & 0.250 \end{pmatrix} \\
&= (0.049, 0.152, 0.232, 0.256, 0.311)
\end{aligned}$$

$$\begin{aligned}
C_{133} &= W_{133} \circ R_{133} \\
&= (0.166, 0.260, 0.453, 0.121) \\
&\quad \circ \begin{pmatrix} 0.083 & 0.125 & 0.250 & 0.208 & 0.333 \\ 0.000 & 0.125 & 0.250 & 0.417 & 0.208 \\ 0.125 & 0.125 & 0.292 & 0.292 & 0.167 \\ 0.042 & 0.208 & 0.208 & 0.208 & 0.333 \end{pmatrix} \\
&= (0.075, 0.135, 0.264, 0.300, 0.225)
\end{aligned}$$

$$\begin{aligned}
C_{141} &= W_{141} \circ R_{141} = (0.339, 0.661) \circ \begin{pmatrix} 0.042 & 0.208 & 0.167 & 0.417 & 0.167 \\ 0.000 & 0.125 & 0.375 & 0.208 & 0.292 \end{pmatrix} \\
&= (0.014, 0.153, 0.304, 0.279, 0.249)
\end{aligned}$$

$$\begin{aligned}
C_{142} &= W_{142} \circ R_{142} \\
&= (0.251, 0.217, 0.531) \circ \begin{pmatrix} 0.000 & 0.083 & 0.292 & 0.292 & 0.333 \\ 0.125 & 0.125 & 0.208 & 0.250 & 0.292 \\ 0.125 & 0.125 & 0.250 & 0.292 & 0.208 \end{pmatrix} \\
&= (0.094, 0.115, 0.251, 0.283, 0.258)
\end{aligned}$$

Based on the membership degrees of the second-level indicators under **A1 Strategy and Organization** obtained in the above calculation, and the corresponding local weights reported in Table 6.13, four fuzzy evaluation vectors were further derived using the weighted average operator in SPSS. These vectors represent the membership degrees of the four first-level indicators under **A1 Strategy and Organization** to the five maturity levels. The specific calculation process is as follows.

$$C_{11} = W_{11} \circ R_{11} = (0.527, 0.473) \circ \begin{pmatrix} 0.035 & 0.104 & 0.230 & 0.386 & 0.246 \\ 0.051 & 0.208 & 0.171 & 0.310 & 0.259 \end{pmatrix} \\ = (0.043, 0.153, 0.202, 0.350, 0.252)$$

$$C_{12} = W_{12} \circ R_{12} = (0.503, 0.497) \circ \begin{pmatrix} 0.042 & 0.125 & 0.292 & 0.250 & 0.292 \\ 0.042 & 0.123 & 0.252 & 0.265 & 0.319 \end{pmatrix} \\ = (0.042, 0.124, 0.272, 0.257, 0.305)$$

$$C_{13} = W_{13} \circ R_{13} \\ = (0.311, 0.199, 0.490) \circ \begin{pmatrix} 0.061 & 0.119 & 0.218 & 0.285 & 0.317 \\ 0.049 & 0.152 & 0.232 & 0.256 & 0.311 \\ 0.075 & 0.135 & 0.264 & 0.300 & 0.225 \end{pmatrix} \\ = (0.066, 0.133, 0.243, 0.287, 0.271)$$

$$C_{14} = W_{14} \circ R_{14} = (0.517, 0.483) \circ \begin{pmatrix} 0.014 & 0.153 & 0.304 & 0.279 & 0.249 \\ 0.094 & 0.115 & 0.251 & 0.283 & 0.258 \end{pmatrix} \\ = (0.052, 0.135, 0.279, 0.281, 0.253)$$

Finally, based on the membership degrees of the first-level indicators under **A1 Strategy and Organization** obtained in the above calculation, and the corresponding local weights reported in Table 6.13, one fuzzy evaluation vector was derived using the weighted average operator in SPSS. This vector represents the membership degrees of **A1 Strategy and Organization** to the five maturity levels. The specific calculation process is as follows.

$$C_1 = W_1 \circ R_1 \\ = (0.235, 0.184, 0.471, 0.111) \\ \circ \begin{pmatrix} 0.043 & 0.153 & 0.202 & 0.350 & 0.252 \\ 0.042 & 0.124 & 0.272 & 0.257 & 0.305 \\ 0.066 & 0.133 & 0.243 & 0.287 & 0.271 \\ 0.052 & 0.135 & 0.279 & 0.281 & 0.253 \end{pmatrix} \\ = (0.054, 0.136, 0.243, 0.295, 0.271)$$

As a result, the comprehensive score of **A1 Strategy and Organization** was then calculated by multiplying each membership degree by its assigned score from 1 to 5 and summing the results. The final score obtained for this KPA is 3.592.

Table 7.2 Membership Degrees of Third-level Indicators under A2

Factor Sets				Maturity Grade Set				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
A2 Infrastructure	B5 Technology	C10 Digital Technology Basis	D25 IoT Application	0.083	0.208	0.167	0.375	0.167
			D26 Big Data Application	0.042	0.167	0.250	0.250	0.292
			D27 Cloud Computing Application	0.042	0.208	0.167	0.167	0.417
			D28 Blockchain Application	0.125	0.083	0.250	0.333	0.208
			D29 AI Application	0.083	0.083	0.208	0.292	0.333
		C11 Digital Infrastructure	D30 Equipment Digitalization	0.083	0.083	0.125	0.417	0.292
	B6 Network	C12 Internet Construction	D31 Internet Access	0.083	0.167	0.083	0.292	0.375
			D32 Internet Performance	0.042	0.208	0.125	0.250	0.375
		C13 Internal Network Construction	D33 Internal Network Access	0.125	0.125	0.208	0.167	0.375
			D34 Internal Network Performance	0.000	0.125	0.208	0.250	0.417
	B7 Capital	C14 Digital Capital Investment	D35 Software and Hardware Investment	0.042	0.083	0.167	0.458	0.250
			D36 System Upgrade and Maintenance Investment	0.042	0.083	0.167	0.333	0.375
			D37 Digital Talent Training Investment	0.000	0.208	0.125	0.375	0.292
			D38 Organizational Restructuring Investment	0.083	0.125	0.208	0.333	0.250
			D39 Process Re-engineering Investment	0.042	0.125	0.083	0.375	0.375

Table 7.2 presents the membership degrees of the third-level indicators under **A2 Infrastructure**. Following the same procedure as illustrated in detail for **A1**, the membership degrees were first organized into fuzzy membership matrices, which were then combined with the corresponding local weights at each hierarchical level through the weighted average operator. Finally, the fuzzy evaluation vector C_2 for **A2 Infrastructure** was obtained as (0.052, 0.132, 0.153, 0.339, 0.325), with a comprehensive score of 3.753.

Table 7.3 Membership Degrees of Third-level Indicators under A3

Factor Sets				Maturity Grade Set					
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5	
A3 Process Management	B8 Process Re-engineering	C15 System Establishment	D40 Quality Assessment System	0.042	0.208	0.375	0.208	0.167	
			D41 Efficiency Supervision System	0.000	0.208	0.333	0.250	0.208	
			D42 Operation Management System	0.042	0.208	0.333	0.250	0.167	
		C16 Continuous Optimization	D43 Feedback Mechanism	0.083	0.167	0.250	0.375	0.125	
			D44 Process–Operation Alignment	0.042	0.250	0.208	0.250	0.250	
		C17 Standardization	D45 Procurement and A/P Standardization	0.042	0.125	0.417	0.167	0.250	
			D46 Sales and A/R Standardization	0.000	0.125	0.375	0.333	0.167	
			D47 Expense Reimbursement Standardization	0.042	0.292	0.167	0.167	0.333	
			D48 General Ledger and Reporting Standardization	0.042	0.250	0.250	0.208	0.250	
		C18 Automation and Digitalization	D49 Procurement and A/P Automation	0.083	0.292	0.125	0.208	0.292	
			D50 Sales and A/R Automation	0.125	0.167	0.208	0.375	0.125	
			D51 Expense Reimbursement Automation	0.083	0.167	0.292	0.333	0.125	
			D52 General Ledger and Reporting Automation	0.042	0.042	0.375	0.375	0.167	
		B9 Process Integration	C19 Vertical Integration	D53 Financial Process Coordination	0.083	0.250	0.333	0.042	0.292
			C20 Horizontal Integration	D54 Financial–Business Process Alignment	0.208	0.167	0.250	0.208	0.167
				D55 Business Operation Support	0.125	0.208	0.250	0.208	0.208
			C21 Management Integration	D56 Centralized Fund Management	0.125	0.125	0.375	0.167	0.208
				D57 Comprehensive Budget Management	0.042	0.375	0.125	0.333	0.125

Factor Sets				Maturity Grade Set				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
B10 Information Systems			D58 Integrated Tax Management	0.083	0.167	0.292	0.292	0.167
			D59 Unified Risk Management	0.125	0.208	0.167	0.292	0.208
	C22 Process Support		D60 Connection Stability	0.167	0.167	0.208	0.250	0.208
			D61 User-friendly Operation	0.125	0.292	0.125	0.167	0.292
			D62 Successful Process Execution	0.083	0.083	0.250	0.333	0.250
	C23 System Integration		D63 FSSC System Integration	0.208	0.042	0.208	0.250	0.292
			D64 FSSC–Business System Integration	0.167	0.167	0.125	0.333	0.208
	C24 Safety and Security		D65 Access Control	0.208	0.125	0.208	0.167	0.292
			D66 Firewall Installation and Update	0.042	0.208	0.250	0.292	0.208
			D67 Vulnerability Scan and Report	0.125	0.167	0.250	0.250	0.208
			D68 Fault Restoration	0.083	0.083	0.333	0.333	0.167
			D69 System Maintenance	0.167	0.250	0.125	0.208	0.250

Table 7.3 presents the membership degrees of the third-level indicators under **A3 Process Management**. As with the previous KPAs, the membership degrees were first organized into fuzzy membership matrices and then combined with the corresponding local weights through the weighted average operator in SPSS. The resulting fuzzy evaluation vector C_3 for **A3 Process Management** was (0.110, 0.183, 0.253, 0.234, 0.220), with a comprehensive score of 3.272.

Table 7.4 Membership Degrees of Third-level Indicators under A4

Factor Sets				Maturity Grade Set				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
Management A4 Data	B11 Data Acquisition	C25 IoT Data Collection	D70 RFID Asset Identification Integrity	0.042	0.250	0.250	0.125	0.333
			D71 RFID Data Entry Accuracy	0.083	0.167	0.208	0.333	0.208
		C26 Real-time	D72 Supply Chain	0.167	0.125	0.292	0.250	0.167

Factor Sets				Maturity Grade Set					
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5	
		Data Connection	Connection						
			D73 Business Travel Platform Connection	0.042	0.125	0.250	0.333	0.250	
			D74 Tax Sharing Center Connection	0.125	0.125	0.292	0.292	0.167	
	B12 Data Application	C27 Heterogeneous Data Storage	D75 Data Storage Capacity	0.083	0.167	0.250	0.250	0.250	
			D76 Data Storage Performance	0.042	0.250	0.250	0.208	0.250	
		C28 Heterogeneous Data Processing	D77 Data Processing Timeliness	0.083	0.208	0.292	0.250	0.167	
			D78 Data Processing Quality	0.042	0.250	0.292	0.208	0.208	
		C29 Data Analysis on Financial Cloud	D79 Cloud Platform Architecture	0.083	0.167	0.250	0.125	0.375	
			D80 Computing Speed	0.042	0.250	0.167	0.333	0.208	
			D81 Data Mining Breadth and Depth	0.083	0.250	0.125	0.375	0.167	
			D82 Model Establishment and Prediction	0.083	0.125	0.208	0.292	0.292	
		C30 Data Visualization	D83 Usage Frequency	0.042	0.125	0.250	0.417	0.167	
			D84 Clarity and Conciseness	0.042	0.250	0.125	0.250	0.333	
			D85 Adaptability	0.083	0.292	0.125	0.292	0.208	
		B13 Data-driven Decision-making	C31 Decision-making Support System	D86 Decision-making Compliance	0.167	0.042	0.375	0.208	0.208
				D87 Decision-making Effectiveness	0.000	0.167	0.292	0.292	0.250
			C32 Intelligent Decision Support System	D88 Human-Computer Interaction	0.042	0.208	0.292	0.292	0.167
				D89 Decision-making Intelligence	0.125	0.250	0.125	0.167	0.333
	B14 Data Security	C33 Data Encryption	D90 Data Storage Encryption	0.083	0.042	0.333	0.250	0.292	
			D91 Data Transmission Encryption	0.042	0.125	0.250	0.250	0.333	
C34 Data Assurance		D92 Data Backup and Recovery	0.083	0.208	0.250	0.292	0.167		
		D93 Audit and Report	0.125	0.083	0.167	0.417	0.208		

Table 7.4 shows the membership degrees of the third-level indicators under **A4 Data Management**. Following the same procedure described earlier, the fuzzy membership matrices constructed from these degrees were aggregated with the corresponding local weights to produce the fuzzy evaluation vector C_4 for **A4 Data Management**. Consequently, this vector was (0.087, 0.155, 0.240, 0.276, 0.242), and the corresponding comprehensive score was 3.430.

Table 7.5 Membership Degrees of Third-level Indicators under A5

Factor Sets				Maturity Grade Set				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
A5 Digital Performance	B15 Effectiveness	C35 Financial Performance	D94 Cost Benefit Ratio	0.125	0.042	0.375	0.083	0.375
			D95 Net Profit Growth Rate	0.083	0.125	0.167	0.458	0.167
			D96 Current Ratio	0.083	0.083	0.250	0.375	0.208
		C36 Service Quality	D97 Accounting Information Transparency	0.042	0.250	0.125	0.292	0.292
			D98 Financial Report Integrity	0.083	0.250	0.167	0.292	0.208
			D99 Financial Analysis Validity	0.083	0.208	0.208	0.250	0.250
		C37 Customer Satisfaction	D100 Service Agreement Fulfillment	0.000	0.250	0.250	0.417	0.083
			D101 Customer Requirement Fulfillment	0.000	0.042	0.250	0.417	0.292
			D102 Customer Loyalty	0.167	0.208	0.167	0.208	0.250
		C38 External Service Performance	D103 Market Share	0.125	0.042	0.333	0.375	0.125
			D104 External Income Ratio	0.083	0.167	0.292	0.250	0.208
		B16 Efficiency	C39 Operational Efficiency	D105 Payment Efficiency	0.000	0.083	0.333	0.417
	D106 Collection Efficiency			0.083	0.125	0.208	0.458	0.125
	D107 Reimbursement Review Efficiency			0.000	0.208	0.292	0.208	0.292
	D108 Report Preparation Efficiency			0.042	0.125	0.250	0.458	0.125
	C40 Management and Decision Efficiency		D109 Fund Management Efficiency	0.000	0.208	0.250	0.208	0.333
			D110 Budget Management Efficiency	0.083	0.083	0.250	0.375	0.208

Factor Sets				Maturity Grade Set				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
			D111 Tax Management Efficiency	0.042	0.292	0.167	0.208	0.292
			D112 Risk Management Efficiency	0.125	0.125	0.208	0.208	0.333
			D113 Decision Execution Efficiency	0.083	0.167	0.167	0.375	0.208
		C41 Information Transfer Efficiency	D114 FSSC Communication Efficiency	0.042	0.167	0.167	0.208	0.417
			D115 FSSC–Business Unit Communication Efficiency	0.000	0.250	0.250	0.250	0.250
			D116 Data Summarization Efficiency	0.000	0.208	0.208	0.292	0.292
			D117 Data Update Efficiency	0.125	0.167	0.208	0.375	0.125

Table 7.5 provides the membership degrees of the third-level indicators under **A5 Digital Performance**. These values were transformed into fuzzy membership matrices and then combined with the relevant local weights through the weighted average operator. As a result, the fuzzy evaluation vector C_5 obtained for **A5 Digital Performance** was (0.062, 0.166, 0.225, 0.308, 0.239), with a comprehensive score of 3.496.

Table 7.6 Membership Degrees of Third-level Indicators under A6

Factor Sets				Maturity Grade Set				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
External Environment A6	B17 Government	C42 Policy Support	D118 Access to Policy Information	0.000	0.167	0.125	0.208	0.500
		C43 Financial Support	D119 Government Funding Acquisition	0.000	0.167	0.125	0.375	0.333
	B18 Ecosystem	C44 Market Adaptation	D120 Market Demand Awareness	0.042	0.125	0.167	0.208	0.458
			D121 External Customer Development	0.000	0.083	0.208	0.500	0.208
			D122 Competitor Monitoring	0.000	0.042	0.208	0.458	0.292
		C45 Digital	D123 Supply Chain	0.042	0.000	0.208	0.375	0.375

Factor Sets				Maturity Grade Set				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
		Ecosystem Construction	Digital Resource Integration					
			D124 Digital Resource Complementarity with Competitors	0.000	0.042	0.125	0.500	0.333
			D125 Industry–University–Research Cooperation	0.042	0.125	0.167	0.417	0.250
			D126 Shared Database Creation	0.042	0.125	0.250	0.250	0.333
	B19 External Disaster	C46 Disaster Risk Management	D127 Budget Emergency Management	0.042	0.042	0.292	0.292	0.333
			D128 Capital Risk Early Warning	0.083	0.125	0.083	0.375	0.333
			D129 Material Control	0.000	0.083	0.208	0.375	0.333
		C47 Work Arrangement	D130 Emergency Support Team Establishment	0.000	0.167	0.083	0.333	0.417
			D131 Remote Work Implementation	0.042	0.083	0.125	0.500	0.250

Table 7.6 presents the membership degrees of the third-level indicators under **A6 External Environment**. Consistent with the method applied across all KPAs, the membership degrees were structured into fuzzy membership matrices and combined with the corresponding local weights to calculate the fuzzy evaluation vector C_6 for **A6 External Environment**, which was (0.021, 0.119, 0.156, 0.333, 0.371), with a corresponding comprehensive score of 3.914.

Taken together, the fuzzy evaluation vectors and comprehensive scores of the six KPAs provide a structured assessment of Ansteel Group FSSC across all criteria. These six vectors are then organized into a fuzzy membership matrix R , which is combined with the weight vector W at the criteria level through the weighted average operator in SPSS. This procedure produces the final fuzzy evaluation vector C , representing the membership degrees of the overall digital maturity to the five maturity levels. The specific calculation process is as follows.

$$\begin{aligned}
C = W \circ R &= (0.146, 0.112, 0.156, 0.401, 0.094, 0.091) \\
&\circ \begin{pmatrix} 0.054 & 0.136 & 0.243 & 0.295 & 0.271 \\ 0.052 & 0.132 & 0.153 & 0.339 & 0.325 \\ 0.110 & 0.183 & 0.253 & 0.234 & 0.220 \\ 0.087 & 0.155 & 0.240 & 0.276 & 0.242 \\ 0.062 & 0.166 & 0.225 & 0.308 & 0.239 \\ 0.021 & 0.119 & 0.156 & 0.333 & 0.371 \end{pmatrix} \\
&= (0.074, 0.152, 0.223, 0.288, 0.263)
\end{aligned}$$

Therefore, the comprehensive score of the digital maturity of Ansteel Group FSSC was calculated by multiplying each membership degree by its assigned score from 1 to 5 and summing the results. The final score obtained is 3.516. In addition, all fuzzy evaluation vectors derived at the four hierarchical levels were further transformed into comprehensive scores. These results are summarized in Table 7.7, which provides a comprehensive overview of the digital maturity scores of Ansteel Group FSSC from the second sub-criteria level to the overall goal level.

Table 7.7 Digital Maturity Scores of Ansteel Group FSSC across Four Hierarchical Levels

Goal Level		Criteria Level		Sub-criteria Level (1st)		Sub-criteria Level (2nd)	
Digital Maturity	Scores	KPAs	Scores	First-level Indicators	Scores	Second-level Indicators	Scores
Ansteel Group FSSC	3.516	A1 Strategy and Organization	3.592	B1 Strategy	3.617	C1 Digital Strategy Goal	3.705
						C2 Digital Strategy Planning	3.518
				B2 Culture	3.660	C3 Digital Thinking	3.625
						C4 Innovation and Change	3.696
				B3 Talent	3.564	C5 Digital Talent	3.679
						C6 Talent Training	3.629
						C7 Talent Security	3.465
				B4 Structure	3.548	C8 Digital Leadership	3.596
						C9 Organizational Restructuring	3.497
		A2 Infrastructure	3.753	B5 Technology	3.664	C10 Digital Technology Basis	3.559
						C11 Digital Infrastructure	3.750
				B6 Network	3.775	C12 Internet Construction	3.708
						C13 Internal Network Construction	3.823
		A3 Process Management	3.272	B8 Process Re-engineering	3.379	C15 System Establishment	3.323
						C16 Continuous Optimization	3.346
						C17 Standardization	3.438
						C18 Automation and Digitalization	3.400
				B9 Process Integration	3.157	C19 Vertical Integration	3.208
		C20 Horizontal Integration	3.084				

Goal Level		Criteria Level		Sub-criteria Level (1st)		Sub-criteria Level (2nd)	
Digital Maturity	Scores	KPAs	Scores	First-level Indicators	Scores	Second-level Indicators	Scores
				B10 Information Systems	3.324	C21 Management Integration	3.227
						C22 Process Support	3.401
						C23 System Integration	3.304
						C24 Safety and Security	3.288
		A4 Data Management	3.430	B11 Data Acquisition	3.333	C25 IoT Data Collection	3.430
						C26 Real-time Data Connection	3.257
				B12 Data Application	3.380	C27 Heterogeneous Data Storage	3.386
						C28 Heterogeneous Data Processing	3.260
						C29 Data Analysis on Financial Cloud	3.469
						C30 Data Visualization	3.396
				B13 Data-driven Decision-making	3.374	C31 Decision-making Support System	3.451
						C32 Intelligent Decision Support System	3.333
		B14 Data Security	3.534	C33 Data Encryption	3.666		
				C34 Data Assurance	3.418		
		A5 Digital Performance	3.496	B15 Effectiveness	3.480	C35 Financial Performance	3.526
						C36 Service Quality	3.408
C37 Customer Satisfaction	3.563						
C38 External Service Performance	3.333						
B16 Efficiency	3.511			C39 Operational Efficiency	3.545		
				C40 Management and Decision Efficiency	3.503		
C41 Information Transfer Efficiency	3.488						

Goal Level		Criteria Level		Sub-criteria Level (1st)		Sub-criteria Level (2nd)	
Digital Maturity	Scores	KPAs	Scores	First-level Indicators	Scores	Second-level Indicators	Scores
		A6 External Environment	3.914	B17 Government	3.970	C42 Policy Support	4.042
						C43 Financial Support	3.875
				B18 Ecosystem	3.895	C44 Market Adaptation	3.905
						C45 Digital Ecosystem Construction	3.884
				B19 External Disaster	3.884	C46 Disaster Risk Management	3.807
						C47 Work Arrangement	3.957

7.3 Case Results and Analysis

Building on the FCE procedure presented above, this study applied all five steps of the evaluation to the five selected FSSCs. In order to illustrate the process clearly, the detailed calculation procedure is fully demonstrated for Ansteel Group FSSC in Section 7.2.5, together with the resulting digital maturity scores across the four hierarchical levels. The same procedure was applied consistently to the other four FSSCs, and their digital maturity scores were obtained from the second sub-criteria level through to the overall goal level. However, to avoid redundancy, their intermediate computational steps are not presented here, since they follow exactly the same logic as the example of Ansteel Group FSSC.

Table 7.8 summarizes the evaluation results for all five FSSCs. From lowest to highest, the table presents the overall digital maturity score of each FSSC, together with the scores of the six KPAs. According to the score intervals defined in Section 7.2.2, Baoding Transportation Development Group FSSC falls within the Defined level, FSSCs in Tianjin TEDA Group, Ansteel Group, and Lubei Group are located at the Managed level, and China FAW Group FSSC has just entered the Optimizing level of digital maturity.

Table 7.8 Digital Maturity Scores of Five FSSCs

FSSC	Over all	A1 Strategy and Organization	A2 Infrastructure	A3 Process Management	A4 Data Management	A5 Digital Performance	A6 External Environment
BTDG	2.955	3.105	2.607	3.425	2.869	2.945	2.726
TEDA	3.307	3.184	3.418	3.398	3.167	3.570	3.553
Ansteel	3.516	3.592	3.753	3.272	3.430	3.496	3.914
Lubei	3.824	3.905	3.399	3.872	3.884	3.854	3.836
FAW	4.184	3.954	4.225	4.080	4.403	4.113	3.790

Several cross-case patterns can be observed. All five FSSCs have moved beyond the basic stages of digital maturity and reached at least the Defined level. This indicates that the standardization of financial processes and the use of digital tools have been widely adopted across different FSSCs. However, only one case, China FAW Group FSSC, progresses to the Optimizing level, which shows that achieving fully optimized and continuously improving digitalization remains a considerable challenge.

Looking across the six KPAs, some common tendencies are clear. Data Management is generally the strongest dimension, with most FSSCs demonstrating solid capabilities in data collection, storage, and analysis, which indicates that digitalization has been widely applied to transform financial and business data into resources for decision-making. Infrastructure

also scores relatively high, reflecting sustained investment in IT and networks that provide a technical basis for digital development. By contrast, External Environment tends to be weaker, as FSSCs often face limited integration with digital ecosystems and limited resilience in disaster risk management, which constrains their ability to leverage external opportunities. Process Management and Digital Performance are situated in the middle range. While financial processes are standardized, and effectiveness and efficiency have improved, gaps remain in cross-functional integration and the provision of external services. Strategy and Organization also remains uneven, as strong leadership and planning are sometimes offset by gaps in digital culture, talent development, and organization structures. These findings suggest that while internal infrastructures and data foundations are steadily advancing, greater effort is needed to improve cross-department and system integration, and expand engagement with external ecosystems. Only through these improvements can FSSCs continue to move from managed coordination toward fully optimized digital maturity.

The following five subsections present the detailed background and digital maturity analysis of each FSSC in ascending order of their overall scores. Each analysis is based on the complete set of digital maturity scores from the second sub-criteria level up to the criteria level. Due to space limitations, full four-level score tables such as Table 7.7 for Ansteel Group FSSC are not repeated for every FSSC. Instead, each case is illustrated by a figure showing the overall score and its distribution across the six KPAs, which provides a concise overview.

7.3.1 Baoding Transportation Development Group FSSC

Background

Baoding Transportation Development Group Co., Ltd. (hereafter referred to as BTDG) is a municipally owned, single-shareholder state-owned enterprise supervised by the State-owned Assets Supervision and Administration Commission (hereafter referred to as SASAC) of Baoding City. The Group is primarily engaged in the investment, financing, construction, and operation of transport infrastructure. In recent years, it has pursued a “public-transport-plus” development model that combines bus operations with a range of complementary services, thereby expanding its business scope and improving the efficiency of the local transport network. To strengthen financial oversight across its diversified projects, the Group established a FSSC to centralize high-volume transactional activities while standardizing policies and workflows and reinforcing internal control for government-linked projects. Functionally, the FSSC consolidates financial data, harmonizes the chart of accounts and document standards, and coordinates intercompany settlements arising from “public-transport-plus” activities. At the same time, the characteristics of the sector, such as

long project cycles, multi-party contracting, and strict compliance, together with policy incentives for enterprise digitalization, have positioned the FSSC as the central platform for transitioning from fragmented, department-specific practices to standardized, data-driven finance.

In the evaluation phase of this study, 20 respondents were surveyed within BTDG, 19 of whom were from the FSSC and 1 from the traditional finance function. By role, 12 respondents were staff, 7 were middle managers, and 1 was a top manager. More importantly, 19 of them reported direct involvement in the digitalization of the FSSC, ensuring that the results reliably reflected its actual state of digital maturity.

Digital Maturity Analysis

The BTDG FSSC attains an overall digital maturity score of 2.955, corresponding to the upper range of the Defined level among the five digital maturity levels. The overall score and its distribution across the six KPAs are shown in Figure 7.1. This outcome suggests that although the FSSC has moved beyond initial and repeatable practices, it is still at an early stage of digitalization. In this context, strategy and organization as well as process management have advanced more rapidly than infrastructure and data management.

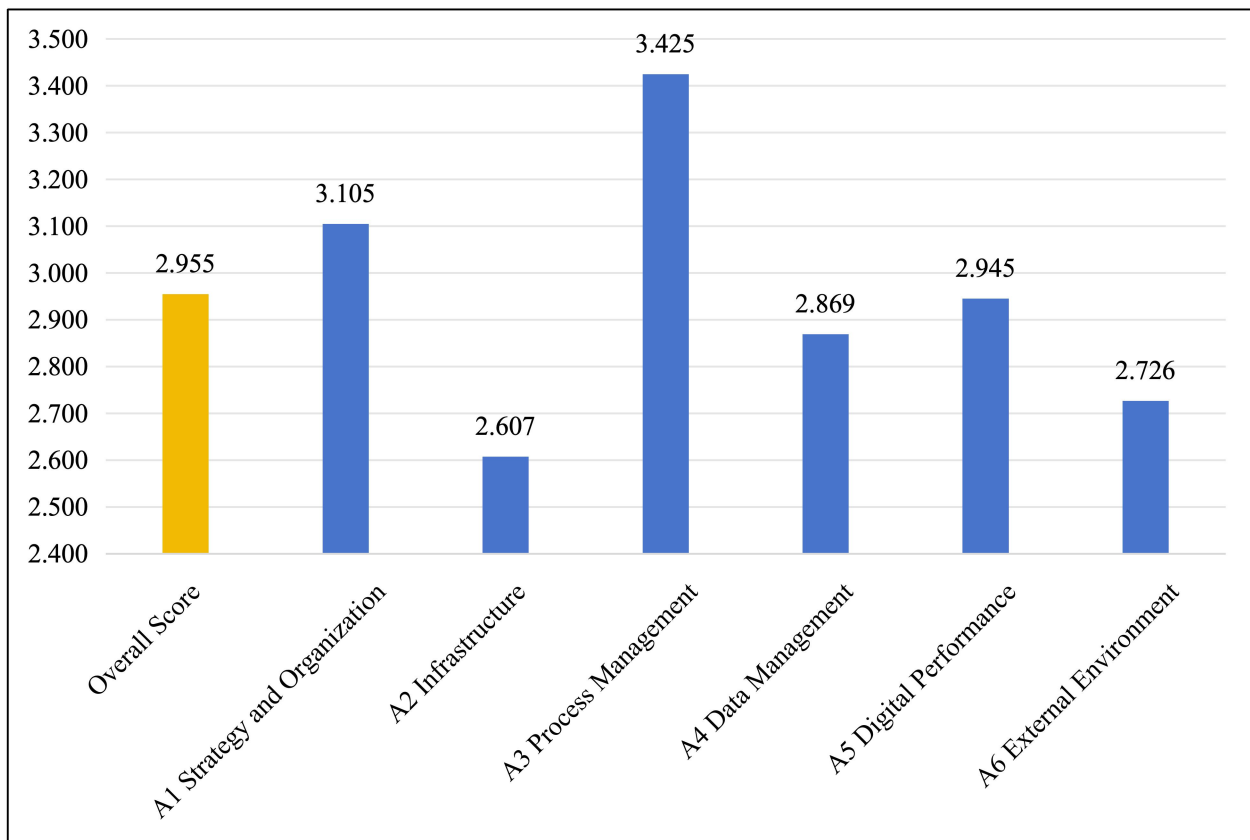


Figure 7.1 Digital Maturity Scores of BTDG FSSC

First, Strategy and Organization scores 3.105. The FSSC shows relatively strong organizational arrangements, with clear structures and a developing talent management system. Sub-scores indicate that organizational restructuring (3.260) and talent security (3.401) are more advanced, while digital leadership (2.865) and digital thinking (2.977) are weaker. This pattern suggests that role clarity and structural adjustments are progressing, but leadership vision and cultural reinforcement lag behind. Strengthening leadership commitment and fostering a more innovative culture will be essential to sustain digitalization over the long term.

Second, Infrastructure is the weakest area with a score of 2.607. Both technology (2.421) and network (2.485) are underdeveloped, with only partial deployments such as ERP modules and limited internet or intranet capacity. Capital investment is slightly stronger at 2.786, but still insufficient to support data-intensive applications. To progress, the FSSC requires substantial investment in core technologies and networks, along with clear performance standards for process speed, data availability, and system reliability.

Third, Process Management is the strongest domain, achieving 3.425. Sub-indicators such as system establishment (3.624), continuous optimization (3.700), and automation and digitalization (3.518) confirm that process re-engineering is firmly embedded in daily operations. Both vertical and horizontal integration at 3.250 and 3.540 respectively also indicate progress in connecting financial processes across projects and departments. However, information system integration remains moderate at 3.308, reflecting the persistence of system silos. The next step is to better connect these processes with data management functions, thereby ensuring that automation not only enhances efficiency but also generates actionable insights.

Fourth, Data Management records 2.869. While heterogeneous data storage (3.082) and visualization (3.128) are relatively stronger, analytical functions are weaker, with data analysis on the financial cloud at only 2.689 and intelligent decision support system at 2.596. This imbalance shows that although the FSSC collects and secures data, it has difficulty converting data into value for decision-making. To address this gap, the FSSC should establish stable datasets, strengthen cloud-based analytical tools, and gradually adopt intelligent systems to facilitate the transformation of raw data into a strategic resource.

Fifth, Digital Performance achieves 2.945. Internal benefits are more visible, with financial performance (3.112) and operational efficiency (3.127) indicating measurable gains from digitalization. However, external service performance lags at 2.620, showing that improvements have not yet extended to external stakeholders. Similarly, management and decision efficiency is limited at 2.785, reflecting slow adoption of data-driven management

practices. Linking process management more tightly with data management would enable the FSSC to improve both internal decision-making efficiency and external service quality.

Sixth, External Environment is among the weaker domains, with a score of 2.726. While some policy (2.833) and financial support (2.730) are available, digital ecosystem construction is weak at 2.436, and disaster risk management is underdeveloped at 2.612. For a transport state-owned enterprise exposed to weather disruptions, safety risks, and demand fluctuations, ensuring the continuity of digital operations through disaster preparedness mechanisms and establishing digital connections with suppliers and customers are essential for enhancing resilience and service reliability.

Taken together, BTDG FSSC demonstrates strong process discipline and organizational readiness, while technological upgrading, data capabilities, and ecosystem integration remain insufficient. Overall, the FSSC is positioned in the upper range of the Defined level, indicating that although standardized practices are in place, higher-level digital integration has yet to be achieved. With further consolidation, the FSSC has the potential to progress toward the Managed level of digital maturity.

7.3.2 Tianjin TEDA Group FSSC

Background

Tianjin TEDA Group Co., Ltd. (referred to as Tianjin TEDA Group) is a municipal state-owned enterprise supervised by the Tianjin SASAC. As the principal developer and investor of the Tianjin Economic-Technological Development Area, the Group plays a pivotal role in urban development, financial investment, manufacturing, and modern services. In line with its broad business activities, the Group established a FSSC to consolidate high-volume financial operations such as accounts payable and receivable, reimbursements, general ledger consolidation, and financial reporting. The FSSC aims to standardize accounting policies, enhance internal control, and exploit economies of scale across subsidiaries, while also serving as a platform for transitioning from fragmented financial practices to integrated, data-driven management.

In the evaluation phase of this study, 21 respondents participated, including 20 from the FSSC and 1 from the traditional finance function. Among them, 13 were staff, 6 were middle managers, and 2 were top managers, with 19 directly engaged in the digitalization of the FSSC. This distribution ensured that the empirical results accurately reflected the actual state of digital maturity within the FSSC.

Digital Maturity Analysis

The Tianjin TEDA Group FSSC achieves an overall digital maturity score of 3.307, positioning it in the lower range of the Managed level among the five digital maturity levels. The overall score and its distribution across the six KPAs are presented in Figure 7.2. This outcome indicates that the FSSC has advanced from fragmented, pilot-level digitalization to a more coordinated program, with relatively balanced progress across its KPAs.

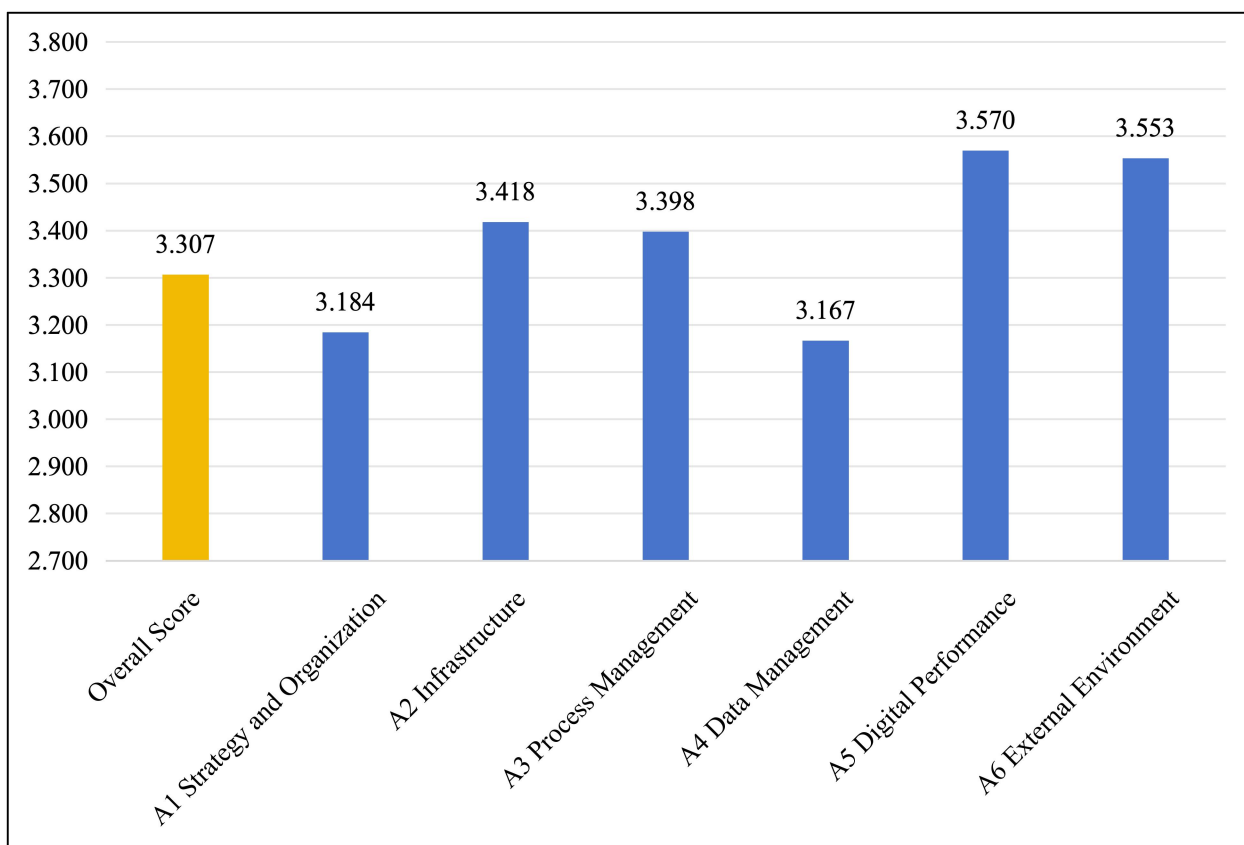


Figure 7.2 Digital Maturity Scores of Tianjin TEDA Group FSSC

First, Strategy and Organization scores 3.184, reflecting a moderately advanced maturity level. Strategic planning and organizational restructuring are relatively strong, with clear digital goals and alignment with strategic priorities. Cultural change has also begun, with innovation and change showing encouraging progress. However, weaker outcomes in digital talent security (3.064) and leadership (3.112) reveal that human capital and managerial engagement lag behind structural arrangements. This imbalance suggests that while the FSSC has established frameworks for digitalization, sustaining progress will require deeper investment in talent training, leadership development, and mechanisms for retaining skilled staff.

Second, Infrastructure reaches 3.418, the highest among input-related KPAs. The FSSC

benefits from reliable ERP platforms, robust internal networks, and stable internet connectivity, all supported by sufficient capital investment. Sub-scores around 3.351–3.476 across technology, network, and capital confirm a consistent maturity level. This strength ensures operational stability and underpins process automation. At present, the infrastructure is primarily supportive rather than transformative. To advance, the FSSC should shift toward scalable cloud architectures, more integrated systems, and proactive cybersecurity measures, ensuring that the infrastructure evolves alongside growing data and analytical requirements.

Third, Process Management achieves 3.398, reflecting solid process re-engineering and integration. Standardization is particularly strong (3.493), with vertical integration (3.524) indicating that financial processes are closely integrated across business units. Information systems also contribute effectively, with process support and security both above 3.450. These results demonstrate that the FSSC has embedded standardized workflows and significant automation into its daily operations. The next step is to connect these processes more directly with decision-making support systems so that routine operations also generate actionable insights. Linking process management with data management would allow the FSSC to continuously monitor efficiency, identify anomalies, and adapt processes dynamically.

Fourth, Data Management is the weakest domain, with a score of 3.167. While data acquisition (3.364) and heterogeneous data processing (3.447) show progress, analytical and visualization capabilities are still limited. Data analysis on the financial cloud is only 3.128, and visualization 3.207, indicating that data is not yet fully transformed into decision support. Moreover, data security is underdeveloped, with data encryption falling below 3.000, thereby raising concerns about resilience and compliance. This gap suggests that although the FSSC collects and stores data effectively, it has not yet established a mature framework for data-driven decision-making. To improve, the FSSC should consolidate datasets into standardized databases, conduct regular reviews, and pilot advanced applications such as cloud-based analytics and intelligent decision support systems. These steps would help transform data from a supporting asset into a strategic driver of financial intelligence.

Fifth, Digital Performance emerges as the strongest domain, scoring 3.570. Efficiency and effectiveness gains are significant, with management and decision efficiency at 3.706 and customer satisfaction at 3.589. These results confirm that digitalization has enhanced both internal operations and service quality. Nevertheless, external service performance is weaker at 3.410, suggesting that improvements have not been fully extended to external stakeholders. To move forward, the FSSC should integrate process and data capabilities more tightly, enabling a shift toward more predictive and adaptive management practices. Establishing formal service-level agreements and benchmarks for external interactions would also help

extend performance improvements beyond internal boundaries.

Sixth, External Environment achieves a score of 3.553, supported by strong policy (3.667) and financial support (3.619). The FSSC also demonstrates adaptability to market changes and participation in digital ecosystem construction, with ecosystem indicators all scoring above 3.460. Preparedness for external disruptions is relatively strong, with disaster risk management at 3.421 and work arrangement at 3.523, ensuring resilience against potential shocks. To progress further, the FSSC should formalize its disaster recovery and incident response mechanisms and seek deeper integration with external partners, thereby embedding itself more fully in the digital ecosystem.

Overall, Tianjin TEDA Group FSSC demonstrates solid infrastructure, well-developed process capabilities, and notable performance outcomes under strong external support. However, its digitalization remains constrained by limited talent management and underdeveloped data management. Therefore, the digital maturity profile indicates a Managed-level FSSC with clear potential to advance toward a more optimized stage of digitalization.

7.3.3 Ansteel Group FSSC

Background

Ansteel Group Corporation (referred to as Ansteel Group) is a central state-owned enterprise supervised by the SASAC of the State Council. As one of China's oldest steel producers and a major industrial base, Ansteel Group has long played a pivotal role in national economic development. In recent years, through strategic restructuring and integration within the steel industry, it has contributed to the formation of the world's largest steel conglomerate, further strengthening its competitiveness and global influence. To improve efficiency and ensure consistent financial management across its numerous subsidiaries, Ansteel Group established a FSSC responsible for integrating key processes such as accounts payable and receivable, reimbursements, general ledger consolidation, and financial reporting. The aim is to standardize operations, reduce duplication, and enhance internal controls. This centralized model not only supports economies of scale but also provides a platform for advancing the digitalization of both the FSSC and the Group as a whole, in alignment with broader national initiatives.

In the evaluation phase of this study, 24 valid responses were collected, including 21 respondents from the FSSC and 3 from traditional finance departments. The group included 14 staff, 8 middle managers, and 2 top managers. Among them, 20 participants were directly

involved in the digitalization of the FSSC, ensuring that the empirical results accurately reflected the actual state of digital maturity within the FSSC.

Digital Maturity Analysis

The Ansteel Group FSSC achieves an overall digital maturity score of 3.516, placing it in the mid-range of the Managed level among the five digital maturity levels. The overall score and its distribution across the six KPAs are presented in Figure 7.3. This result indicates that digital practices are consistently embedded across most areas, although gaps in process and data management still limit further progression toward an optimized state of digitalization.

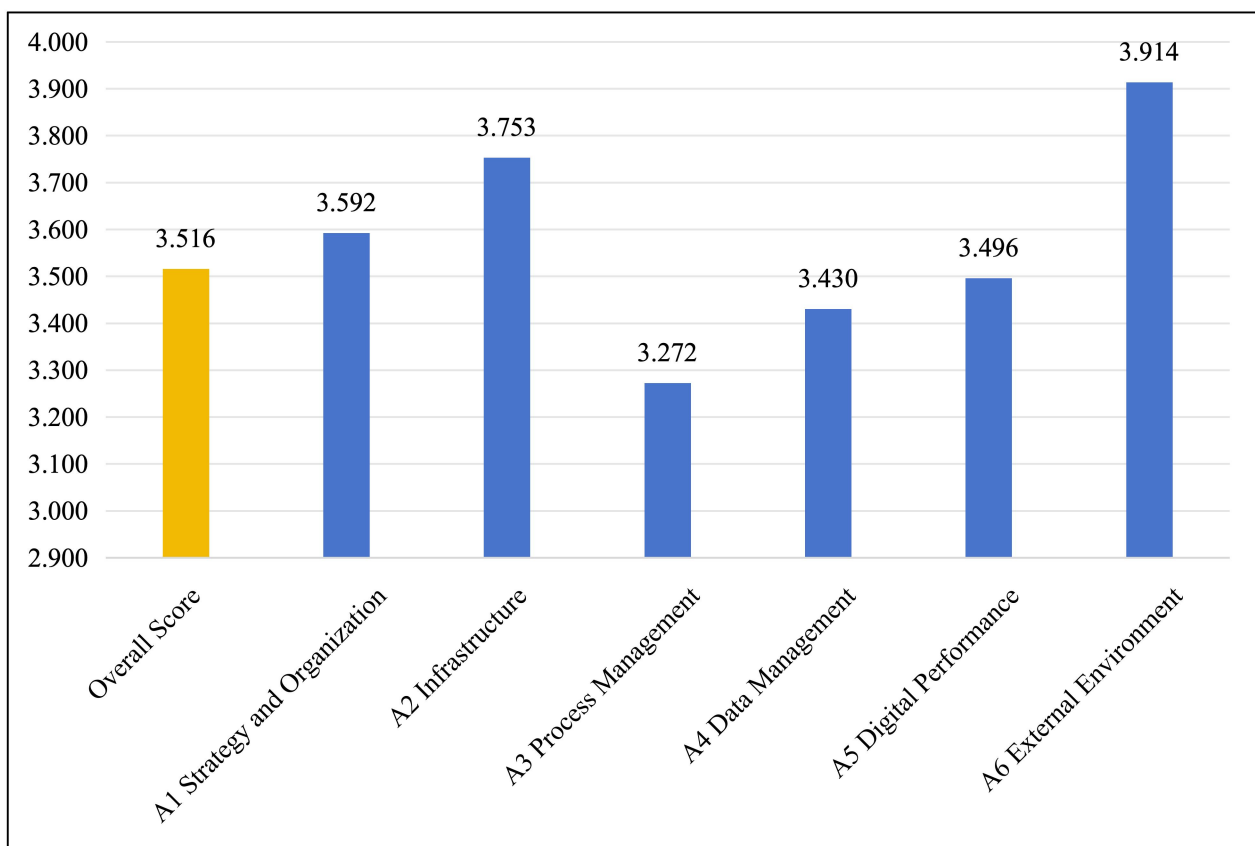


Figure 7.3 Digital Maturity Scores of Ansteel Group FSSC

First, Strategy and Organization scores 3.592, reflecting steady progress in aligning digitalization with the Group’s overall strategy. Specific indicators show relatively strong results for digital strategy goal (3.705) and innovation and change (3.696), suggesting that the FSSC has developed a clear direction and fostered a willingness to adapt. By contrast, both talent security (3.465) and organizational restructuring (3.497) are less advanced, indicating challenges in retaining skilled professionals and adapting the organization structure to digital demands. The FSSC should strengthen its talent development system and optimize its organization structure to ensure that digital initiatives are effectively supported and sustained.

Second, Infrastructure records a high score of 3.753, demonstrating that the FSSC benefits from a solid technological foundation. Both internal network construction (3.823) and digital capital investment (3.801) are particularly strong, showing that the FSSC has committed substantial resources to ensure stable digital operations. Nevertheless, although the foundational systems are operational, future development should focus on integrating advanced technologies, particularly blockchain and AI, to drive transparency and automation, as well as enhancing cybersecurity measures to protect the increasing volume of financial and business data.

Third, Process Management is comparatively weaker, with a score of 3.272. Although standardization reaches 3.438 and automation 3.400, integration across processes is less mature. Horizontal integration is only 3.084, and management integration stands at 3.227, reflecting limited end-to-end connectivity across departments and business units, together with insufficient alignment of management processes. Information systems also remain fragmented, with system integration scoring just 3.304. These findings highlight that while processes have been partially streamlined, departmental boundaries and coordination gaps persist. Strengthening cross-functional workflows and pursuing more comprehensive system integration will be crucial to achieving smoother and more efficient processes in the FSSC.

Fourth, Data Management achieves 3.430, indicating moderate capability. Progress is significant in areas such as data encryption (3.666) and analysis on the financial cloud (3.469), showing that security and analytical foundations are well established. Other dimensions remain underdeveloped, with real-time data connection at only 3.257 and heterogeneous data processing at 3.260, suggesting that data are not yet fully integrated for dynamic use. Decision-making support system scores 3.451, but intelligent decision support system remains lower at 3.333, confirming that financial intelligence is still at an early stage. To improve, the FSSC should broaden connection platforms to strengthen real-time data connectivity and apply AI more effectively within data management to enhance the quality of decision-making.

Fifth, Digital Performance stands at 3.496, reflecting tangible outcomes from digital initiatives. Operational efficiency scores 3.545, while customer satisfaction reaches 3.563, confirming that digitalization has improved both productivity and service experience. Financial performance is also strong (3.526), though external service performance lags at 3.333, showing that benefits are more evident internally than externally. To advance, the FSSC should build on its internal effectiveness and efficiency gains by strengthening collaboration with subsidiaries and business partners, so that external interactions also benefit from digital improvements.

Sixth, External Environment achieves the highest score of 3.914, highlighting a highly favorable context for digitalization. Policy support is particularly strong at 4.042, and market adaptation reaches 3.905, showing that national strategies and industry dynamics both encourage digitalization. The FSSC also demonstrates resilience, with disaster risk management at 3.807 and work arrangement at 3.957, indicating robust preparedness for external disruptions. Leveraging these external advantages, the FSSC should align its internal digital initiatives with broader national policies and actively participate in industry ecosystems to sustain progress.

Taken together, Ansteel Group FSSC exhibits balanced maturity with solid strengths in strategy and organization, infrastructure, and external support. However, its digitalization is constrained by weaknesses in process and system integration as well as in advanced data application and intelligent decision-making. Overall, the FSSC is positioned at the Managed level of digital maturity, which is stable but still evolving toward the Optimizing level.

7.3.4 Lubei Group FSSC

Background

Shandong Lubei Enterprise Group General Company (referred to as Lubei Group) is a local state-owned enterprise supervised by the SASAC of Binzhou City. It operates across the chemical, new materials, and environmental protection industries and is recognized for its commitment to circular economy practices and green development initiatives. To improve financial efficiency and strengthen oversight across its diverse business segments, Lubei Group established a FSSC. The FSSC centralizes key financial functions such as accounts payable and receivable, reimbursements, general ledger consolidation, and financial reporting, with the aim of standardizing operations, eliminating redundant efforts, and strengthening internal controls. This centralized model not only yields economies of scale in financial services but also provides a platform for advancing its digitalization efforts in line with the broader strategic goals of the Group.

In the evaluation phase of this study, 21 valid questionnaire responses were collected, including 12 from the FSSC and 9 from traditional finance departments. The respondents comprised 12 staff, 5 middle managers, and 4 top managers. Among them, 11 participants were directly involved in the digitalization of the FSSC, while 10 were indirectly involved. This sample composition ensured that the results were reliable and accurately reflected the state of digital maturity within the FSSC.

Digital Maturity Analysis

The Lubei Group FSSC achieves an overall digital maturity score of 3.824, placing it in the upper range of the Managed level among the five digital maturity levels. The overall score and its distribution across the six KPAs are shown in Figure 7.4. This outcome indicates that digitalization is well established and consistently managed throughout the FSSC, although certain foundational gaps, particularly in infrastructure, still need to be addressed before the FSSC can reach an optimized stage.

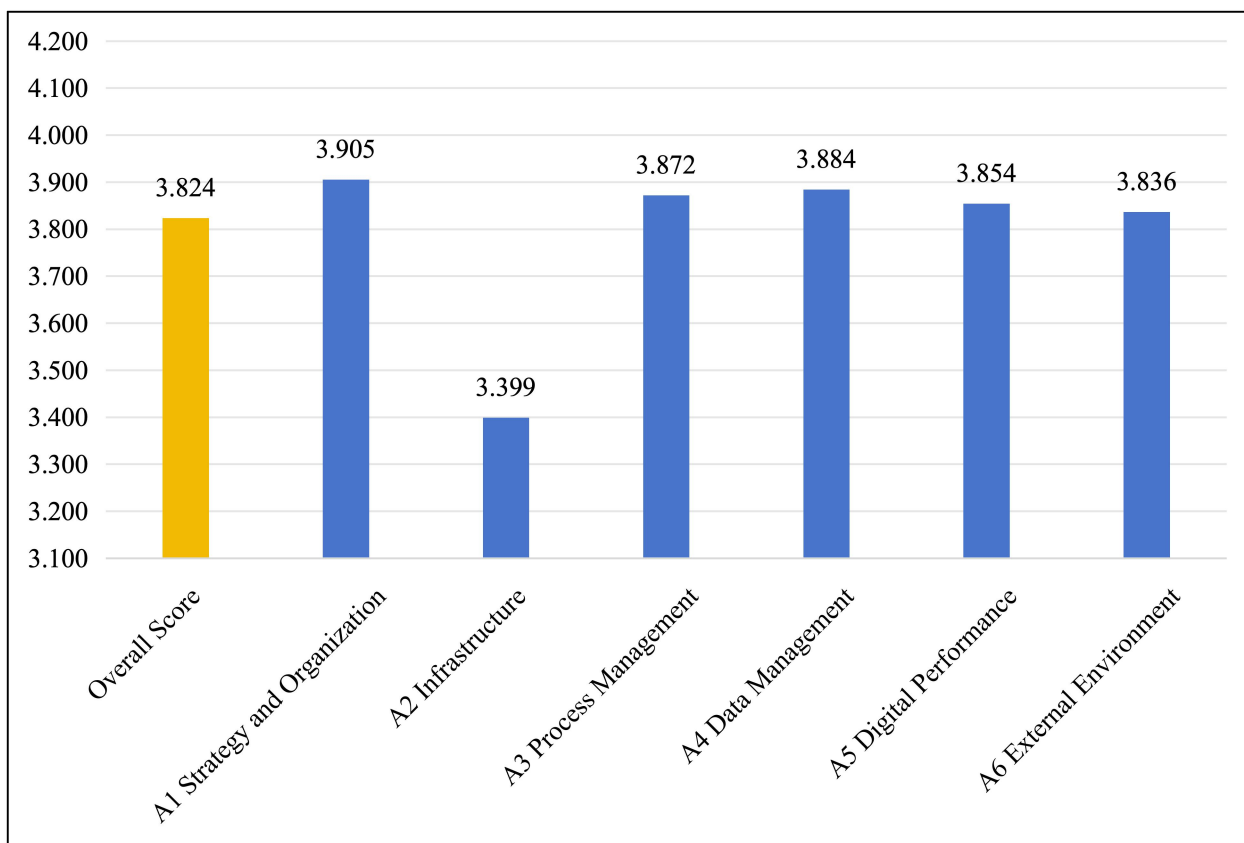


Figure 7.4 Digital Maturity Scores of Lubei Group FSSC

First, Strategy and Organization is a significant strength with a score of 3.905. Digital strategies are closely aligned with corporate objectives, and innovation and change reaches 4.064, reflecting an active culture of transformation. At the same time, digital thinking among employees is not yet firmly embedded at 3.619 and organizational restructuring remains incomplete at 3.789, indicating underlying cultural and structural inertia. The FSSC should further promote a digital-first mindset through talent training programme and refine its organization structure to support digital workflows.

Second, Infrastructure is the least developed domain, scoring 3.399. The FSSC has reliable network connectivity and steady capital investment in digitalization at 3.486, but its

core digital infrastructure is weakly developed at 3.143. The current technological infrastructure supports basic operations but lacks advanced capabilities and flexibility. The FSSC should prioritize upgrades to integrated systems and expand equipment digitalization to ensure wider adoption of intelligent devices, thereby providing a stronger foundation for future digitalization.

Third, Process Management is well-developed at 3.872, reflecting standardized processes. The FSSC has performed strongly in process automation (4.038) and in integrating financial processes across units, with vertical integration scoring 4.000, which demonstrates streamlined operations. However, continuous optimization is not yet routine at 3.703 and management integration remains moderate at 3.749, suggesting that regular refinement and coordination between management functions still require improvement. The FSSC should introduce structured feedback mechanisms and strengthen the integration of fund, budget, tax, and risk management processes to enhance continuous optimization and ensure closer alignment between operations and management.

Fourth, Data Management is robust at 3.884. The FSSC demonstrates strength in data acquisition and storage, and has introduced advanced analytics tools, with the intelligent decision support system scoring 3.951, reflecting a data-driven approach to intelligent decision-making. However, the processing of complex datasets and certain security measures such as encryption remain relatively weak, at 3.751 and 3.786 respectively, meaning that not all data assets are fully utilized or safeguarded. The FSSC should invest in more powerful data processing tools such as data lakes and reinforce data security to enhance the utilization and protection of its data resources.

Fifth, Digital Performance scores 3.854, showing that the benefits of digitalization are being realized in both effectiveness and efficiency. Stakeholders are experiencing improved outcomes, with customer satisfaction reaching 3.960 and external service performance rated 3.940. However, service quality remains at 3.776 and information transfer efficiency at 3.756, revealing minor inconsistencies in financial reporting practices and some communication barriers between departments. The FSSC should enhance the transparency, integrity, and validity of reporting outputs and improve information-sharing to ensure that these gains are consistent across all areas.

Sixth, External Environment is highly favourable, scoring 3.836. The FSSC benefits from moderate government backing, with policy support at 3.667 and financial support at 3.857, and maintains active industry partnerships that create a favourable environment for digitalization. It also demonstrates strong resilience, with disaster risk management at 3.867 and well-established flexible work arrangements at 4.059, ensuring continuity of operations

during disruptions. The FSSC should align its own digitalization projects with government initiatives and deepen industry partnerships to capitalize on these external advantages.

Overall, Lubei Group FSSC exhibits a well-rounded digital maturity profile, marked by strong strategic alignment, streamlined processes, effective data application, and a supportive external environment. Its main limitation lies in a slightly underdeveloped infrastructure, alongside the need for ongoing organizational improvements. Consequently, the FSSC sits at the Managed level of digital maturity and is well positioned to progress toward the Optimizing level with targeted enhancements.

7.3.5 China FAW Group FSSC

Background

China FAW Group Co., Ltd. (referred to as China FAW Group) is a central state-owned enterprise under the SASAC of the State Council and one of China's largest automotive manufacturers. Headquartered in Changchun and founded in 1953, China FAW Group produces a broad range of passenger and commercial vehicles and operates multiple joint ventures with global automakers. To strengthen financial management and efficiency across its many subsidiaries, the Group established a FSSC to centralize key financial functions such as accounts payable and receivable, reimbursements, general ledger consolidation, and financial reporting. This centralized model harmonizes financial policies, streamlines repetitive tasks, and strengthens oversight mechanisms across the Group, thereby ensuring consistency and control at scale. It also serves as a platform for facilitating digital finance innovation, consolidating financial data and systems to support data-driven decision-making, and aligning with the Group's broader push toward digital transformation in operations and management.

In the evaluation phase of this study, 21 valid questionnaire responses were collected, including 16 from the FSSC and 5 from traditional finance departments. The respondents consisted of 12 staff, 5 middle managers, and 4 top managers. Among them, 18 participants were directly involved in the digitalization of the FSSC, ensuring that the analysis results reliably and accurately reflected the actual state of digital maturity within the FSSC.

Digital Maturity Analysis

The China FAW Group FSSC achieves an overall digital maturity score of 4.184, placing it in the lower range of the Optimizing level among the five digital maturity levels. The overall score and its distribution across the six KPAs are presented in Figure 7.5. This

outcome indicates that digitalization is deeply embedded and approaching an optimized state, with only minor gaps remaining, making China FAW Group FSSC the most digitally mature case in this study.

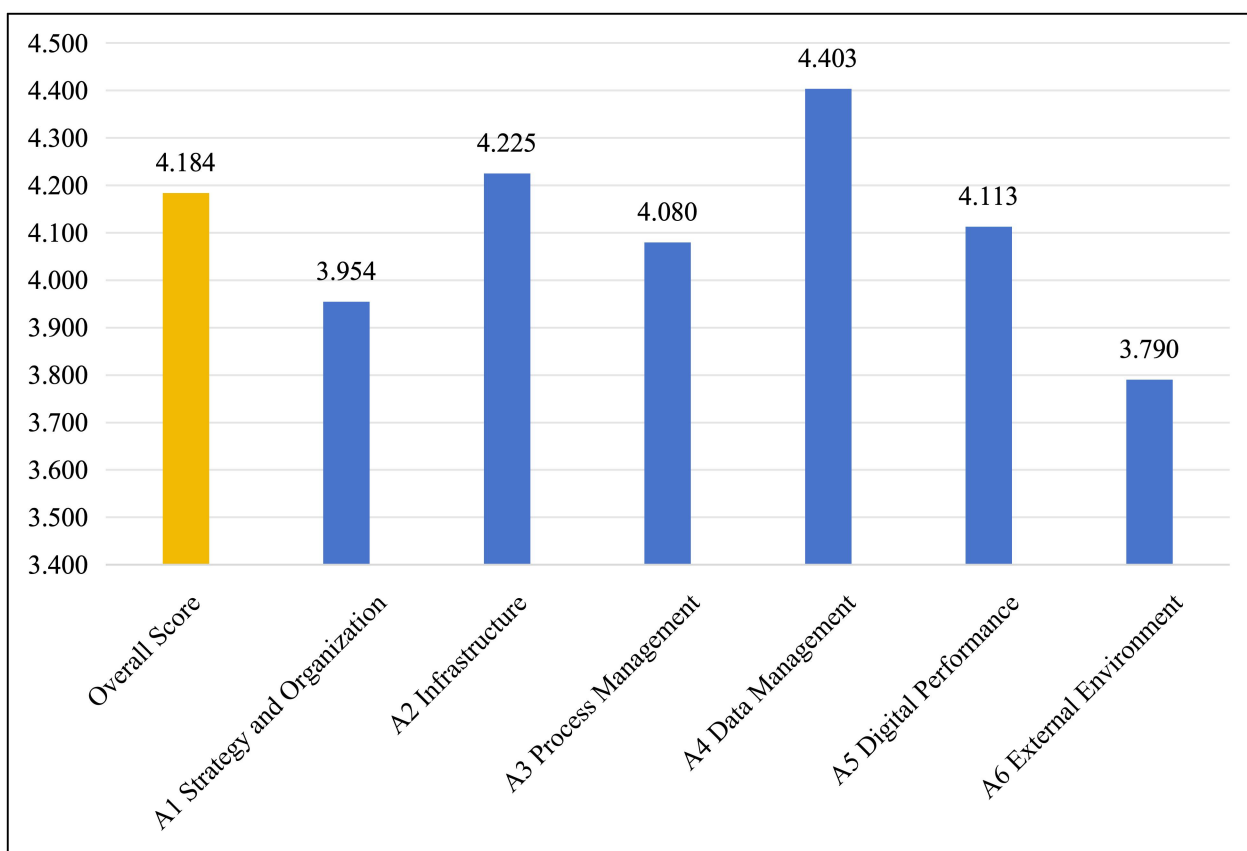


Figure 7.5 Digital Maturity Scores of China FAW Group FSSC

First, Strategy and Organization scores 3.954, reflecting tight alignment of digital strategy goals and planning with the actual situation and business strategies, and strong leadership support in an optimized and adaptive organization structure. Innovation culture and talent cultivation and retention are robust, with sub-scores between 3.936 and 4.126, while the digital thinking among staff is slightly weaker at 3.832. The FSSC should continue fostering a digital-first culture and developing digital talent to maintain momentum.

Second, Infrastructure is highly mature at 4.225, supported by modern information systems, extensive networks, and strong ongoing investment. Technology records 4.142, network 4.238, and capital investment 4.274, all of which provide a reliable foundation for the digitalization of the FSSC. To fully optimize, the FSSC should continue deepening the application and integration of advanced technologies, including the IoT, big data, cloud computing, blockchain, and AI, so as to drive continuous innovation and sustainable digital advancement.

Third, Process Management stands at 4.080, indicating well-standardized and efficient processes. System establishment is strong at 4.191, reflecting sound institutional frameworks, and continuous optimization also performs well at 4.095, supported by effective feedback loops. Safety and security reaches 4.432, confirming robust safeguards in information systems. By contrast, integration remains weaker, with horizontal integration at 3.898 and system integration at 3.904, revealing remaining silos. The FSSC should further strengthen cross-department collaboration and enhance system connectivity to achieve seamless end-to-end operations.

Fourth, Data Management is the strongest domain with a score of 4.403, reflecting advanced capabilities in data collection, processing, and analysis. Most sub-indicators are above 4.500, including heterogeneous data storage at 4.736 and data visualization at 4.748, demonstrating that the FSSC effectively transforms vast financial datasets into actionable insights under robust governance. The only gap is the intelligent decision support system at 3.997, suggesting that the FSSC should further expand AI-driven analytics, integrate machine learning and predictive modeling, and develop real-time decision support tools, thereby transforming data into a comprehensive driver of financial intelligence.

Fifth, Digital Performance totals 4.113, demonstrating significant improvements in both effectiveness and efficiency. Internal service quality and customer satisfaction are high, at 4.369 and 4.466 respectively, while external service performance is slightly lower at 3.986. Efficiency gains in operations and management are evident, with scores around 3.940, but information transfer remains a constraint at 3.833. The FSSC should improve communication channels with other business units to improve coordination, while also expanding external customer engagement and loyalty to enhance revenues and market share.

Sixth, External Environment is comparatively weaker at 3.790, though still supportive overall. Government policy and financial support for digitalization are present, with scores of 3.803 and 3.870 respectively, and the FSSC demonstrates resilience with disaster risk management at 4.093. However, participation in the construction of the broader digital ecosystem remains limited at 3.563, and flexible work arrangements score 3.723. Deepening collaboration with external stakeholders and enhancing remote work implementation would enable the FSSC to better leverage ecosystem opportunities and enhance adaptability.

Overall, China FAW Group FSSC emerges as the most digitally mature of the five cases, excelling across all domains with only minor weaknesses in cross-functional integration and in external collaboration within the digital ecosystem. Therefore, the FSSC is positioned at the threshold of the Optimizing level of digital maturity, showing that its digitalization is already well established but requires ongoing refinement to advance further.

7.4 Final Model Refinement

The analyses presented in the previous section offer a concise overview of the digital maturity of each participating FSSC. While these summaries highlight the main findings and comparative tendencies, the most detailed analyses are not included in the main body of the thesis in order to avoid redundancy. For transparency and completeness, however, the full application of the model was shared directly with the participants who had originally taken part in the evaluation survey in each enterprise. These detailed reports outlined the complete process of applying the digital maturity model, from the calculation of scores at the second sub-criteria level through the aggregation to the overall goal level. By doing so, the reports allowed participants to observe how the model transformed their survey inputs into digital maturity scores, levels, and improvement recommendations for their FSSC.

The purpose of providing these reports to the respondents is twofold. On the one hand, participants were asked to review the entire computational procedure of the model in order to judge whether the application of the FCE method was accurate, unbiased, and logically consistent. This step is designed to confirm whether the model can be applied in practice without distortion or methodological weaknesses, thereby testing its practical applicability. On the other hand, participants were also invited to evaluate the substantive outcomes of the analysis. They considered whether the overall digital maturity score and level, together with the distribution of scores across the six KPAs and the more granular indicators, corresponded to their own perception of the digitalization state of their FSSC. They also assessed whether the explanatory discussion and suggested pathways for improvement were realistic, relevant, and useful for supporting progress to the next level of digital maturity. This step is intended to verify the reliability and validity of the model by comparing its results with the practical knowledge of those directly or indirectly engaged in digitalization.

The feedback process therefore went beyond asking participants to confirm whether the results were reasonable. It also encouraged them to reflect on the suitability of the evaluation indicator system itself, the adequacy of the maturity level classification, and the robustness of the application procedure. In relation to the evaluation indicator system for digital maturity, participants were invited to identify any KPAs or indicators whose definitions or scoring outcomes did not align with their lived experience of digitalization in the FSSC. They were able to suggest deletions, modifications, or renaming of indicators, to propose the addition of new measures, and to comment on whether the relative weights assigned through the AHP procedure adequately captured the importance of different aspects of digital maturity. In relation to the digital maturity levels, they were asked whether the five-level framework adequately represented the trajectory of their organization. If they felt that the levels were misaligned with practice, they could propose revisions, such as the elimination of redundant

levels, the modification of existing level definitions, or the creation of new categories that more precisely capture the developmental stages of digitalization. Finally, participants were also encouraged to assess the application process. If they felt that the FCE procedure was too complex, insufficiently transparent, or misaligned with practical requirements, they were free to suggest alternative methods or improvements that might increase the model's applicability in real-world contexts.

The implementation of this feedback round took place between February and April 2025. While the initial evaluation involved 107 valid respondents across the five enterprises, some were unable to participate in the final feedback stage due to work commitments. In total, 95 valid responses were collected. These comprised 20 participants from Ansteel Group, 18 from Baoding Transportation Development Group, 20 from China FAW Group, 16 from Lubei Group, and 21 from Tianjin TEDA Group. The high level of engagement across all five cases provided a rich basis for the final refinement of the model. By combining the critical reflections of practitioners with the structured outputs of the evaluation procedure, the final version of the digital maturity model is not only theoretically rigorous and methodologically sound but also empirically validated as a practical tool for determining and improving the development level of digitalization of FSSC in Chinese state-owned enterprise.

7.4.1 Feedback Analysis

The first aspect of feedback concerned the evaluation indicator system. Almost all participants affirmed that the scores of each KPA and indicator, as well as the interpretations derived from the analysis, were consistent with their own perception of the actual state of digitalization in their FSSC. They emphasized that no major discrepancies or distortions were observed. The recommendations for improvement derived from these scores were also regarded as realistic and implementable rather than abstract or impractical. As a result, participants generally agreed that the evaluation indicator system for digital maturity should remain unchanged, including the six KPAs, the three-level hierarchy of indicators, and the assigned local and global weights. A small number of minor modification suggestions were raised, but these were due to misinterpretations of indicator definitions. After further clarification and discussion with the respondents concerned, these issues were resolved and the suggestions were withdrawn.

The second aspect of feedback related to the classification of maturity levels. Participants largely agreed that the overall digital maturity scores and the levels assigned to their FSSC aligned with their actual situation. In other words, the five-level framework successfully captured the digitalization stage of each individual case when considered in isolation. However, when the results of the five FSSCs were compared together, participants found that

three of the FSSCs were all located within the Managed level. Although differences existed in their absolute scores, the existing five-level framework was unable to distinguish them meaningfully at the level classification. This limitation was perceived as a weakness for benchmarking, planning future improvements, and facilitating mutual learning through competition. Therefore, many respondents suggested that additional levels should be introduced within the framework to increase its precision. Drawing on these suggestions, this study refined the original classification into an eight-level framework. This enhanced framework preserves the original structure but introduces further granularity. The details of this refined classification and its advantages are presented in the following section.

The third aspect of feedback focused on the application procedure. Respondents confirmed that the use of the FCE method to apply the digital maturity model was transparent, relatively straightforward, and practically applicable. They expressed confidence in the accuracy of the procedure and did not identify major shortcomings. At the same time, several participants suggested that alternative methodological options might be explored in future research as potential complements or substitutes. In particular, they mentioned techniques such as the Technique for Order Preference by Similarity to Ideal Solution, Grey Relational Analysis, and Data Envelopment Analysis, which could be applied to evaluate digital maturity from different analytical perspectives. These approaches, while not adopted in this study, provide useful directions for subsequent work and highlight the possibility of triangulating results across different methodological lenses.

In summary, the first two aspects of feedback confirm that the model produces results consistent with the participants' own perceptions, thereby verifying its reliability and validity. The refinement of the maturity level framework further strengthens these qualities by enhancing the ability of the model to differentiate among FSSCs and support benchmarking. The third aspect of feedback demonstrates that the model can be applied in practice without methodological bias or unnecessary complexity, thereby verifying its practical applicability. Collectively, these findings confirm that the digital maturity model for FSSC in Chinese state-owned enterprise is not only theoretically rigorous but also practically relevant.

7.4.2 Model Adjustment

The five-level digital maturity framework has proven effective for evaluating FSSCs in Chinese state-owned enterprises. However, as discussed above, particularly in the second aspect of feedback results, the overall scores of several FSSCs were found to cluster around the threshold values between adjacent levels. Such clustering reduces the discriminatory power of the model, making it difficult to distinguish clearly between FSSCs positioned near the thresholds. In more complex organizational contexts, this limitation may hinder the ability

of the framework to fully reflect the gradual and evolutionary trajectory of digitalization.

To overcome this issue, and drawing on the suggestions provided by participants in the second aspect of feedback results, this study refines the maturity framework by extending it from five to eight levels. The design logic of the eight-level framework is as follows. Since the clustering problem is primarily observed in the higher levels, namely Defined, Managed, and Optimizing, the two lower levels, Initial and Repeatable, remain unchanged. The three higher levels are subdivided into “basic” and “advanced” categories, resulting in six refined levels. Together with the two unchanged levels, the framework now comprises eight distinct digital maturity levels. Each level is associated with a specific score range from 0 to 5, thereby providing clearly specified thresholds. Furthermore, as with the original five-level framework, each level is linked to its own set of KPAs and key practices. Based on the six identified KPAs, the characteristics and key practices of each level are summarized alongside the underlying learning mechanisms and enabling systems that operate across levels. The subsequent subsections elaborate on each level and its progression.

Initial (0–1)

At the Initial level, FSSC in Chinese state-owned enterprise is at a very early, exploratory stage of digitalization. Leadership and staff have little or no awareness of the strategic importance of digitalization, and there is no formal digital strategy or planning in place. The organization lacks any dedicated digitalization team or governance structure for digital initiatives. Technological infrastructure is rudimentary or non-existent, and financial processes remain fragmented and entirely manual, often relying on isolated, non-integrated systems. Data assets, while potentially valuable, are scattered and underutilized, with no framework for data management. Consequently, the FSSC gains no tangible benefits from digitalization at this stage, and operational performance is characterized by high costs and inefficiency. The FSSC is also essentially unable to adapt to external changes in policy or market conditions.

In summary, by the end of the Initial level, the FSSC has no clear digital foundation, lacks structured practices, and remains unprepared to progress toward digital maturity.

Repeatable (1–2)

At the Repeatable level, FSSC in Chinese state-owned enterprise moves into the initial stage of deliberate digitalization. Leadership begins to acknowledge the importance of digitalization and sets preliminary directions for improving future competitiveness and performance. A basic digital strategy is formulated in outline, and the organization initiates

foundational training for staff to develop digital skills, though these efforts are sporadic and not yet comprehensive. The FSSC makes initial investments in simple technologies and basic information systems, typically limited to specific functions or pilot areas. Early steps are taken to standardize some financial processes, especially repetitive transactions, and introduce rudimentary automation, creating a repeatable pattern for certain tasks. Data is increasingly recognized as a valuable asset. The FSSC starts collecting and storing data in a more structured way and attempts to link parts of the data value chain, although these efforts remain experimental and fragmented. The FSSC gains limited benefits from digitalization, with slight efficiency improvements and an unclear overall impact. External responsiveness remains minimal at this stage, as the FSSC continues to operate with an internal focus.

In summary, by the end of the Repeatable level, the FSSC has initiated a basic digital strategy, adopted initial technologies, and introduced limited process standardization and automation, but its data use is fragmented, performance gains are limited, and external responsiveness remains underdeveloped.

Defined – Basic (2–2.5)

At the Defined – Basic level, FSSC in Chinese state-owned enterprise enters a more structured mid-stage of digital maturity. A foundational digital strategy has been formally adopted, providing clear direction for digitalization. Leadership now drives a coordinated approach to implementation, and initial steps are taken to establish governance structures for digital initiatives by forming a dedicated digitalization team. Specifically, the organization undertakes initial restructuring to align its structure, roles, and responsibilities with digital objectives. Talent development becomes more systematic, as the FSSC moves beyond sporadic training to introduce more structured training programs. Foundational digital technologies are deployed across core finance areas, strengthening the infrastructure needed for digital operations. Key financial processes are now standardized and partially automated, reducing manual effort and improving consistency in operations. The FSSC also implements basic data management practices. Data collection is more structured with attention to data quality, and the organization develops initial analytical capabilities to support internal decision-making. At this stage, early gains in cost reduction and efficiency from digitalization are becoming evident, although these gains remain inconsistent across different areas. There is also an initial awareness and response to external changes, but proactive external engagement is still at an early stage. For example, the FSSC monitors relevant policy or market shifts and makes limited adjustments as needed.

In summary, by the end of the Defined – Basic level, the FSSC has adopted a formal digital strategy, restructured its organization, introduced foundational technologies,

standardized key processes, and initiated structured data practices, but its performance gains remain unstable and its external engagement is still reactive.

Defined – Advanced (2.5–3)

The Defined – Advanced level signifies a deeper and more expansive implementation of digitalization of FSSC in Chinese state-owned enterprise on the solid foundation established earlier. The digital strategy is now clear, comprehensive, and under active execution across the organization. Leadership refines the strategy into a transformation plan for the medium to long term and dedicates an expanded team with defined roles to carry it out. The technological infrastructure is extended to a broader range of financial functions and integrated more thoroughly, enabling greater automation and cross-departmental process integration. This means that digital tools and systems are no longer fragmented or confined to limited areas. Instead, processes in different departments are linked and data flows between them, improving end-to-end efficiency. Data management practices advance significantly at this stage, as data is now shared across functional areas, and the FSSC makes regular use of data analysis and visualization tools to support decision-making. For example, dashboards and analytical reports might be used by management to gain insights into operations. As a result of these improvements, the benefits of digitalization stabilize and become more prominent. The FSSC achieves steady cost savings and efficiency gains, and performance improvements are consistently realized rather than just in isolated cases. Additionally, the FSSC adopts a more proactive approach toward its external environment. It begins to anticipate external trends or regulatory changes and initiates responses, such as adjusting processes or adopting new compliance systems, before those changes fully impact operations.

In summary, by the end of the Defined – Advanced level, the FSSC has established a clear medium- or long-term digitalization plan, expanded its dedicated team, extended digital infrastructure across financial functions, integrated processes across departments, enabled cross-functional data sharing and analysis, and achieved stable performance gains, while beginning to respond proactively to external changes.

Managed – Basic (3–3.5)

At the Managed – Basic level, FSSC in Chinese state-owned enterprise enters an advanced stage of digital maturity where digitalization is embedded as a core operational and strategic capability. The digital strategy is now being effectively executed and fully integrated with the enterprise's overall strategy. In practice, this means the FSSC's digital objectives are aligned with business objectives, and digital initiatives have become an integral part of mainstream planning. The FSSC maintains a dedicated, well-resourced

digitalization team overseeing continuous technology adoption, system upgrades, and process improvement. The technological infrastructure is stable, comprehensive, and fully integrated. Furthermore, advanced information systems connect across the FSSC and the broader organization, providing a robust platform for end-to-end financial processes. Almost all core financial processes are now highly automated and tightly integrated with business processes. Cross-departmental barriers have been broken down, and workflows now extend across functions, enabling collaborative and efficient operations from transaction processing to managerial decision-making. Data management capabilities become highly mature at this level. The FSSC establishes a complete end-to-end data value chain, in which data is collected, stored, and utilized seamlessly across systems, along with strong data governance and security measures. This robust data environment facilitates real-time data flows and ensures that decision-makers have timely access to reliable data. Decision-making across the FSSC and its supported business units becomes increasingly data-driven. While not yet incorporating full AI, the FSSC employs advanced data analysis techniques and basic decision-making support systems to support both operational and strategic decisions. By this stage, the benefits of digitalization are significant and consistently realized. The FSSC achieves major improvements in effectiveness and efficiency, and these improvements are sustained over time. The FSSC also demonstrates the ability to respond rapidly and proactively to external changes. Through adaptive strategies and flexible resource allocation, it shows resilience to market or environmental fluctuations, positioning itself as a key enabler of organizational adaptability.

In summary, by the end of the Managed – Basic level, the FSSC has fully aligned its digital and business strategies, established an integrated infrastructure, achieved highly automated processes, built a complete data value chain, realized sustained performance gains, and developed the capacity to respond proactively to external changes.

Managed – Advanced (3.5–4)

At the Managed – Advanced level, FSSC in Chinese state-owned enterprise achieves leading-edge digital capabilities. Digitalization is deeply embedded not only in operations but also in the organizational structures and culture. The FSSC's digital strategy and business strategy are in mature alignment, supported by a highly developed digital governance framework. Leadership for digital initiatives is also strong, as senior management actively promotes a clear digital vision across the FSSC. The technological infrastructure at this stage is highly sophisticated, incorporating advanced technologies such as big data, cloud computing, blockchain, and AI into the FSSC's processes and services. Process management now incorporates early forms of intelligent automation, as some processes begin to have AI-driven or expert-system components that allow for optimization or decision-making

support. Information systems are fully integrated across the enterprise, enabling the FSSC to operate in a unified digital environment. Data management is enhanced to support high-quality data analytics and predictive modeling, enabling the FSSC to perform forward-looking analysis, including risk forecasting and financial scenario analysis, with a high degree of precision. Decision-making at all levels benefits from these predictive insights, making it more accurate and strategic. The benefits of digitalization at this stage surpass industry benchmarks, achieving service quality and operational efficiency above the industry average. In the external context, the FSSC takes an active approach to risk and collaboration. Risk mitigation is embedded, as the FSSC uses digital tools to anticipate and safeguard against external risks such as economic changes and cyber threats. It also actively engages in digital collaborations with upstream and downstream stakeholders in the supply chain and government platforms. At this stage, its service offerings may extend beyond the enterprise, for example by providing outsourcing financial services to external clients, which significantly enhances its external service capability.

In summary, by the end of the Managed – Advanced level, the FSSC has achieved mature strategic alignment, applied advanced technologies, introduced intelligent automation with fully integrated systems, developed data-driven predictive capabilities, attained above-industry-average performance, and actively engaged in digital collaborations, thereby setting the stage to become an industry leader at the next level.

Optimizing – Basic (4–4.5)

At the Optimizing – Basic level, FSSC in Chinese state-owned enterprise becomes a central driver of enterprise digitalization. The FSSC promotes continuous innovation through its digital strategy and cultivates a strong digital culture supported by flexible and adaptive structures. Leadership places digital innovation at the core of digitalization, encouraging exploration and improvement in both strategy and operations. The technological infrastructure is intelligent and self-regulating, with systems capable of making routine adjustments autonomously. This creates a resilient digital foundation that can adapt to changing conditions without requiring constant human intervention. Financial processes reach a stage of high intelligence. They are not only automated but also dynamically optimized. The FSSC can adjust processes on demand in response to internal performance requirements or external conditions, ensuring operational excellence and agility. For example, AI algorithms are used for anomaly detection in financial processes. Data management reaches an advanced stage, as the FSSC functions as an enterprise's big data center. Real-time data flows and analytics are embedded in operations, and the FSSC leverages real-time decision-making support systems to provide strategic foresight and support risk forecasting. For example, dashboards might update continuously with key financial metrics,

and predictive models run in real time to identify risks or opportunities, allowing managers to make informed decisions quickly. Digitalization now delivers significant strategic benefits. The FSSC enhances the competitiveness of the enterprise by enabling innovation in business models, accelerating responses to market demands, and generating insights that are difficult for competitors to replicate. The FSSC also extends far beyond its traditional internal role and engages in broad collaboration across the ecosystem, for instance by seamlessly exchanging data or services with suppliers, customers, regulators, and other partners through digital platforms. The FSSC has developed a mature capability to deliver digital services externally, providing financial processing, data analytics, and other value-added services to clients or affiliated organizations within the business group. These external services and collaborations are robust and reliable, making the FSSC a strategic partner in the broader business network.

In summary, by the end of the Optimizing – Basic level, the FSSC has embedded continuous innovation, established self-regulating infrastructure, achieved intelligent process optimization, built an enterprise-wide big data center, realized strategic and competitive benefits, and extended its role into the broader ecosystem through mature external service delivery.

Optimizing – Advanced (4.5–5)

The Optimizing – Advanced level represents the pinnacle of digital maturity, where FSSC in Chinese state-owned enterprise becomes a benchmark for digitalization in the industry. At this stage, the FSSC's strategies and practices are truly leading-edge, often pioneering new approaches that others seek to follow. Digital strategy and organizational governance are characterized by continuous innovation and refinement, ensuring that the FSSC remains at the forefront of both technological and managerial practices. The organization structure is fully optimized for agility and innovation, with cross-functional teams and governance mechanisms that adapt quickly to new digital opportunities. The technological infrastructure is fully intelligent and AI-driven. Almost every system and tool incorporates AI and achieves advanced automation, enabling autonomous operations with minimal human intervention. FSSC's processes are fully intelligent, flexible, and capable of real-time self-optimization. Processes adjust instantly to data inputs or environmental changes without requiring manual decision-making. The FSSC effectively operates as the digital brain of the enterprise, functioning as an intelligent decision support center that not only executes rule-based decisions but also performs real-time risk monitoring and alerting. At this stage, AI augments decision-making and handles routine matters autonomously, while human experts concentrate on strategic oversight. The FSSC achieves peak operational excellence, with both effectiveness and efficiency maximized to the highest level. It also has significant strategic influence, as its insights and capabilities shape enterprise-wide strategic

decisions. The cumulative advantages of digitalization are exemplary, placing the FSSC well ahead of industry peers. In the external context, the FSSC assumes a role of industry-shaping leadership within the digital ecosystem. It not only participates in collaborations with partners and regulators but also leads and coordinates them. For example, the FSSC may drive the development of industry-wide data exchange standards or collaborative digital platforms. Furthermore, it provides high-value digital services to external stakeholders such as advanced analytics, consulting, or platform services, thereby creating new revenue streams and extending influence beyond its own enterprise.

In summary, by the end of the Optimizing – Advanced level, the FSSC has driven industry-leading innovation, operated a fully intelligent AI-driven infrastructure, achieved real-time self-optimizing processes, become an intelligent decision support center, attained peak operational excellence and strategic influence, and provided ecosystem leadership by delivering high-value digital services externally. The FSSC at this level will continue to innovate and improve even at the peak of digital maturity, ensuring it retains its position as a digital leader. This level represents a fully matured digital FSSC that not only leads the transformation of its own enterprise but also contributes to shaping the broader industry environment.

Organizational Learning Process

With the refined framework, the staged progression implies a staged organizational learning process, which unfolds through a set of underlying learning mechanisms. In this study, organizational learning refers to how the FSSC develops digitalization through repeated execution, review, and improvement, and then stabilizes these digital practices as organizational capabilities rather than isolated actions. A single learning mechanism can be summarized through four embedded pathways that operate across the eight levels. These pathways are explicitly reflected in the evaluation indicator system, with most learning-related indicators concentrated in Process Management and Data Management. As these two KPAs are grouped under the “Processing” component in the IPO-based digitalization process, they represent the core activities through which FSSCs implement transformation and accumulate organizational learning.

First, experiential learning occurs when the FSSC identifies operational problems during daily work and improves processes through feedback, adjustment, and iteration. This pathway is consistent with process re-engineering practices such as building feedback mechanisms and strengthening alignment between optimized processes and actual business needs. Second, cross-functional learning occurs when the FSSC and other business units coordinate process design and execution, share data, and solve problems jointly. This pathway is reflected in

process and system integration between them as well as in the ability of FSSC to offer operational support. Third, data-driven learning occurs when the FSSC gradually moves from basic reporting toward analysis, prediction, and decision support. This pathway aligns with data management practices such as establishing analytical models within the financial cloud and developing decision-making support systems based on AI. Fourth, institutionalization occurs when previously learned and effective practices are incorporated into standards and rules, so that improvement becomes repeatable and scalable rather than dependent on individuals. This pathway is reinforced by the establishment of formal governance systems, including quality assessment, efficiency supervision, and operation management, which embed continuous monitoring into routines. More importantly, it is supported by the framework design in which each level is linked to a distinct set of KPAs and key practices, forming a roadmap for targeted progression. Therefore, the eight-level framework further illustrates how organizational learning is manifested at different stages of digital maturity.

At the Initial and Repeatable levels, the learning mechanism is mainly local and exploratory, with limited accumulation across the organization. At the Initial level, the FSSC has no digital awareness, weak infrastructure, manual processes, and scattered data. Any improvement is driven by individual experience and remains unstable. At the Repeatable level, early standardization and rudimentary automation emerge in selected functions, and basic training begins, which creates limited repeatable patterns for certain tasks. However, data application remains fragmented and the learning cycle is slow because feedback is not yet systematically captured and shared.

At the Defined levels, the learning mechanism shifts from localized experimentation toward a more structured and expandable form. A formal strategy and team formation provide direction and resources for planned implementation. The key transition is from isolated process improvement toward broader coordination and integration. At Defined – Basic, processes become standardized and semi-automated, and data collection becomes more structured with basic analysis. At Defined – Advanced, the FSSC expands automation and begins cross-departmental integration, while data sharing and visualization improve performance visibility. These changes strengthen experiential learning through clearer operational signals and promote cross-functional learning by requiring shared understanding of process logic and responsibilities and shared access to data across units.

At the Managed levels, the learning mechanism is no longer sporadic but becomes embedded in routine operations and decision-making. At Managed – Basic, the FSSC achieves highly automated and integrated processes and builds an end-to-end data value chain with basic decision support, enabling a faster feedback loop between actions and outcomes. This stage is consistent with data-driven decision-making becoming more common across the

FSSC and supported units. At Managed – Advanced, predictive capability and more precise decision support further strengthen data-driven learning, and intelligent automation enables the organization to refine processes and decision rules through system-level optimization rather than manual intervention, based on accumulated operational and performance insights.

At the Optimizing levels, the learning mechanism evolves from being embedded to becoming continuous and self-reinforcing. At Optimizing – Basic, the framework emphasizes dynamic optimization, real-time foresight, and strategic benefit, indicating that learning is no longer limited to improving existing tasks but also supports innovation and broader ecosystem collaboration. At Optimizing – Advanced, the FSSC functions as an intelligent decision support center, achieves real-time self-optimizing processes, and continues to innovate even at the peak of digital maturity, representing the most institutionalized form of learning where improvement is integrated into governance and AI-enabled systems. Taken together, the extended framework not only describes capability differences across the eight maturity levels, but also makes explicit how the FSSC progressively stabilizes, integrates, and optimizes digital practices through a staged organizational learning process.

Human and Cultural Factors

While the organizational learning process explains how digital capabilities evolve across levels, the staged progression also depends on enabling conditions within the organizational context. In the context of FSSCs in Chinese state-owned enterprises, two enabling conditions are particularly important: the human factor and the cultural factor.

The human factor is a critical enabling condition because it concerns the people-related conditions that support digitalization, including the development of new skills, the transition to new roles, and sustained participation from both staff and leaders. First, capability and skills are foundational. As digital maturity increases, employees are expected to move from rule-based execution to process understanding and data-driven judgment. This requirement is reflected in the evaluation indicator system through the availability of digital talent and employee proficiency in using digital tools and maintaining systems. It is also reflected in structured training arrangements, including training in digital technologies and interdisciplinary domains that support process execution and integration. In the maturity framework, this shift is visible from early stages where digital application remains underdeveloped and training is sporadic, to later stages where employees responsible for providing advanced financial analysis for the front-end business operations and making strategic decisions for the entire enterprise are able to fully utilize data, while talent cultivation becomes more systematic and organization-wide.

Second, progression across the eight maturity levels inherently involves role transition. As digital maturity advances, employees are required to redefine their professional identities in order to adapt to the evolving functions of the FSSC. This transition reflects a movement from bookkeeping staff to process managers and ultimately to decision support specialists. Such transformation is not merely a change in task allocation, but a psychological shift that requires employees to accept job adjustments and develop broader perspectives beyond narrow functional boundaries. This is supported by indicators that capture adaptation and adjustment, together with job rotation mechanisms that foster cross-functional understanding and collaboration between finance and business units. Furthermore, role transition is not only an individual-level change. It also requires clearly defined roles and responsibilities within organizational restructuring, which is consistent with the Defined levels that introduce and expand dedicated digitalization teams to align organization structures with digital objectives.

Third, motivation, participation, and acceptance shape whether digital practices can be sustained. In Chinese state-owned enterprises, digitalization increases transparency and changes how performance is monitored and assessed. It therefore requires employees to accept new ways of working, to standardize personal experience into digital systems, and to be evaluated through data-based performance metrics. Under such conditions, effective participation depends on fair appraisal and credible incentive arrangements that recognize both traditional competencies and digital contributions. This is reflected in indicators such as the establishment of talent appraisal systems, the construction of incentive mechanisms, and the provision of promotion channels that support retention and long-term engagement. These elements become increasingly critical in the higher stages of the maturity framework, emphasizing a shift from short-term mobilization toward stable organizational commitment and proactive involvement from both staff and managers.

Finally, leadership and governance provide the organizational foundation that enables individual skills to contribute to ongoing advancement. Digitalization requires strong leadership awareness and a clear digital vision to ensure coordination and governance rather than dispersed efforts. This is consistent with indicators that capture the formal positioning, practical expertise, and active participation of digital leaders within the FSSC, which strengthen resource commitment and the continuity of digital initiatives. It is also reflected in the refined level descriptions, which demonstrate an evolution of leadership from limited awareness and reactive orientation to setting preliminary digital priorities, to driving coordinated implementation, and ultimately to providing coherent strategic direction and fostering digital innovation.

The cultural factor is another enabling condition as shared norms and expectations shape how digitalization is understood, affecting digital thinking, innovation-oriented attitudes, and

structural arrangements that support or constrain change. First, the degree of risk tolerance influences whether digitalization is treated as a cautious compliance task or as a continuous improvement journey. At lower digital maturity, the preference for stability often discourages experimentation and leads to minimal use of new systems, especially when increased data visibility exposes operational weaknesses. This slows down the pace of improvement and reduces organizational readiness for change. As digital maturity increases, progression is facilitated by a cultural shift where controlled experimentation is seen as reasonable, process re-engineering is considered normal, and data is used to reveal issues for further refinement rather than solely for monitoring purposes. In the evaluation indicator system, this is reflected through culture-oriented indicators that assess the cultivation of data-driven thinking through communication and exchange, the willingness to accept and manage digital risks, and the translation of innovative ideas into real practice. This shift also aligns with the higher-stage descriptions in which a strong digital culture and continuous innovation become explicit features of the Optimizing levels, supported by flexible and adaptive structures.

Second, hierarchy and empowerment norms shape whether responsibility for processes and data remains concentrated at the top or becomes distributed to support local optimization and timely decisions. At lower digital maturity, decision-making is often centralized, and front-end business adjustments may be perceived as unauthorized and risky, which positions data mainly as an upward reporting tool rather than a basis for managerial action. As digital maturity increases, effective implementation requires a cultural expectation that responsibility for outcomes is clearer, that decisions can be made closer to operational signals, and that the use of data in daily management is legitimate rather than exceptional. In the evaluation indicator system, this is reflected through structure-related indicators that focus on reduction of unnecessary layers to enhance communication, and decentralization that supports specialized functions working together rather than remaining isolated. In addition, the cultural logic gradually becomes visible at the Defined levels, where the FSSC undertakes initial restructuring that reinforces clarity of accountability and authority distribution, which lays the cultural and structural foundation for later stages that emphasize agility.

Third, cross-functional collaboration norms determine whether digitalization can move beyond internal standardization to enterprise-wide integration. At lower digital maturity, collaboration is often constrained by routines that preserve functional boundaries and restricted data sharing, so integration depends on individual negotiation. Higher digital maturity therefore relies on a cultural norm that prioritizes sustained coordination among distinct divisions for finance, business, strategy, and IT, because integrated platforms, unified standards, and reliable data exchange and information sharing cannot be achieved through optimization within a single department. In the evaluation indicator system, this is reflected through integration-oriented practices such as interconnection and mutual support among

core financial processes, synchronization of financial activities with business events, and enterprise-level integration across fund, budget, and tax management. Moreover, this transformation is strengthened as cross-departmental process integration and data sharing expand at the Defined – Advanced level, barriers are broken down at the Managed – Basic level, and the Optimizing levels further highlight extensive collaboration supported by a well-established teamwork spirit.

Taken together, the extended framework demonstrates that digital maturity for FSSCs in Chinese state-owned enterprises cannot be realized through technological, data, and process capabilities alone, but depends equally on the alignment of human and cultural conditions. The human dimension ensures that talent, training, roles, motivation, and leadership are developed to support sustained execution and innovation. The cultural dimension shapes whether data-driven thinking, risk appetite, empowerment, and collaboration are normalized as part of daily organizational practice. Only when these human and cultural foundations co-evolve with structural and technological development can digitalization progress in a stable and scalable manner.

Overall, each digital maturity level is associated with specific practices across the six KPAs, providing FSSCs in Chinese state-owned enterprises with a clear roadmap for progression and targeted improvement. The refined eight-level framework, with its increased granularity, enhances the precision of maturity assessments and the discriminatory power of the model, allowing organizations to more accurately identify their current stage of digitalization and benchmark themselves against peers. Moreover, the detailed key practices at each level offer actionable insights to guide strategy formulation and implementation in addressing the gaps required to advance to higher digital maturity levels. Beyond structural differentiation, the refined framework also makes explicit the staged organizational learning process and the human and cultural factors that enable digitalization, thereby clarifying how capability development is stabilized and institutionalized over time. Table 7.9 presents the eight levels, their score ranges, and a concise overview of the corresponding KPAs and key practices, facilitating straightforward comparison across different levels. Therefore, the eight-level digital maturity model for FSSC in Chinese state-owned enterprise integrates theoretical rigor with practical relevance, capturing not only the evolutionary trajectory from early-stage digital efforts to industry-leading excellence, but also the underlying learning mechanisms and enabling systems that sustain digital transformation.

Table 7.9 Refined Digital Maturity Levels

Level	Score Range	Strategy and Organization	Infrastructure	Process Management	Data Management	Digital Performance	External Environment
Initial	0–1	No digital awareness; no strategy or team	Very poor or no IT foundation	Manual, fragmented processes	Scattered, underutilized data	No benefits; high costs and inefficiency	No adaptation to external changes
Repeatable	1–2	Initial awareness; outline strategy; basic training	Basic technologies in selected functions	Early standardization; rudimentary automation	Partial data chain; fragmented use	Limited benefits; minor performance gains	Minimal external responsiveness
Defined – Basic	2–2.5	Formal strategy adopted; team formation	Foundational IT systems deployed	Standardized and semi-automated processes	Structured data collection; basic analysis	Early benefits; unstable performance gains	Initial monitoring of policy/market changes
Defined – Advanced	2.5–3	Clear medium- or long-term plan; expanded team	Broader IT application	Greater automation; cross-departmental integration	Cross-functional data sharing; visualization	Stable cost savings and efficiency	Proactive environmental response begins
Managed – Basic	3–3.5	Integration of digital and enterprise strategies	Stable, comprehensive infrastructure	Highly automated and integrated processes	Complete data chain; basic decision support	Significant, consistent improvements	Rapid, proactive response to external changes
Managed – Advanced	3.5–4	Mature alignment; strong digital leadership	Advanced technologies in all functions	Intelligent automation; full integration	High-quality prediction; precise decision support	Above-industry-average performance	Active risk mitigation; digital collaboration
Optimizing – Basic	4–4.5	Innovative strategies, culture, and structures	Intelligent, self-regulating infrastructure	High intelligence; dynamic optimization	Big data center; real-time foresight	Strategic benefits; competitive advantage	Broad ecosystem collaboration; external services
Optimizing – Advanced	4.5–5	Industry-leading innovation and governance	Fully intelligent, AI-driven infrastructure	Fully intelligent processes; real-time self-optimization	Digital brain; intelligent decision support and risk alert	Peak operational excellence and influence	Industry-shaping ecosystem leadership

Chapter 8 Conclusion

8.1 Key Findings

This study established a five-phase procedure for model design, encompassing problem definition, initial development, model improvement, weight determination, and model evaluation, to develop and validate a digital maturity model for determining and improving the development level of digitalization of FSSC in Chinese state-owned enterprise.

In the problem definition phase, the study identified a clear gap in the existing literature on the digitalization of FSSCs in Chinese state-owned enterprises. Although financial digitalization is widely recognized as essential for enterprise transformation, few studies have examined the digitalization of FSSC as a distinct research domain or developed dedicated evaluation models tailored to its characteristics. As a result, many FSSCs in practice lack clear awareness of their current stage of digitalization and face challenges such as weak strategies, rigid structures, fragmented processes, and limited data capabilities in decision support. This gap leaves FSSCs without structured tools to determine the development level of their digitalization and support continuous improvement. Therefore, this study aims to develop a maturity model for the digitalization of FSSCs in Chinese state-owned enterprises, enabling systematic evaluation and practical guidance.

During the initial development phase, the study conceptualized the digitalization of FSSC by drawing on systems theory, specifically the IPO model, to ensure a holistic view of how inputs are transformed through processes into outputs within the enterprise environment. Guided by this framework, six KPAs were identified in the evaluation indicator system for digital maturity, including Strategy and Organization, Infrastructure, Process Management, Data Management, Digital Performance, and External Environment. These domains were derived from a combination of prior maturity models and aligned with the IPO model to ensure comprehensive coverage. Through an extensive review of the literature, a set of two-level indicators was identified to operationalize the KPAs and establish a more detailed foundation for the system. Furthermore, the model defined five digital maturity levels, including Initial, Repeatable, Defined, Managed, and Optimizing, representing an evolution from unstructured and rudimentary financial operations to fully integrated and data-driven services. Each level is characterized by specific key practices across the six KPAs, providing a roadmap for digital maturity development.

In the model improvement phase, the system was refined through multiple Delphi rounds with a panel of 50 experts drawn equally from academics and practitioners. Through iterative feedback, the panel refined the previously identified KPAs and two-level indicators by

deleting, modifying, and adding specific items, and ultimately introduced an additional level of indicators. This process achieved consensus on a final four-layer evaluation indicator system for digital maturity of FSSC in Chinese state-owned enterprise comprising six KPAs, 19 first-level indicators, 47 second-level indicators, and 131 third-level indicators. The final indicator set comprehensively covers strategic planning and organizational management, physical and technological infrastructure, process standardization, integration, and digitalization, data value chain governance, performance outcomes, and responsiveness to external factors, providing a detailed evaluation framework of digital maturity factors from broad domains down to specific metrics.

In the weight determination phase, the study applied the AHP method, with 10 assessors providing judgments to calculate both local and global weights for KPAs and all levels of indicators, ensuring consistency and comparability across the system. The results indicated that Data Management emerged as the top-priority KPA, reflecting the centrality of managing the end-to-end data value chain in the digitalization. Process Management was typically the next highest weighted area, highlighting that process-related factors serve as pivotal drivers of digitalization. Strategy and Organization and Infrastructure had moderate weights, while Digital Performance and External Environment were assigned lower weights, suggesting that the assessment places greater emphasis on foundational enablers such as strategic alignment and infrastructure capability than on outcome measures and external environmental factors when determining digital maturity. These weighting results form an integral part of the system, thereby providing a quantitative foundation for the model.

Finally, in the model evaluation phase, the model was validated by applying it to five case studies of FSSCs from different Chinese state-owned enterprises. Using the FCE method, a total of 107 valid survey responses were collected, with around 20 from each FSSC, to evaluate their digital maturity in relation to the detailed indicators. These data, combined with the determined weights, yielded an overall digital maturity score and corresponding digital maturity level for each case. The five cases ranged from the Defined level to the Optimizing level. Moreover, the breakdown of scores by KPAs in each case highlights specific strengths and weaknesses, thereby indicating priority areas for improvement within FSSCs. More importantly, feedback from 95 participants indicated that the evaluation results aligned with their own perceptions of the digital maturity of their FSSC and that the model is applicable across diverse contexts within Chinese state-owned enterprises, verifying the reliability, validity, and practical applicability of the model. However, these results revealed a limitation in that with only five digital maturity levels, several FSSCs clustered in the same category despite clear score differences. Therefore, an eight-level framework was introduced by subdividing the three higher levels into basic and advanced sub-levels. This final refinement makes the model more effective for distinguishing different digital maturity levels, while also

clarifying the organizational learning process and the human and cultural factors that support maturity progression.

Taken together, these five phases ensure both the theoretical rigor and the practical relevance of the study. Ultimately, the developed and validated digital maturity model for FSSC in Chinese state-owned enterprise consists of two integral components: a complete evaluation indicator system for digital maturity, comprising six KPAs and a three-level hierarchy of indicators each assigned relative weights, and a refined maturity framework that defines eight distinct digital maturity levels.

8.2 Theoretical and Practical Contributions

From a theoretical perspective, this study makes several important contributions to the research on financial shared service, digitalization, and maturity model. First, the study brings research on financial shared service into the digital era by reframing FSSC not merely as a transactional finance unit but as a strategic, data-driven decision-support center for value creation. Building on the context of enterprise digital transformation, the study reinterprets the evolving role of FSSC and positions its digitalization as a core component of both financial and enterprise digitalization. As a result, it highlights a fundamental shift of FSSC from centralized transaction processing and operational efficiency toward value creation and strategic decision support, thereby extending the traditional scope of FSSC research.

Second, the study extends digitalization research into the specific context of FSSC by clarifying the definition and essence of digitalization of FSSC, addressing the fragmented and incomplete understanding of this process. It conceptualizes the digitalization of FSSC as the management of the entire data value chain through the integration of digital technologies with processes in FSSC. Furthermore, by applying the IPO model, the study explains how the digitalization of FSSC operates as an open system in which inputs are transformed through internal processes into outputs, while being continuously influenced by the external environment. This theoretical articulation establishes the digitalization of FSSC as a distinct research phenomenon that bridges the fields of FSSC, systems theory, and digital transformation. On this basis, the study lays a theoretical foundation for the further development and application of evaluation systems and transformation frameworks tailored to the digitalization of FSSC.

Third, the study contributes to the maturity model research by developing the first digital maturity model specifically designed to evaluate and guide the digitalization of FSSCs in Chinese state-owned enterprises. Unlike existing maturity models that focus on general enterprise or financial digitalization, this model integrates universal principles of digital

maturity with the unique organizational, operational, and institutional characteristics of FSSCs in Chinese state-owned enterprises, including hierarchical organization and policy requirements. Moreover, by introducing systems theory into the design of the maturity model, the framework explicitly incorporates internal structures, external environments, and the coordination and interaction among different KPAs, thereby capturing the dynamic and interdependent nature of digitalization. Therefore, the study responds to calls in the literature for more comprehensive and flexible maturity models and addresses the rigidity and linearity of earlier maturity models by offering a more holistic and adaptive theoretical framework.

Finally, the study makes a contribution by proposing and applying a complete five-phase procedure for model design, which guides the rigorous development and validation of the digital maturity model. Specifically, the study adopts an integrated mixed-methods approach by combining qualitative techniques, including literature analysis and Delphi consultation, with quantitative methods such as AHP and FCE within a coherent and iterative procedure. This integration strengthens both theoretical rigor and practical relevance, ensuring that the model is conceptually grounded while remaining applicable in real organizational contexts. Through this procedure, the study provides a structured and reliable methodological framework for the construction of maturity evaluation indicator systems, encompassing the identification and refinement of KPAs and indicators, the determination of relative weights, and the classification of maturity levels, as well as the selection of appropriate methods for model application. In this way, it offers a reusable methodological paradigm for systematically developing and validating maturity models as design science artifacts.

From a practical perspective, this study provides a clear, measurable, and actionable framework that enables FSSCs in Chinese state-owned enterprises to systematically evaluate, plan, and improve their digitalization. By offering a structured and maturity-based evaluation system, the study allows FSSCs to clearly identify their current stage of digitalization and define concrete pathways for continuous improvement, addressing long-standing challenges of fragmented and inconsistent implementation. On this basis, the digital maturity model developed in this study offers specific practical contributions to relevant stakeholders.

First, for FSSC managers, the model serves as both a diagnostic and a planning tool. By evaluating their operations against detailed indicators, managers can pinpoint specific strengths and weaknesses. For example, a FSSC may demonstrate strong IT infrastructure and highly automated processes while remaining weak in data governance and analytical capabilities. The digital maturity levels then provide a clear roadmap for improvement, allowing the FSSC to determine its current stage, identify the requirements for advancing to the next level, and benchmark itself against peers or industry standards. In this way, the

model transforms the abstract objective of digitalization into concrete stages and actionable steps, giving managers a common framework to guide and measure progress over time.

Second, for enterprise leaders, the model provides a strategic overview that aligns the initiatives of the FSSC with the broader digital strategy of the enterprise. By including Strategy and Organization as well as External Environment among the core areas, the model ensures that improvements within the FSSC contribute to enterprise-wide objectives and remain consistent with external requirements. Leaders can also use maturity assessment to guide resource allocation and managerial interventions. For instance, a FSSC with lower digital maturity may require additional investment or closer oversight, while a more advanced center can act as a benchmark and source of best practices for others.

Third, for policymakers and regulators, the model offers a standardized framework for assessing and guiding digital maturity across the state sector. Authorities could integrate the model into regulatory measures, such as requiring Chinese state-owned enterprises to report the digital maturity levels of their FSSCs or using the assessment results to identify organizations that need targeted support. By incorporating multiple key dimensions of successful digitalization such as strategic alignment, strong data governance, and continuous improvement, the model encourages a balanced approach to digitalization in regulatory assessments.

Beyond these contributions, the distinctiveness of the digital maturity model developed in this study lies in its explicit focus on FSSCs in Chinese state-owned enterprises. First, the applicability of the model is intentionally bounded by its design context, as it is designed specifically to address the fragmented understanding and implementation of digitalization in this setting. Accordingly, the model is not designed as a universally applicable assessment tool for digital maturity, but as a problem-driven artifact intended to support the digitalization efforts of FSSCs in a specific institutional environment.

Second, the distinctiveness is further embedded in the development process of the model. During the initial development, the evaluation indicator system and maturity framework are constructed to reflect the hybrid nature of FSSC and align with its IPO-based digitalization process, based on literature at the intersection of these fields. Subsequent refinement and weight determination rely on multiple rounds of Delphi consultation and AHP involving experts primarily from Chinese academia and industry. As a result, both the composition of KPAs and indicators and the resulting weighting scheme reflect the research insights and practical experience of experts who are deeply familiar with the realities of the digitalization of FSSCs in Chinese state-owned enterprises. Finally, the model is evaluated exclusively through its application to five FSSCs from different industries within Chinese state-owned

enterprises, reinforcing its reliability, validity, and practical applicability within this specific context.

Third, the distinctiveness is also evident in the substantive content and application of the model. Unlike generic enterprise-level digital maturity models used for broad organizational contexts and emphasizing overall capabilities, this model is grounded in the specific functional role, operational logic, and institutional environment of FSSCs in Chinese state-owned enterprises. More specifically, the model reflects the distinctive organizational characteristics, including multiple hierarchical structures and complex governance arrangements, as well as the adoption of digital technologies that are particularly relevant to the digitalization of FSSC such as cloud platforms, blockchain, and AI for data analysis and security. In terms of its strong emphasis on process management and data management, the model captures the centralized, process-intensive, and data-driven nature of FSSCs in the digital era, as well as their evolving positioning as enterprise-level big data centers that transform standardized processes and large volumes of internal and external data into essential support for both operational management and strategic decision-making. Finally, the model integrates alignment with external institutional requirements, reflecting significant government oversight and regulatory compliance that characterize the operating environment of Chinese state-owned enterprises.

Taken together, these features make the model particularly suitable for evaluating and guiding the digitalization of FSSCs in Chinese state-owned enterprises, while also implying limited direct generalizability to FSSCs in private enterprises, those operating in different national environments, shared service centers in non-financial domains, or organizational units that do not operate under the shared service model. Applying the model in other organizational or regional contexts requires substantive adaptation across its design assumptions, development process, and application to ensure contextual appropriateness. Therefore, this limited generalizability should not be viewed as a weakness, but as a deliberate design choice consistent with the DSR paradigm, which prioritizes practical relevance in a specific problem context over universal applicability.

Overall, this study makes both theoretical and practical contributions. Theoretically, it extends and complements existing maturity model frameworks within the broader context of digitalization research by redefining the digitalization of FSSC and developing a tailored digital maturity model. Practically, the digital maturity model derives its value from providing FSSCs in Chinese state-owned enterprises with a diagnostic and improvement tool closely aligned with their operational realities and transformation challenges. By offering clear targets and measurable criteria, the model enables FSSCs to advance their digitalization in a systematic and transparent manner. If widely adopted, it has the potential to foster more

data-driven, efficient, and integrated financial operations, ultimately enhancing overall performance and contributing to the broader digital transformation of enterprises and the state sector.

8.3 Limitations

Although the study established a five-phase procedure for model design to develop and validate the digital maturity model for FSSC in Chinese state-owned enterprise, each step also presents certain limitations. These limitations reflect the methodological choices made in the procedure, as well as the challenges inherent in exploring a new research area. The following discussion examines the key limitations at each step in turn.

First, in the initial development phase, both the construction of the evaluation indicator system and the classification of maturity levels relied heavily on prior literature, especially existing models such as the CMM for FSSC and digital maturity models for enterprise and finance. Given the lack of previous research directly targeting the digitalization of FSSC, this literature-based approach was necessary to examine an under-explored field. However, the KPAs, indicators, and maturity levels derived in this way may not represent the most precise configuration, as they reflect patterns and commonalities combined from earlier models rather than being grounded entirely in FSSC-specific empirical evidence. Even so, literature analysis remains an effective method for laying the foundation in such an under-researched field.

Second, in the model improvement and weight determination phases, the process relied heavily on expert judgment, which inevitably introduces subjectivity. The Delphi panel's collective opinions shaped the inclusion, definition, and refinement of KPAs and indicators, while the AHP process required assessors to assign relative importance through pairwise comparisons. Although multiple Delphi rounds and consistency tests were used to enhance objectivity, the final model architecture and weighting scheme still reflect the perspectives of the particular experts involved. Different expert panels might have emphasized other factors or assigned different weights, potentially resulting in variations in the structure and priorities of the model.

Third, in the model evaluation phase, several methodological and empirical limitations emerge. The FCE method depends mainly on self-assessments by FSSC personnel, which can be prone to bias or misinterpretation despite the safeguards of fuzzy scoring. Furthermore, the evaluation was cross-sectional, capturing only a single point in time. Longitudinal validation is needed to confirm whether the model effectively tracks progress and predicts improvements over time. More importantly, the empirical validation was also limited to five

case studies of FSSCs in Chinese state-owned enterprises. While these cases were diverse, such a small sample cannot represent the full range of FSSC contexts, so the findings should be regarded as indicative rather than definitive. Additionally, the original five-level maturity framework lacked sufficient granularity, as several FSSCs were placed in the same category. The introduction of an eight-level framework addressed this limitation by enabling finer differentiation, but this adjustment was implemented after the initial evaluation and has not yet been rigorously validated. The optimal number of digital maturity levels and the precise score thresholds between them may need further investigation.

Fourth, across all phases, the comprehensiveness of the model results in significant complexity. With 131 third-level indicators covering six KPAs, the evaluation is quite detailed but could be time-consuming to conduct. FSSCs with limited capacity may find it difficult to evaluate every indicator and apply the full framework. In addition, some redundancy among indicators may persist despite the streamlining achieved through the Delphi process. In practice, FSSC managers may choose to focus on what they consider the most relevant subset of indicators, which could lead to inconsistencies in model application. Moreover, the sheer volume of data points can make it challenging to interpret the results. For example, it may not be obvious how a low score on a particular sub-dimension affects the overall digital maturity without a clear analytical framework or tool.

Finally, across all phases, the direct applicability of the model beyond FSSCs in Chinese state-owned enterprises is inherently limited. As the model is developed and validated within a specific institutional and organizational context, its direct application to other settings may require contextual adaptation. This limitation defines the boundary conditions of the model rather than undermining its validity within its intended scope.

8.4 Recommendations for Future Research

Building on the limitations discussed in the previous section, future research should continue to refine, expand, and extend the digital maturity model for FSSC in Chinese state-owned enterprise. Guided by the five-phase procedure for model design, further work can strengthen methodological rigor, broaden application contexts, and deepen theoretical understanding to ensure the long-term reliability, validity, and practical applicability of the model.

First, future studies could strengthen and expand the methods used to develop, validate, and apply the digital maturity model. In the initial development, model improvement, weight determination, and model evaluation phases, the reliance on literature analysis, Delphi consultation, AHP, and FCE methods inevitably introduced imprecision, subjectivity, and

methodological constraints. To address this, future studies should refine and validate the model with larger and more diverse datasets and complementary methods, ensuring that it more accurately reflects the realities of the digitalization of FSSCs in Chinese state-owned enterprises. Specifically, Confirmatory Factor Analysis could be employed to verify whether the grouping of indicators in the evaluation indicator system accurately reflects theoretical dimensions, while Cluster Analysis could be used to identify natural patterns of digital maturity across FSSCs, thereby complementing the predefined maturity levels. A Fuzzy AHP approach could also be considered, incorporating uncertainty directly into the weighting process. In addition, alternative evaluation techniques such as the Technique for Order Preference by Similarity to Ideal Solution, Grey Relational Analysis, and Data Envelopment Analysis could be applied to test the robustness of results. Furthermore, longitudinal research would be highly valuable. By tracking the same FSSCs over time, researchers could assess whether improvements in digital maturity are reflected in the progression of KPAs and key practices at each level, thereby testing the predictive validity of the model. Finally, the development of a software platform or online tool to operationalize the model would further support both self-assessment and large-scale data collection, providing a richer empirical basis for refinement, validation, extension, and broader applicability.

Second, the scope of future studies can be expanded by adapting and extending the digital maturity model to different organizational and institutional contexts in order to examine its broader applicability. Future studies should critically reassess the model content, especially the External Environment KPA. In the current model, external alignment is mainly reflected in consistency with national policies and government directives. However, for FSSCs in private enterprises or in other national environments, external pressures are more likely to arise from market competition and industry standards. Accordingly, adapting the model requires revising relevant indicators, recalibrating their weights, and reclassifying maturity levels. Moreover, applying the model in different contexts should be supported by local expert involvement. As the original evaluation indicator system and maturity framework rely on expert input from Chinese academia and industry, future studies should engage domain experts familiar with the target context to ensure the continued relevance and validity of the framework. Beyond the financial domain, future studies could also explore the applicability of the model's underlying principles to other types of shared service centers such as human resources or IT, where digitalization processes and performance objectives may differ. In addition, extending the framework to organizational units that do not operate under the shared service model requires rethinking core assumptions related to centralization, process standardization, and service orientation. In all such extensions, comparative studies across organizational forms, sectors, and national settings are particularly valuable for distinguishing universal dimensions of digital maturity from those that are context-specific.

Third, further theoretical exploration can deepen the understanding of the digital maturity of FSSC. Future studies could further explore the structure and mechanisms of the evaluation indicator system and maturity framework. Based on the structural representation of the evaluation indicator system for digital maturity proposed in Figure 4.1, future studies could move beyond conceptual presentation to empirically examine the relationships among the input, processing, output and environment components and their associated KPAs and multi-level indicators. While this study adopts the IPO model to illustrate the fundamental logic of the digitalization of FSSC in Chinese state-owned enterprise, it does not explicitly test the causal relationships suggested by this structure. Therefore, future studies could investigate how inputs such as strategy and organization and infrastructure influence internal processing capabilities in process and data management, and how these processing capabilities subsequently shape digital performance outcomes. Moreover, particular attention could be given to feedback mechanisms through which output performance feeds back to inform and reshape subsequent strategic inputs, thereby forming dynamic feedback loops within the digitalization system. Additionally, future studies could explore the relationships both within individual KPAs and across different KPAs, including how capabilities embedded in one component reinforce or constrain those in others. With regard to the external environment, further empirical work is required to clarify how external factors influence the internal digitalization system, as well as how different environmental KPAs interact with one another and have specific influences on internal KPAs. Structural equation modeling provides an appropriate analytical approach for examining these complex relationships, enabling the validation of the direction, strength, and significance of both direct and indirect effects. Through such analysis, future studies could establish an empirically grounded IPO structure of the digitalization of FSSC, thereby refining the configuration of KPAs and indicators in the evaluation indicator system.

Furthermore, drawing on the eight-level maturity framework proposed in Table 7.9, future studies could deepen the theoretical interpretation of the digital maturity of FSSC by incorporating insights from dynamic capability theory. In particular, this perspective could be used to explain how capabilities such as agility, innovation, and change management enable FSSCs to progress across digital maturity levels, and how dynamic capabilities are developed and reconfigured as digitalization advances. Such theoretical integration would complement the established level division by clarifying the underlying mechanisms through which digital maturity evolves over time. Moreover, the eight-level maturity framework introduced in this study requires further empirical testing to confirm that the distinctions between basic and advanced stages at higher levels are meaningful in practice. Taken together, deeper investigation of both the evaluation indicator system and the maturity framework would enhance the precision and explanatory power of the digital maturity model for FSSC.

In addition, future studies should more rigorously examine the relationship between organizational performance and digital maturity by collecting data on both financial and operational outcomes, thereby validating the underlying premise of the model. This line of inquiry could also be extended to explore how the digital maturity of FSSC interacts with, and contributes to, the overall digital maturity and performance of enterprise. With the development of digital technology, there may be a need to update the digital maturity model to integrate emerging factors such as blockchain, AI, or more advanced analytics. Finally, qualitative methods such as in-depth case studies and interviews could complement quantitative approaches by uncovering the real-world challenges, drivers, and best practices. Therefore, such insights would enrich the practical guidance offered by the model and enhance its value as a tool for managing digital transformation.

Overall, this study provides both a theoretical foundation and a practical pathway for understanding and advancing the digitalization of FSSC in Chinese state-owned enterprise. By integrating systems thinking, methodological rigor, and empirical validation, it contributes to bridging the gap between conceptual research and managerial application. While limitations remain, the developed digital maturity model lays a solid basis for ongoing refinement and adaptation. It is hoped that future researchers and practitioners will continue to extend and apply this framework, enabling FSSCs across different contexts to evolve toward higher levels of intelligence, integration, and strategic value in the digital era.

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Appendix 1

Expert Opinion Survey on Preliminary Three-layer Evaluation Indicator System for Digital Maturity of FSSC in Chinese State-owned Enterprise

Section 1 Investigation into Basic Information of Experts

This investigation is solely for analyzing the basic information of experts. Your personal information will be kept strictly confidential. Please fill in your personal details and select the appropriate options. If further explanation is required, please indicate it in the remarks section.

1. Your highest level of education:
 - A. Associate Degree
 - B. Bachelor's Degree
 - C. Master's Degree
 - D. Doctoral Degree

2. Your age:
 - A. 25 years old or younger
 - B. 26–35 years old
 - C. 36–45 years old
 - D. 46–55 years old
 - E. Over 55 years old

3. How long have you worked in this field:
 - A. 5 years or less
 - B. 6–10 years
 - C. 11–15 years
 - D. 16–20 years
 - E. More than 20 years

4. Your current or previous position in this field:
 - A. Top Manager
 - B. Middle Manager
 - C. Professor
 - D. Associate Professor

5. Your familiarity with evaluation content:

- A. Very Familiar
- B. Familiar
- C. Neither
- D. Unfamiliar
- E. Very Unfamiliar

6. Your basis for evaluation

6.1. Degree of dependence on theoretical analysis:

- A. Large
- B. Medium
- C. Small

6.2. Degree of dependence on practical experience:

- A. Large
- B. Medium
- C. Small

6.3. Degree of dependence on domestic and foreign counterparts:

- A. Large
- B. Medium
- C. Small

6.4. Degree of dependence on intuition:

- A. Large
- B. Medium
- C. Small

Section 2 Evaluation on Representativeness of KPAs

KPAs	Description
A1 Strategy and Organization	Strategic planning for digitalization of FSSC and organizational arrangements that enable its effective implementation
A2 Infrastructure	Foundational physical and technological infrastructure that supports digitalization of FSSC
A3 Process Management	Consolidation of dispersed financial processes across various departments and their standardization, integration, and digitalization within FSSC
A4 Data Management	Management of entire data value chain from data collection to decision-making
A5 Digital Performance	Achievement and progress attributable to digitalization of FSSC
A6 External Environment	Responsiveness of FSSC to external environmental changes

This study identified 6 preliminary KPAs. Please rate the representativeness of these KPAs.

Score	Very Unrepresentative 1	Unrepresentative 2	Neither 3	Representative 4	Very Representative 5
A1 Strategy and Organization					
A2 Infrastructure					
A3 Process Management					
A4 Data Management					
A5 Digital Performance					
A6 External Environment					

Section 3 Evaluation on Relevance of First-level Indicators

KPAs	First-level Indicators
A1 Strategy and Organization	B1 Strategy, B2 Culture, B3 Talent, B4 Structure
A2 Infrastructure	B5 Technology, B6 Network, B7 Capital
A3 Process Management	B8 Process Re-engineering, B9 Process Integration, B10 Information Systems
A4 Data Management	B11 Data Acquisition, B12 Data Analysis, B13 Data-driven Decision-making, B14 Data Security
A5 Digital Performance	B15 Effectiveness, B16 Efficiency
A6 External Environment	B17 Government, B18 Ecosystem, B19 COVID-19

This study identified 19 preliminary first-level indicators. Please rate the relevance of these indicators.

Score	Very Irrelevant 1	Irrelevant 2	Neither 3	Relevant 4	Very Relevant 5
A1 Strategy and Organization					
B1 Strategy					
B2 Culture					
B3 Talent					
B4 Structure					
In addition to the first-level indicators listed above, what additional first-level indicators do you think should be included under Strategy and Organization:					
A2 Infrastructure					
B5 Technology					
B6 Network					
B7 Capital					
In addition to the first-level indicators listed above, what additional first-level indicators do you think should be included under Infrastructure:					

Score	Very Irrelevant 1	Irrelevant 2	Neither 3	Relevant 4	Very Relevant 5
A3 Process Management					
B8 Process Re-engineering					
B9 Process Integration					
B10 Information Systems					
In addition to the first-level indicators listed above, what additional first-level indicators do you think should be included under Process Management:					
A4 Data Management					
B11 Data Acquisition					
B12 Data Analysis					
B13 Data-driven Decision-making					
B14 Data Security					
In addition to the first-level indicators listed above, what additional first-level indicators do you think should be included under Data Management:					
A5 Digital Performance					
B15 Effectiveness					
B16 Efficiency					
In addition to the first-level indicators listed above, what additional first-level indicators do you think should be included under Digital Performance:					
A6 External Environment					
B17 Government					
B18 Ecosystem					
B19 COVID-19					
In addition to the first-level indicators listed above, what additional first-level indicators do you think should be included under External Environment:					

Section 4 Evaluation on Rationality of Second-level Indicators

This study identified 44 preliminary second-level indicators. Please rate the rationality of these indicators.

A1 Strategy and Organization

Score	Very Irrational 1	Irrational 2	Neither 3	Rational 4	Very Rational 5
B1 Strategy					
C1 Digital Strategy Goal					
C2 Digital Strategy Planning					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Strategy:					
B2 Culture					
C3 Digital Thinking					
C4 Innovation and Change					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Culture:					
B3 Talent					
C5 Digital Talent					
C6 Talent Training					
C7 Talent Security					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Talent:					
B4 Structure					
C8 Digital Leadership					
C9 Organizational Restructuring					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Structure:					

A2 Infrastructure

Score	Very Irrational 1	Irrational 2	Neither 3	Rational 4	Very Rational 5
B5 Technology					
C10 Digital Technology Basis					
C11 Digital Infrastructure					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Technology:					
B6 Network					
C12 Internet Construction					
C13 Internal Network Construction					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Network:					
B7 Capital					
C14 Digital Capital Investment					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Capital:					

A3 Process Management

Score	Very Irrational 1	Irrational 2	Neither 3	Rational 4	Very Rational 5
B8 Process Re-engineering					
C15 Management and Monitoring					
C16 Continuous Optimization					
C17 Standardization					
C18 Automation and Intelligence					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Process Re-engineering:					
B9 Process Integration					
C19 Vertical Integration					
C20 Horizontal Integration					
C21 Management Integration					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Process Integration:					
B10 Information Systems					
C22 Process Support					
C23 System Integration					
C24 Safety and Security					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Information Systems:					

A4 Data Management

Score	Very Irrational 1	Irrational 2	Neither 3	Rational 4	Very Rational 5
B11 Data Acquisition					
C25 IoT Data Collection					
C26 Real-time Data Connection					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Data Acquisition:					
B12 Data Analysis					
C27 Heterogeneous Data Storage					
C28 Heterogeneous Data Processing					
C29 Cloud Platform Architecture					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Data Analysis:					
B13 Data-driven Decision-making					
C30 Big Data Center					
C31 Intelligent Decision Support System					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Data-driven Decision-making:					
B14 Data Security					
C32 Data Security Protection					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Data Security:					

A5 Digital Performance

Score	Very Irrational 1	Irrational 2	Neither 3	Rational 4	Very Rational 5
B15 Effectiveness					
C33 Financial Performance					
C34 Service Quality					
C35 Customer Satisfaction					
C36 Social and Environmental Benefits					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Effectiveness:					
B16 Efficiency					
C37 Operational Efficiency					
C38 Management and Decision Efficiency					
C39 Information Transfer Efficiency					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Efficiency:					

A6 External Environment

Score	Very Irrational 1	Irrational 2	Neither 3	Rational 4	Very Rational 5
B17 Government					
C40 Policy Support					
C41 Financial Support					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Government:					
B18 Ecosystem					
C42 Digital Ecosystem Construction					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under Ecosystem:					
B19 COVID-19					
C43 Epidemic Risk Management					
C44 Work Arrangement					
In addition to the second-level indicators listed above, what additional second-level indicators do you think should be included under COVID-19:					

Appendix 2

Semi-structured Interview Protocol for Developing Third-level Indicators of Digital Maturity of FSSC in Chinese State-owned Enterprise

The purpose of the interview is to obtain expert insights on how to subdivide the existing second-level indicators into third-level indicators, introduce new factors where necessary, and evaluate the appropriateness and applicability of the proposed indicators. The interview is divided into two sections: the first section consists of predefined questions to ensure consistency and comparability across interviews, while the second section involves open-ended discussions to allow experts to contribute additional perspectives and practical examples.

Section 1 Predefined Questions

1. Subdivision of Indicators

- How do you think the existing second-level indicators can be further subdivided into more concrete dimensions?
- For example, in the case of C33 Data Encryption, do you think it should be decomposed into separate third-level indicators such as Data Storage Encryption and Data Transmission Encryption? Why?

2. Introduction of New Factors

- Are there any new factors you believe should be introduced as third-level indicators under the current second-level indicators?
- Why do you think these factors are necessary for assessing the digital maturity of FSSC in Chinese state-owned enterprise?

3. Rationale for Subdivisions

- For the subdivisions you propose, what is the rationale behind these distinctions?
- How do they help better capture the progression of digital maturity of FSSC in Chinese state-owned enterprise?

4. Measurement Considerations

- For each suggested third-level indicator, how would you suggest it can be generally measured in practice?

- Could you provide examples of typical metrics or approaches used in your organization or research experience?

Section 2 Open-ended Questions

1. Based on your professional experience, are there any additional third-level indicators that should be included in the evaluation indicator system but are not yet covered by the predefined questions?

2. Do you find any of the proposed indicators redundant, overlapping, or impractical for use in Chinese state-owned enterprises' FSSCs?

3. What challenges do you foresee in applying these third-level indicators in practice?

4. Do you have any suggestions for improving the comprehensiveness, clarity, or applicability of the evaluation indicator system?

5. Is there anything else you would like to add regarding the design of the third-level indicators or the evaluation indicator system as a whole?

Appendix 3

Preliminary Third-level Indicators of Digital Maturity of FSSC in Chinese State-owned Enterprise

This appendix presents the preliminary set of 140 third-level indicators developed for evaluating the digital maturity of FSSC in Chinese state-owned enterprise. Generated during the indicator extension stage described in Section 5.2, these indicators represent a structured operationalization of the second-level indicators and are presented under each KPA.

A3.1 Third-level Indicators under Strategy and Organization

D1 Actual Situation Alignment: Setting digital strategies without reference to reality can lead to wasted resources and failed initiatives. This indicator captures how well FSSC's strategic objectives reflect its operational maturity, resources, leadership, and structure. It is measured through expert evaluations of the alignment between the strategy and the actual situation.

D2 Business Strategy Alignment: Digital initiatives only create value when aligned with the broader enterprise strategy. This indicator reflects the extent to which FSSC's digital strategy integrates with corporate goals. It is assessed by expert scoring of the alignment between digital and business strategies.

D3 Customer Value Maximization: The ultimate purpose of digitalization is to enhance value for customers, both internal and external. This indicator reflects whether the digital strategy addresses key customer needs such as customization, speed, and risk reduction. Measurement relies on expert judgment of how well digital initiatives contribute to maximizing customer value.

D4 Long Term Strategic Development: Short-term adjustments are insufficient for sustainable transformation, while long-term planning is essential. This indicator captures the comprehensiveness and scientific rigor of digitalization implementation plans. It is measured by expert assessments of the accuracy and sustainability of these plans.

D5 Transformation Model Selection: Choosing the right transformation path is a decisive step in digitalization. This indicator reflects whether FSSC adopts disruptive or incremental transformation models that match its goals. It is measured by expert scoring of the fit between chosen models and strategic objectives.

D6 Resource Allocation Plan: Effective digitalization depends on scientific allocation of

financial, technical, and human resources. This indicator represents the accuracy and comprehensiveness of FSSC's resource allocation plan. Experts assess its rationality and degree of alignment with digital priorities.

D7 Data-driven Culture Construction: A digital strategy cannot succeed without a supportive organizational culture. This indicator reflects how well FSSC fosters data-driven thinking through cultural exchanges and communication activities. It is measured by the frequency and quality of these initiatives, as assessed by experts.

D8 Risk Appetite: The willingness to accept and manage risks influences the pace and success of digitalization. This indicator represents the extent to which managers and staff embrace the risks brought by digital initiatives. It is measured through expert scoring of organizational attitudes toward digital risk-taking.

D9 R&D Investment: Long-term competitiveness requires strategic commitment to research and development, since resource input is the foundation of sustained innovation. This indicator reflects the extent of FSSC's commitment to technological innovation through research and development activities. It is measured by the proportion of R&D expenditure relative to FSSC's total income or cost.

D10 Innovative Idea Implementation: Ideas alone do not generate value unless they are effectively translated into practice. This indicator evaluates how well FSSC fosters an innovation-friendly culture by turning staff and managerial proposals into real improvements. It is measured by the proportion of implemented ideas relative to the total submitted.

D11 Patent Grant Rate: Innovation outcomes are most visible when they lead to intellectual property that is formally recognized. This indicator captures FSSC's ability to transform technological and product development into granted patents. It is measured by the proportion of successfully granted patents relative to the total number of patent applications within a given period.

D12 Digital Talent Ratio: A sufficient pool of digital specialists is necessary for transformation. This indicator represents the proportion of digital professionals within FSSC's workforce. It is measured as the ratio of digital talents to the total number of employees.

D13 Digital Application Proficiency: Beyond numbers, the expertise of digital talent determines success. This indicator reflects employees' ability to apply digital tools and maintain systems proficiently. It is measured as the proportion of staff capable of proficient

digital application relative to the total workforce.

D14 Adaptation and Adjustment: Digitalization inevitably brings changes in roles and responsibilities, requiring resilience and flexibility. This indicator reflects employees' ability to adapt to job adjustments caused by digitalization. It is measured by expert evaluations of adaptability across the workforce.

D15 Accounting Training: Re-engineered processes require enhanced financial literacy, particularly for non-financial staff. This indicator represents the frequency and effectiveness of accounting training provided in FSSC. It is measured through expert scoring of training outcomes.

D16 Business Training: Financial personnel also need business knowledge to integrate processes effectively. This indicator reflects the extent of business-related training aimed at developing cross-disciplinary expertise. It is measured by expert evaluations of training coverage and effectiveness.

D17 Digital Technology Training: Developing digital skills among staff ensures they can maintain systems and use new tools effectively. This indicator reflects training efforts in digital technology applications. It is measured by the frequency and quality of training sessions, as assessed by experts.

D18 Talent Appraisal System Establishment: Scientific appraisal ensures fair evaluation of traditional and digital skills. This indicator reflects the development of comprehensive appraisal systems, including tools like the balanced scorecard adapted to digital needs. Measurement relies on expert assessments of their completeness and scientific rigor.

D19 Promotion Channel Provision: Career development opportunities motivate employees and enhance retention. This indicator reflects whether exclusive promotion channels exist for FSSC staff. It is measured by expert judgment of the availability and clarity of such channels.

D20 Talent Incentive Mechanism Construction: An effective incentive mechanism sustains enthusiasm for digitalization. This indicator reflects the rationality of combining material rewards with non-material recognition. It is measured by expert evaluations of the scientific design and fairness of incentives.

D21 Job Rotation Implementation: Cross-functional knowledge is vital for enhancing collaboration between finance and business units, and job rotation provides an effective way to achieve this. This indicator captures the extent to which FSSC implements job rotation to

broaden employees' perspectives. It is measured by calculating the proportion of staff who have participated in rotation programs.

D22 Leadership Position: Formal recognition of digital leaders within FSSC ensures institutional support for digitalization. This indicator reflects the formal positioning of digital leadership roles within FSSC hierarchies. It is measured by expert scoring of leadership ranks and authority levels.

D23 Leadership Engagement: Active participation of digital leaders shapes organizational culture and accelerates digital initiatives. This indicator reflects the degree of FSSC leaders' involvement in digital projects. It is measured through expert evaluations of their engagement in implementation.

D24 Leadership Experience: Digital leaders with vision and expertise can address strategic challenges and drive transformation. This indicator reflects the extent to which FSSC leaders possess practical experience in applying digital technologies to management. It is assessed by expert evaluations of their ability to identify, analyze, and resolve digitalization challenges while shaping FSSC's digital vision.

D25 Role and Responsibility: Clear accountability prevents inefficiency and confusion. This indicator reflects whether staff involved in digitalization understand their responsibilities. It is measured through expert assessments of role clarity.

D26 Flat Organization: Flattened structures enhance communication and adaptability in digital contexts. This indicator represents the degree to which FSSC reduces management layers to increase agility. It is measured by the number of hierarchical levels retained.

D27 Decentralized Functional Structure: A well-defined organization structure should align with digital strategy requirements. This indicator reflects whether FSSC has established specialized divisions for finance, business, strategy, and IT. It is measured through expert judgment of the presence and clarity of such divisions.

A3.2 Third-level Indicators under Infrastructure

D28 IoT Application: IoT enhances financial process automation by connecting devices to real-time data streams. This indicator reflects the extent to which IoT has been applied and integrated into FSSC operations. It is measured through expert evaluations of usage rates and integration depth in processes.

D29 Big Data Application: Big data enables FSSC to manage massive amounts of structured and unstructured data for deeper analysis. This indicator captures how widely big data tools are applied across different processes. Measurement relies on expert scoring of application levels and integration outcomes.

D30 Cloud Computing Application: Cloud platforms provide flexibility, scalability, and cost efficiency in digital infrastructure. This indicator reflects the degree of cloud adoption and its integration into FSSC operations. It is measured by expert assessments of application levels and integration outcomes.

D31 Blockchain Application: Blockchain enhances transparency and data security in financial transactions. This indicator represents the extent to which blockchain solutions are embedded in FSSC processes. Measurement is based on expert judgment of usage rates and integration depth.

D32 AI Application: AI brings automation and intelligence to FSSC operations, reducing manual workload. This indicator reflects how extensively AI tools are applied within core processes. It is measured through expert scoring of application levels and integration outcomes.

D33 Equipment Digitalization: Digitalized equipment provides the physical foundation for transformation. This indicator captures the number of digital-ready devices such as computers and mobile systems in FSSC. It is measured as the proportion of digitalized equipment relative to total equipment.

D34 Internet Access: External connectivity enables FSSC to acquire information and resources from beyond the enterprise boundary. This indicator reflects the number of devices connected to the Internet. It is measured as the proportion of connected devices to the total number of FSSC devices.

D35 Internet Performance: Stable and efficient Internet performance is essential for reliable operations. This indicator reflects the performance level of external Internet connections. It is measured by technical indicators such as bandwidth, throughput, delay, and packet loss.

D36 Internal Network Access: Internal networks enhance coordination across departments and processes within FSSC. This indicator reflects the number of devices connected to enterprise systems and cloud platforms. It is measured as the proportion of internally connected devices to the total equipment base.

D37 Internal Network Performance: The effectiveness of internal communication depends on network stability. This indicator reflects the technical performance of internal networks. It is measured through bandwidth, throughput, delay, and packet loss.

D38 Software and Hardware Investment: Sufficient capital input into software and hardware is critical during digitalization. This indicator reflects spending on new technologies and equipment during the preparation stage. It is measured as the proportion of software and hardware expenditure relative to FSSC's total income or cost.

D39 System Upgrade and Maintenance Investment: System sustainability depends on continuous upgrading and maintenance. This indicator captures financial resources devoted to keeping systems current with operational needs. It is measured by the proportion of upgrade and maintenance costs to FSSC's total income or cost.

D40 Digital Talent Training Investment: Human capital investment ensures staff can effectively apply and maintain digital technologies. This indicator represents spending on digital talent training programs. It is measured as the proportion of training expenditure relative to FSSC's total income or cost.

D41 Organizational Restructuring Investment: Adapting organizational design ensures structural fit with digitalization goals. This indicator reflects expenditures on restructuring into flattened, specialized forms. It is measured by the proportion of restructuring costs to FSSC's total income or cost.

D42 Process Re-engineering Investment: Digitalization requires redesigning traditional financial workflows for efficiency and integration. This indicator represents spending on re-engineering processes to adapt to digital tools. It is measured as the proportion of re-engineering expenditure relative to FSSC's total income or cost.

A3.3 Third-level Indicators under Process Management

D43 Quality Assessment System: High-quality financial processes are essential for maintaining accuracy and compliance in a digitalized FSSC. This indicator refers to the establishment of a quality assessment system that continuously monitors and improves service delivery. It is measured by examining whether such a system exists and evaluating its completeness, validity, and rationality, as judged by experts.

D44 Efficiency Supervision System: Efficiency directly determines how much time FSSC staff can devote to higher-value activities beyond basic processing. This indicator captures

the construction of a supervision mechanism to monitor process efficiency and promote time savings. Measurement is based on the degree of completeness, validity, and rationality of the efficiency supervision system, evaluated by experts.

D45 Operation Management System: Effective operation management ensures that all financial and business processes are systematically coordinated under digital frameworks. This indicator reflects whether a comprehensive operation management system has been implemented across different types of processes. It is measured by expert evaluations of the system's completeness, validity, and rationality.

D46 Feedback Mechanism: Continuous improvement requires active feedback loops that identify and address hidden process issues. This indicator represents the presence of formal mechanisms encouraging staff to provide timely input for optimization. Measurement focuses on the degree of construction, functionality, and rationality of these mechanisms.

D47 Process–Operation Alignment: Digital processes create value only when they align with the actual requirements of both financial and business activities. This indicator evaluates the extent to which optimized processes accurately reflect and adapt to real operational needs. Measurement is based on expert assessments of the degree of alignment between optimized processes and actual business needs.

D48 Procurement and A/P Standardization: Procurement and accounts payable are prone to errors without standardized workflows, making standardization critical for reliability. This indicator represents the degree to which these processes follow uniform procedures. It is measured as the proportion of procurement and accounts payable volume executed through standardized methods.

D49 Sales and A/R Standardization: Standardization of sales and accounts receivable processes is vital for ensuring accuracy in revenue recognition and customer transactions. This indicator reflects the extent of uniformity in handling sales and receivables. Measurement is based on the proportion of sales and accounts receivable volume executed through standardized workflows.

D50 Expense Reimbursement Standardization: Expense reimbursement is highly frequent and prone to irregularities, so standardization enhances both efficiency and control. This indicator captures how much of the reimbursement process is executed using uniform procedures. It is measured by calculating the proportion of standardized reimbursement transactions.

D51 General Ledger and Reporting Standardization: General ledger and reporting form the backbone of financial transparency, requiring rigorous standardization. This indicator reflects the extent of uniform procedures in ledger and reporting processes. It is measured by the proportion of standardized ledger and reporting volume to total volume.

D52 Procurement and A/P Automation: Automation reduces manual workload and accelerates procurement and payables. This indicator reflects the extent to which these processes are connected to information systems using technologies such as RPA. Measurement is based on the proportion of transactions executed automatically compared to total volume.

D53 Sales and A/R Automation: Automated receivables handling improves cash flow management and reduces operational risks. This indicator evaluates the level of digital integration in sales and receivables processes. It is measured by the proportion of automated transactions compared to total volume.

D54 Expense Reimbursement Automation: Automation streamlines reimbursement and minimizes delays and human errors. This indicator captures the extent of system-based execution of reimbursement processes. It is measured as the proportion of automated reimbursements compared to total volume.

D55 General Ledger and Reporting Automation: Automating general ledger and reporting processes ensures timeliness and reliability of financial disclosures. This indicator reflects the digital integration of these core processes. Measurement is based on the proportion of automated executions within total ledger and reporting volume.

D56 Financial Process Coordination: Isolated financial processes limit efficiency, while coordination creates synergies across tasks. This indicator represents the degree of integration among the four major financial processes in FSSC. It is measured by expert assessments of their interconnection and mutual support.

D57 Financial–Business Process Alignment: Seamless alignment between financial and business processes enables real-time reflection of business operations in financial records. This indicator evaluates how well financial activities synchronize with business events. Experts score the degree of alignment based on observed integration in practice.

D58 Business Operation Support: FSSC’s value increases when financial processes actively provide insights for business decision-making. This indicator reflects the ability of financial processes to offer operational support such as forecasting, cost analysis, and on-site advice.

Measurement is based on the extent of decision-support services delivered in practice, as assessed by experts.

D59 Centralized Fund Management: Centralizing fund management enhances liquidity and return on funds. This indicator represents the maturity of fund control mechanisms within FSSC. It is measured by expert evaluations of the degree of centralization and standardization.

D60 Comprehensive Budget Management: Robust budget systems ensure effective planning and monitoring across departments. This indicator reflects the development and integration of comprehensive budget management practices. Measurement focuses on the degree of comprehensiveness, standardization, and control achieved, as assessed by experts.

D61 Integrated Tax Management: Tax management is critical for compliance and cost optimization in large enterprises. This indicator evaluates the degree of integration and standardization of tax-related processes within FSSC, and their alignment with enterprise needs, measured by expert assessments.

D62 Unified Risk Management: Unified risk control enhances enterprise resilience against strategic, operational, technological, and financial uncertainties. This indicator evaluates the extent to which standardized risk assessment and mitigation measures are established, as measured by expert scoring of their unification and standardization.

D63 Connection Stability: Reliable digitalization requires stable connections between financial processes and information systems. This indicator reflects whether such connections function without disruption. Measurement is based on expert assessments of connection stability and observed performance.

D64 User-friendly Operation: A system's usability influences adoption and efficiency among staff. This indicator evaluates whether financial shared systems provide intuitive and accessible interfaces. Measurement is drawn from user experience feedback and operator evaluations.

D65 Successful Process Execution: The ultimate goal of digitalization is reliable execution of processes within systems supported by stable system connections and user-friendly operations. This indicator measures the proportion of processes that can be successfully executed through financial shared systems relative to the total number of processes in FSSC.

D66 Process Risk Control: Effective digitalization requires comprehensive risk management

across all stages. This indicator reflects the extent to which financial shared systems implement preventive, concurrent, and post-event controls for processes executed within them. It is measured by expert evaluations of the systems' ability to provide full coverage of risk control throughout the process lifecycle.

D67 Problematic Document Ratio: Reliable process support also depends on minimizing errors in document handling. This indicator captures the frequency of issues such as erroneous entries, transmission losses, missing approvals, misclassification, and improper storage. It is measured by the proportion of problematic documents relative to the total number of documents processed within a given period.

D68 FSSC System Integration: Integration across internal subsystems ensures consistency and efficiency. This indicator reflects the extent of vertical integration within financial shared systems. It is measured by the proportion of subsystems included in the unified platform relative to the enterprise's total.

D69 FSSC–Business System Integration: Cross-departmental integration is key for aligning finance with enterprise operations. This indicator evaluates the connection between FSSC systems and ERP or other business platforms. Measurement is based on the degree of compatibility and number of established interfaces, as evaluated by experts.

D70 System Update Cycle: Timely system updates are essential to maintain version consistency across subsystems and ensure stable connections during transitions between old and new systems. This indicator reflects the update frequency and cycle of financial shared systems and their subsystems within FSSC. It is measured by expert evaluations of whether system updates are carried out regularly and effectively to support integration.

D71 Access Control: Protecting sensitive data requires strict access monitoring. This indicator reflects the strength of access control measures in FSSC systems. It is measured by the frequency of monitoring and detection of unauthorized access attempts.

D72 Firewall Installation and Update: Timely firewall protection guards systems against evolving threats such as constantly changing computer viruses. This indicator evaluates the presence and frequency of firewall updates. Measurement also considers their effectiveness in preventing intrusions.

D73 Vulnerability Scan and Report: Proactive vulnerability detection is essential for system security. This indicator captures the regularity and accuracy of system scans and error reports. It is measured by how often and how effectively vulnerabilities are reported.

D74 Fault Restoration: Rapid restoration of system functionality minimizes operational disruptions. This indicator reflects the ability to fix detected vulnerabilities in time. It is measured by the proportion of vulnerabilities successfully resolved relative to total reports.

D75 System Maintenance: Regular system maintenance sustains long-term reliability and protection against threats. This indicator evaluates the frequency and effectiveness of maintenance routines. Measurement is based on documented maintenance activities and expert evaluations of their impact.

A3.4 Third-level Indicators under Data Management

D76 RFID Asset Identification Integrity: Accurate identification of assets across the supply chain is critical for ensuring transparency and efficiency in digital finance. This indicator refers to embedding RFID tags in assets and using readers to capture data automatically into databases. It is measured by the proportion of assets tagged with RFID relative to the total number of assets.

D77 RFID Data Entry Accuracy: Reliable financial records depend on the precision of asset data captured by RFID technology. This indicator reflects whether information is correctly entered into databases without error. Measurement is based on the proportion of accurately recorded assets compared to all RFID-tagged items.

D78 Supply Chain Connection: Seamless integration with procurement, production, and sales platforms allows FSSC to obtain real-time business data. This indicator reflects the stability and efficiency of system connections across the supply chain. It is measured through the stability and quality of data transmission between FSSC and supply chain platforms.

D79 Business Travel Platform Connection: Business travel transactions are a major source of financial data, and their integration enhances efficiency and compliance. This indicator evaluates whether FSSC systems connect with travel platforms to collect order and invoice data in real time. Measurement focuses on the stability and quality of such data transmission.

D80 Tax Sharing Center Connection: Tax compliance requires direct integration with government tax systems. This indicator reflects the ability of FSSC to connect financial shared systems with tax sharing centers and external authorities. Measurement is based on the stability and quality of data transmission between the two systems.

D81 Data Storage Capacity: Digitalization requires handling massive and diverse datasets. This indicator reflects the ability of FSSC's data warehouse and data lake to store structured

and unstructured data from multiple sources. It is measured by the proportion of used to total storage capacity.

D82 Data Storage Performance: Storing data is insufficient without efficient retrieval and updating. This indicator captures the reading and writing speeds of storage systems, which must meet operational needs. Measurement is based on technical performance metrics of the data warehouse and data lake.

D83 Data Processing Timeliness: Real-time processing supports more responsive analysis in FSSC. This indicator refers to the speed with which raw data is cleansed, aggregated, and converted into useful information. It is measured by evaluating whether processing is completed within the specified time frame.

D84 Data Processing Quality: Analysis accuracy depends on the completeness and reliability of processed data. This indicator assesses how precisely FSSC cleanses and converts raw data into actionable information. Measurement is based on the accuracy and completeness of processed data.

D85 Cloud Platform Architecture: Migrating financial shared systems to a financial cloud provides flexibility and scalability. This indicator captures whether FSSC systems are deployed on a cloud platform. It is measured by the proportion of systems deployed on the financial cloud relative to the total number of systems.

D86 Computing Speed: High computing capacity enables rapid financial simulations and analytics. This indicator reflects the speed of computation within the financial cloud. Measurement is based on actual data calculation speed compared against benchmark standards.

D87 Data Mining Breadth and Depth: Data mining must cover both a wide range of dimensions and an in-depth analysis of essential variables. This indicator captures how comprehensively FSSC applies mining techniques across different scenarios. It is measured by expert evaluations of coverage and analytical depth.

D88 Model Establishment and Prediction: Predictive modeling enhances financial planning and decision-making accuracy. This indicator refers to the ability to establish and update analytical models within FSSC's cloud environment. It is measured by expert evaluations of the interpretability, acceptance, and accuracy of predictions compared with actual results.

D89 Usage Frequency: The value of visualization lies in its adoption by decision-makers. This indicator represents how frequently data visualization tools are used in daily operations. It is measured by the proportion of active users or visits relative to the total user base.

D90 Clarity and Conciseness: Effective visualization requires clear presentation of information without unnecessary complexity. This indicator captures the design quality of charts and tables. It is measured through expert evaluations of clarity and conciseness of visual elements.

D91 Adaptability: Visualization systems must adapt to changing business needs and different technical environments. This indicator reflects the flexibility of visualization outputs across different scenarios and devices. Measurement focuses on the degree of adaptability to both business demands and platforms, as judged by experts.

D92 Decision-making Timeliness: Timely decision support is critical to ensure that managers receive actionable insights when they are most needed. This indicator evaluates the speed at which the decision-making support system generates recommendations in response to business requirements. It is measured by expert evaluations of whether the system delivers decisions within the required timeframe.

D93 Decision-making Compliance: Decision support must operate within legal and regulatory frameworks to maintain organizational legitimacy. This indicator assesses whether the outputs of the decision-making support system conform to established laws, standards, and industry norms. Measurement is based on compliance reviews against regulatory requirements.

D94 Decision-making Effectiveness: The core purpose of the decision-making support system is to guide front-end business operations effectively. This indicator reflects how well the system contributes to forecasting and operational improvements. It is measured by comparing expected and actual business performance outcomes to verify whether the decisions achieve the intended results.

D95 Human–Computer Interaction: Collaboration between staff and intelligent systems increases efficiency in decision-making. This indicator refers to the frequency and quality of interaction between employees and RPA or AI tools. Measurement is based on logged interaction frequency in decision processes.

D96 Decision-making Intelligence: The decision-making support system is evolving toward autonomous intelligence using AI and advanced analytics. This indicator captures the

proportion of decisions made through intelligent processes compared to manual ones. Measurement relies on system records of intelligent versus traditional decision-making.

D97 Data Storage Encryption: Data security requires robust encryption mechanisms during storage. This indicator reflects the extent to which blockchain-based distributed ledger technologies are used to protect stored data. Measurement is based on the degree of utilization and the effectiveness of encryption practices.

D98 Data Transmission Encryption: Secure communication is critical when data moves across systems. This indicator evaluates the use of blockchain and other encryption tools to prevent breaches in transmission. Measurement is based on the degree of utilization and their effectiveness in preventing unauthorized access.

D99 Data Security System Establishment: Strong data security requires comprehensive institutional frameworks. This indicator reflects the establishment of FSSC's data security management systems, including policies, rules, and procedures. It is measured by expert assessments of whether such systems are in place, the degree of their completeness, and their effectiveness in practice.

D100 Data Backup and Recovery: Regular backup ensures resilience against data loss or system failures. This indicator reflects whether FSSC maintains adequate backup procedures and recovery capabilities. Measurement is based on backup frequency and recovery success rates.

D101 Audit and Report: Auditing guarantees compliance and reliability in financial reporting. This indicator reflects whether FSSC conducts regular audits and produces compliance reports. It is measured by audit frequency and the quality of reports relative to legal requirements.

A3.5 Third-level Indicators under Digital Performance

D102 Cost Benefit Ratio: Profitability is a fundamental measure of FSSC performance, as digitalization should ultimately generate financial returns. This indicator reflects the ratio of net profit to total cost, highlighting whether digitalization creates additional income streams such as outsourcing services. It is measured by calculating the proportion of net profit relative to total cost within a given period.

D103 Net Profit Growth Rate: Sustainable growth demonstrates the long-term viability of FSSC digitalization. This indicator measures the increase in net profit over time, reflecting

stability in revenue generation. It is calculated as the percentage change between ending and beginning values for the period.

D104 Current Ratio: Ensuring liquidity and solvency is critical for stable operations. This indicator assesses the ability of FSSC to meet short-term obligations by comparing current assets to current liabilities. Measurement is conducted by calculating this ratio in the current accounting period.

D105 Accounting Information Transparency: Transparent disclosure enhances trust among stakeholders and strengthens regulatory compliance. This indicator reflects the clarity and detail of financial reports produced by FSSC. It is measured using disclosure ratings such as evaluations from stock exchanges.

D106 Financial Report Integrity: Comprehensive reporting ensures stakeholders receive a complete picture of financial performance. This indicator represents the inclusion of all necessary accounting titles and significant transactions in reports. Measurement is based on whether reports meet integrity and completeness requirements.

D107 Financial Analysis Validity: Accurate analysis underpins decision-making and strategic planning. This indicator reflects whether financial analyses reliably describe current enterprise conditions. It is measured by comparing analysis results with actual situations, focusing on error rates.

D108 Service Agreement Fulfillment: Meeting contractual obligations is central to maintaining customer satisfaction. This indicator reflects FSSC's ability to deliver services as agreed in service contracts. It is measured by the proportion of fulfilled agreements relative to the total signed.

D109 Customer Complaint Handling: As business volume grows, errors and complaints are inevitable, making effective complaint handling critical to preserving customer confidence. This indicator captures FSSC's responsiveness in providing accessible channels, timely reactions, and remedial actions. It is measured by the proportion of complaints resolved relative to the total received.

D110 Customer Requirement Fulfillment: Beyond handling complaints, FSSC must proactively meet customer requirements. This indicator reflects the effectiveness of addressing client needs in routine operations. It is measured by the proportion of customer requirements that have been satisfactorily fulfilled.

D111 Customer Loyalty: Long-term customer relationships depend on consistent service quality and responsiveness. This indicator captures the degree of client retention, particularly whether customers choose to renew contracts with FSSC. It is measured by the proportion of returning customers compared to the overall customer base.

D112 Customer Development: Customer satisfaction also depends on the capacity to expand and diversify the client base, especially external customers. This indicator reflects FSSC's ability to cultivate new clients while maintaining existing relationships. It is measured by the proportion of new customers acquired relative to the total customer base.

D113 Market Share: Expanding market presence indicates the competitiveness of a digitalized FSSC. This indicator reflects the share of revenue from financial shared services compared to the total market. Measurement involves calculating FSSC's revenue share in the relevant service market.

D114 External Income Ratio: Diversification of income sources signals the maturity of outsourcing capabilities. This indicator represents the proportion of revenue derived from external service provision. It is measured by comparing outsourcing revenue to total shared service income.

D115 Payment Efficiency: Automation in procurement and payables should shorten payment cycles. This indicator reflects how efficiently accounts payable are managed. It is measured through turnover ratios, specifically procurement cost divided by average accounts payable.

D116 Collection Efficiency: Automation in sales and receivables should accelerate collection cycles. This indicator evaluates how efficiently accounts receivable are managed. It is measured by accounts receivable turnover, calculated as sales revenue divided by average receivables.

D117 Reimbursement Review Efficiency: Digital tools like electronic imaging systems accelerate expense reimbursements. This indicator reflects the speed and accuracy of reimbursement document reviews. It is measured by the ratio of reviewed bills to the total review time.

D118 Report Preparation Efficiency: Automated processes reduce delays in preparing consolidated financial reports. This indicator reflects how quickly FSSC can produce financial statements. Measurement involves the ratio of prepared reports to the total preparation time.

D119 Fund Management Efficiency: Properly managed funds improve asset utilization and enterprise profitability. This indicator reflects how efficiently FSSC supports business operations through fund management. It is measured by capital turnover, defined as sales revenue divided by average total assets.

D120 Budget Management Efficiency: Timely and accurate budgets ensure efficient planning and control. This indicator reflects the efficiency of preparing, implementing, and monitoring budgets. It is measured by expert evaluations of whether the time invested is proportionate to the scope and volume of budget management tasks completed.

D121 Tax Management Efficiency: Efficient tax planning reduces risks and ensures compliance. This indicator reflects how efficiently FSSC handles tax declarations and strategies. It is measured by expert evaluations of whether the time devoted to tax planning is proportionate to the scope and volume of tasks accomplished.

D122 Risk Management Efficiency: Efficient risk management reduces exposure to diverse risks and uncertainties. This indicator assesses the efficiency of identifying and mitigating risks. It is measured by expert evaluations of whether the time spent on risk management is proportionate to the scope and volume of tasks completed.

D123 Decision Execution Efficiency: The value of decision-making lies in timely execution. This indicator reflects both the speed of decision formulation within FSSC and the responsiveness of enterprise in implementing them. Measurement is based on expert evaluations of whether the time required for decision-making and execution is proportionate to the scope and volume of decisions carried out.

D124 FSSC Communication Efficiency: Flattened hierarchies improve information sharing among departments within FSSC. This indicator reflects how quickly and frequently internal communication occurs. It is measured by response times and the number of recorded exchanges.

D125 FSSC–Business Unit Communication Efficiency: Efficient communication between FSSC and business units ensures process alignment. This indicator reflects the responsiveness and frequency of cross-departmental interactions within the enterprise. It is measured by response times and the number of recorded exchanges.

D126 Data Summarization Efficiency: Efficient aggregation of financial and business data ensures timely analysis. This indicator reflects how quickly FSSC consolidates enterprise-wide data. Measurement is based on expert assessments of whether the time spent

on data summarization is proportionate to the scope and volume of data consolidated.

D127 Data Update Efficiency: Regular updates guarantee that business decisions rely on current information. This indicator reflects how often financial and business data are refreshed in FSSC systems. It is measured by the frequency of updates recorded against operational requirements.

A3.6 Third-level Indicators under External Environment

D128 Access to Policy Information: Government policy directly shapes the environment for FSSC digitalization, making timely access to information critical. This indicator reflects FSSC's ability to monitor announcements, interpret regulations, and maintain policy awareness. Measurement focuses on the speed and effectiveness of obtaining and understanding government policy updates.

D129 Government Funding Acquisition: Securing government funding supports stable digitalization and demonstrates the societal value of transformation. This indicator represents FSSC's capacity to obtain subsidies by showcasing compliance, transparency, and sustainable development potential. It is measured by the frequency of funding acquisition and the ability to prove feasibility to authorities.

D130 Market Demand Awareness: Adapting to changing customer preferences is essential for maintaining competitiveness. This indicator captures FSSC's ability to sense market trends through market research and social media monitoring. Measurement is based on the frequency of market research and expert evaluations of the depth of customer insight achieved.

D131 Competitor Monitoring: Keeping track of competitor behavior allows timely strategic adjustments. This indicator reflects how well FSSC observes market share shifts and competitive actions. It is measured by the frequency and depth of intelligence collection on competitors.

D132 Supply Chain Digital Resource Integration: Collaboration with supply chain partners strengthens the digital ecosystem and reduces silos. This indicator represents the degree of data, technology, and knowledge sharing between FSSC and its supply chain partners, including suppliers, producers, and sellers. Measurement is based on the extent of integration observed across partnerships.

D133 Digital Resource Complementarity with Competitors: Even competitors can jointly

advance digitalization through shared resources. This indicator reflects the ability of FSSC to complement digital strengths with competitors for mutual benefit. It is measured by the degree of complementarity achieved in integration of data, technology, and knowledge.

D134 Industry–University–Research Cooperation: External partnerships provide access to advanced knowledge and innovation. This indicator captures FSSC’s collaboration with universities, research institutions, and consulting firms. It is measured by the number and scale of projects and intellectual property outcomes generated.

D135 Shared Database Creation: Shared databases enable cross-enterprise cooperation within a digital ecosystem. This indicator reflects the establishment of common platforms where FSSCs in the digital ecosystem exchange standardized data. Measurement is based on the degree of construction, presence of coordinating bodies, and consistency of financial standards.

D136 Budget Emergency Management: Unexpected disasters demand resilient budget management. This indicator assesses whether FSSC has established complete systems for budgetary emergencies. It is measured by the scientific rigor and comprehensiveness of these emergency frameworks.

D137 Capital Risk Early Warning: Capital risks must be promptly identified when disasters occur to prevent them from escalating into major crises. This indicator reflects the establishment of early-warning systems for capital risks during emergencies. It is measured by the scientific soundness and completeness of such systems.

D138 Material Control: Controlling resources during disasters helps limit costs and operational disruption. This indicator captures FSSC’s ability to manage materials and expenses rationally under emergency conditions. Measurement focuses on the rationality and effectiveness of material control.

D139 Emergency Support Team Establishment: Dedicated response teams reduce risks during crises. This indicator reflects whether FSSC has organized and trained financial emergency support teams to address sudden events. It is measured by the degree of establishment and the effectiveness of such teams in risk reduction.

D140 Remote Work Implementation: Digital resilience requires continuity of operations even outside traditional offices. This indicator reflects the implementation of remote working systems enabling staff to perform tasks online. Measurement is based on the proportion of staff working remotely, and their satisfaction with these arrangements.

Appendix 4
Expert Opinion Survey on Preliminary Third-level Indicators of Digital Maturity of FSSC in Chinese State-owned Enterprise

Section 1 Investigation into Basic Information of Experts

This investigation is solely for analyzing the basic information of experts. Your personal information will be kept strictly confidential. Please fill in your personal details and select the appropriate options. If further explanation is required, please indicate it in the remarks section.

1. Your familiarity with evaluation content:
 - A. Very Familiar
 - B. Familiar
 - C. Neither
 - D. Unfamiliar
 - E. Very Unfamiliar

2. Your basis for evaluation
 - 2.1. Degree of dependence on theoretical analysis:
 - A. Large
 - B. Medium
 - C. Small

 - 2.2. Degree of dependence on practical experience:
 - A. Large
 - B. Medium
 - C. Small

 - 2.3. Degree of dependence on domestic and foreign counterparts:
 - A. Large
 - B. Medium
 - C. Small

 - 2.4. Degree of dependence on intuition:
 - A. Large
 - B. Medium
 - C. Small

Section 2 Evaluation on Rationality of Third-level Indicators under A1

This study identified 27 preliminary third-level indicators under Strategy and Organization. Please rate the rationality of these third-level indicators (Only Section 2 is provided in full as a representative example).

B1 Strategy

Score	Very Irrational 1	Irrational 2	Neither 3	Rational 4	Very Rational 5
C1 Digital Strategy Goal					
D1 Actual Situation Alignment					
D2 Business Strategy Alignment					
D3 Customer Value Maximization					
In addition to the third-level indicators listed above, what additional third-level indicators do you think should be included under Digital Strategy Goal:					
C2 Digital Strategy Planning					
D4 Long Term Strategic Development					
D5 Transformation Model Selection					
D6 Resource Allocation Plan					
In addition to the third-level indicators listed above, what additional third-level indicators do you think should be included under Digital Strategy Planning:					

B2 Culture

Score	Very Irrational 1	Irrational 2	Neither 3	Rational 4	Very Rational 5
C3 Digital Thinking					
D7 Data-driven Culture Construction					
In addition to the third-level indicators listed above, what additional third-level indicators do you think should be included under Digital Thinking:					

Score	Very Irrational 1	Irrational 2	Neither 3	Rational 4	Very Rational 5
C4 Innovation and Change					
D8 Risk Appetite					
D9 R&D Investment					
D10 Innovative Idea Implementation					
D11 Patent Grant Rate					
In addition to the third-level indicators listed above, what additional third-level indicators do you think should be included under Innovation and Change:					

B3 Talent

Score	Very Irrational 1	Irrational 2	Neither 3	Rational 4	Very Rational 5
C5 Digital Talent					
D12 Digital Talent Ratio					
D13 Digital Application Proficiency					
D14 Adaptation and Adjustment					
In addition to the third-level indicators listed above, what additional third-level indicators do you think should be included under Digital Talent:					
C6 Talent Training					
D15 Accounting Training					
D16 Business Training					
D17 Digital Technology Training					
In addition to the third-level indicators listed above, what additional third-level indicators do you think should be included under Talent Training:					
C7 Talent Security					
D18 Talent Appraisal System Establishment					
D19 Promotion Channel Provision					
D20 Talent Incentive Mechanism Construction					
D21 Job Rotation Implementation					

In addition to the third-level indicators listed above, what additional third-level indicators do you think should be included under Talent Security:

B4 Structure

Score	Very Irrational 1	Irrational 2	Neither 3	Rational 4	Very Rational 5
C8 Digital Leadership					
D22 Leadership Position					
D23 Leadership Engagement					
D24 Leadership Experience					
In addition to the third-level indicators listed above, what additional third-level indicators do you think should be included under Digital Leadership:					
C9 Organizational Restructuring					
D25 Role and Responsibility					
D26 Flat Organization					
D27 Decentralized Functional Structure					
In addition to the third-level indicators listed above, what additional third-level indicators do you think should be included under Organizational Restructuring:					

Section 3 Evaluation on Rationality of Third-level Indicators under A2

Structure and rating method identical to Section 2, including 15 preliminary third-level indicators (D28–D42) under the KPA Infrastructure (see Section A3.2 for details).

Section 4 Evaluation on Rationality of Third-level Indicators under A3

Structure and rating method identical to Section 2, including 33 preliminary third-level indicators (D43–D75) under the KPA Process Management (see Section A3.3 for details).

Section 5 Evaluation on Rationality of Third-level Indicators under A4

Structure and rating method identical to Section 2, including 26 preliminary third-level indicators (D76–D101) under the KPA Data Management (see Section A3.4 for details).

Section 6 Evaluation on Rationality of Third-level Indicators under A5

Structure and rating method identical to Section 2, including 26 preliminary third-level indicators (D102–D127) under the KPA Digital Performance (see Section A3.5 for details).

Section 7 Evaluation on Rationality of Third-level Indicators under A6

Structure and rating method identical to Section 2, including 13 preliminary third-level indicators (D128–D140) under the KPA External Environment (see Section A3.6 for details).

Appendix 5
Questionnaire on Indicator Weight of Digital Maturity of FSSC
in Chinese State-owned Enterprise

Section 1 Evaluation Indicator System and Scoring Instructions

1. Scoring Object

The evaluation indicator system used in this questionnaire is based on the Final Four-layer Evaluation Indicator System for Digital Maturity of FSSC in Chinese State-owned Enterprise (see Table 5.16 in Chapter 5). The full list of indicators is therefore not reproduced here to avoid duplication.

2. Scoring Criteria

A pairwise comparison of KPAs and indicators at each hierarchical level is conducted to assess their relative importance, using Saaty's 1–9 scale to determine the significance and relative weight of each element, as defined below.

Score	Definition	Explanation
1	Equal Importance	Both elements are equally important.
3	Moderate Importance	One element is slightly more important than the other.
5	Strong Importance	One element is strongly more important than the other.
7	Very Strong Importance	One element is significantly more important than the other.
9	Extreme Importance	One element is absolutely more important than the other.
2, 4, 6, 8	Intermediate Values	Used for comparisons that fall between two adjacent judgments.
Reciprocals 1/X (1/3, 1/5, etc.)	Reverse Comparison	If element A_i is X times more important than element A_j , then element A_j is 1/X times as important as element A_i .

Section 2 Scoring at Each Level

Please rate the listed KPAs and indicators at each hierarchical level according to their perceived importance based on your professional knowledge and experience. The results of this survey will serve as the primary basis for determining the relative weights of the KPAs and indicators.

1. Scoring Relative Importance of KPAs to Goal Level

Digital Maturity	A1 Strategy and Organization	A2 Infrastructure	A3 Process Management	A4 Data Management	A5 Digital Performance	A6 External Environment
A1 Strategy and Organization	1					
A2 Infrastructure		1				
A3 Process Management			1			
A4 Data Management				1		
A5 Digital Performance					1	
A6 External Environment						1

2. Scoring Relative Importance of First-level Indicators to KPAs

A1 Strategy and Organization	B1 Strategy	B2 Culture	B3 Talent	B4 Structure
B1 Strategy	1			
B2 Culture		1		
B3 Talent			1	
B4 Structure				1

A2 Infrastructure	B5 Technology	B6 Network	B7 Capital
B5 Technology	1		
B6 Network		1	
B7 Capital			1

A3 Process Management	B8 Process Re-engineering	B9 Process Integration	B10 Information Systems
B8 Process Re-engineering	1		
B9 Process Integration		1	
B10 Information Systems			1

A4 Data Management	B11 Data Acquisition	B12 Data Application	B13 Data-driven Decision-making	B14 Data Security
B11 Data Acquisition	1			
B12 Data Application		1		
B13 Data-driven Decision-making			1	
B14 Data Security				1

A5 Digital Performance	B15 Effectiveness	B16 Efficiency
B15 Effectiveness	1	
B16 Efficiency		1

A6 External Environment	B17 Government	B18 Ecosystem	B19 External Disaster
B17 Government	1		
B18 Ecosystem		1	
B19 External Disaster			1

3. Scoring Relative Importance of Second-level Indicators to First-level Indicators

B1 Strategy	C1 Digital Strategy Goal	C2 Digital Strategy Planning
C1 Digital Strategy Goal	1	
C2 Digital Strategy Planning		1

B2 Culture	C3 Digital Thinking	C4 Innovation and Change
C3 Digital Thinking	1	
C4 Innovation and Change		1

B3 Talent	C5 Digital Talent	C6 Talent Training	C7 Talent Security
C5 Digital Talent	1		
C6 Talent Training		1	
C7 Talent Security			1

B4 Structure	C8 Digital Leadership	C9 Organizational Restructuring
C8 Digital Leadership	1	
C9 Organizational Restructuring		1

B5 Technology	C10 Digital Technology Basis	C11 Digital Infrastructure
C10 Digital Technology Basis	1	
C11 Digital Infrastructure		1

B6 Network	C12 Internet Construction	C13 Internal Network Construction
C12 Internet Construction	1	
C13 Internal Network Construction		1

B8 Process Re-engineering	C15 System Establishment	C16 Continuous Optimization	C17 Standardization	C18 Automation and Digitalization
C15 System Establishment	1			
C16 Continuous Optimization		1		
C17 Standardization			1	
C18 Automation and Digitalization				1

B9 Process Integration	C19 Vertical Integration	C20 Horizontal Integration	C21 Management Integration
C19 Vertical Integration	1		
C20 Horizontal Integration		1	
C21 Management Integration			1

B10 Information Systems	C22 Process Support	C23 System Integration	C24 Safety and Security
C22 Process Support	1		
C23 System Integration		1	
C24 Safety and Security			1

B11 Data Acquisition	C25 IoT Data Collection	C26 Real-time Data Connection
C25 IoT Data Collection	1	
C26 Real-time Data Connection		1

B12 Data Application	C27 Heterogeneous Data Storage	C28 Heterogeneous Data Processing	C29 Data Analysis on Financial Cloud	C30 Data Visualization
C27 Heterogeneous Data Storage	1			
C28 Heterogeneous Data Processing		1		
C29 Data Analysis on Financial Cloud			1	
C30 Data Visualization				1

B13 Data-driven Decision-making	C31 Decision-making Support System	C32 Intelligent Decision Support System
C31 Decision-making Support System	1	
C32 Intelligent Decision Support System		1

B14 Data Security	C33 Data Encryption	C34 Data Assurance
C33 Data Encryption	1	
C34 Data Assurance		1

B15 Effectiveness	C35 Financial Performance	C36 Service Quality	C37 Customer Satisfaction	C38 External Service Performance
C35 Financial Performance	1			
C36 Service Quality		1		
C37 Customer Satisfaction			1	
C38 External Service Performance				1

B16 Efficiency	C39 Operational Efficiency	C40 Management and Decision Efficiency	C41 Information Transfer Efficiency
C39 Operational Efficiency	1		
C40 Management and Decision Efficiency		1	
C41 Information Transfer Efficiency			1

B17 Government	C42 Policy Support	C43 Financial Support
C42 Policy Support	1	
C43 Financial Support		1

B18 Ecosystem	C44 Market Adaptation	C45 Digital Ecosystem Construction
C44 Market Adaptation	1	
C45 Digital Ecosystem Construction		1

B19 External Disaster	C46 Disaster Risk Management	C47 Work Arrangement
C46 Disaster Risk Management	1	
C47 Work Arrangement		1

4. Scoring Relative Importance of Third-level Indicators to Second-level Indicators

C1 Digital Strategy Goal	D1 Actual Situation Alignment	D2 Business Strategy Alignment	D3 Customer Value Maximization
D1 Actual Situation Alignment	1		
D2 Business Strategy Alignment		1	
D3 Customer Value Maximization			1

C2 Digital Strategy Planning	D4 Long Term Strategic Development	D5 Transformation Model Selection	D6 Resource Allocation Plan
D4 Long Term Strategic Development	1		
D5 Transformation Model Selection		1	
D6 Resource Allocation Plan			1

C4 Innovation and Change	D8 Risk Appetite	D9 Innovative Idea Implementation
D8 Risk Appetite	1	
D9 Innovative Idea Implementation		1

C5 Digital Talent	D10 Digital Talent Ratio	D11 Digital Application Proficiency	D12 Adaptation and Adjustment
D10 Digital Talent Ratio	1		
D11 Digital Application Proficiency		1	
D12 Adaptation and Adjustment			1

C6 Talent Training	D13 Accounting Training	D14 Business Training	D15 Digital Technology Training
D13 Accounting Training	1		
D14 Business Training		1	
D15 Digital Technology Training			1

C7 Talent Security	D16 Talent Appraisal System Establishment	D17 Promotion Channel Provision	D18 Talent Incentive Mechanism Construction	D19 Job Rotation Implementation
D16 Talent Appraisal System Establishment	1			
D17 Promotion Channel Provision		1		
D18 Talent Incentive Mechanism Construction			1	
D19 Job Rotation Implementation				1

C8 Digital Leadership	D20 Leadership Position	D21 Leadership Engagement
D20 Leadership Position	1	
D21 Leadership Engagement		1

C9 Organizational Restructuring	D22 Role and Responsibility	D23 Flat Organization	D24 Decentralized Functional Structure
D22 Role and Responsibility	1		
D23 Flat Organization		1	
D24 Decentralized Functional Structure			1

C10 Digital Technology Basis	D25 IoT Application	D26 Big Data Application	D27 Cloud Computing Application	D28 Blockchain Application	D29 AI Application
D25 IoT Application	1				
D26 Big Data Application		1			
D27 Cloud Computing Application			1		
D28 Blockchain Application				1	
D29 AI Application					1

C12 Internet Construction	D31 Internet Access	D32 Internet Performance
D31 Internet Access	1	
D32 Internet Performance		1

C13 Internal Network Construction	D33 Internal Network Access	D34 Internal Network Performance
D33 Internal Network Access	1	
D34 Internal Network Performance		1

C14 Digital Capital Investment	D35 Software and Hardware Investment	D36 System Upgrade and Maintenance Investment	D37 Digital Talent Training Investment	D38 Organizational Restructuring Investment	D39 Process Re-engineering Investment
D35 Software and Hardware Investment	1				
D36 System Upgrade and Maintenance Investment		1			
D37 Digital Talent Training Investment			1		
D38 Organizational Restructuring Investment				1	
D39 Process Re-engineering Investment					1

C15 System Establishment	D40 Quality Assessment System	D41 Efficiency Supervision System	D42 Operation Management System
D40 Quality Assessment System	1		
D41 Efficiency Supervision System		1	
D42 Operation Management System			1

C16 Continuous Optimization	D43 Feedback Mechanism	D44 Process–Operation Alignment
D43 Feedback Mechanism	1	
D44 Process–Operation Alignment		1

C17 Standardization	D45 Procurement and A/P Standardization	D46 Sales and A/R Standardization	D47 Expense Reimbursement Standardization	D48 General Ledger and Reporting Standardization
D45 Procurement and A/P Standardization	1			
D46 Sales and A/R Standardization		1		
D47 Expense Reimbursement Standardization			1	
D48 General Ledger and Reporting Standardization				1

C18 Automation and Digitalization	D49 Procurement and A/P Automation	D50 Sales and A/R Automation	D51 Expense Reimbursement Automation	D52 General Ledger and Reporting Automation
D49 Procurement and A/P Automation	1			
D50 Sales and A/R Automation		1		
D51 Expense Reimbursement Automation			1	
D52 General Ledger and Reporting Automation				1

C20 Horizontal Integration	D54 Financial–Business Process Alignment	D55 Business Operation Support
D54 Financial–Business Process Alignment	1	
D55 Business Operation Support		1

C21 Management Integration	D56 Centralized Fund Management	D57 Comprehensive Budget Management	D58 Integrated Tax Management	D59 Unified Risk Management
D56 Centralized Fund Management	1			
D57 Comprehensive Budget Management		1		

D58 Integrated Tax Management			1	
D59 Unified Risk Management				1

C22 Process Support	D60 Connection Stability	D61 User-friendly Operation	D62 Successful Process Execution
D60 Connection Stability	1		
D61 User-friendly Operation		1	
D62 Successful Process Execution			1

C23 System Integration	D63 FSSC System Integration	D64 FSSC–Business System Integration
D63 FSSC System Integration	1	
D64 FSSC–Business System Integration		1

C24 Safety and Security	D65 Access Control	D66 Firewall Installation and Update	D67 Vulnerability Scan and Report	D68 Fault Restoration	D69 System Maintenance
D65 Access Control	1				
D66 Firewall Installation and Update		1			
D67 Vulnerability Scan and Report			1		
D68 Fault Restoration				1	
D69 System Maintenance					1

C25 IoT Data Collection	D70 RFID Asset Identification Integrity	D71 RFID Data Entry Accuracy
D70 RFID Asset Identification Integrity	1	
D71 RFID Data Entry Accuracy		1

C26 Real-time Data Connection	D72 Supply Chain Connection	D73 Business Travel Platform Connection	D74 Tax Sharing Center Connection
D72 Supply Chain Connection	1		
D73 Business Travel Platform Connection		1	
D74 Tax Sharing Center Connection			1

C27 Heterogeneous Data Storage	D75 Data Storage Capacity	D76 Data Storage Performance
D75 Data Storage Capacity	1	
D76 Data Storage Performance		1

C28 Heterogeneous Data Processing	D77 Data Processing Timeliness	D78 Data Processing Quality
D77 Data Processing Timeliness	1	
D78 Data Processing Quality		1

C29 Data Analysis on Financial Cloud	D79 Cloud Platform Architecture	D80 Computing Speed	D81 Data Mining Breadth and Depth	D82 Model Establishment and Prediction
D79 Cloud Platform Architecture	1			
D80 Computing Speed		1		
D81 Data Mining Breadth and Depth			1	
D82 Model Establishment and Prediction				1

C30 Data Visualization	D83 Usage Frequency	D84 Clarity and Conciseness	D85 Adaptability
D83 Usage Frequency	1		
D84 Clarity and Conciseness		1	
D85 Adaptability			1

C31 Decision-making Support System	D86 Decision-making Compliance	D87 Decision-making Effectiveness
D86 Decision-making Compliance	1	
D87 Decision-making Effectiveness		1

C32 Intelligent Decision Support System	D88 Human–Computer Interaction	D89 Decision-making Intelligence
D88 Human–Computer Interaction	1	
D89 Decision-making Intelligence		1

C33 Data Encryption	D90 Data Storage Encryption	D91 Data Transmission Encryption
D90 Data Storage Encryption	1	
D91 Data Transmission Encryption		1

C34 Data Assurance	D92 Data Backup and Recovery	D93 Audit and Report
D92 Data Backup and Recovery	1	
D93 Audit and Report		1

C35 Financial Performance	D94 Cost Benefit Ratio	D95 Net Profit Growth Rate	D96 Current Ratio
D94 Cost Benefit Ratio	1		
D95 Net Profit Growth Rate		1	
D96 Current Ratio			1

C36 Service Quality	D97 Accounting Information Transparency	D98 Financial Report Integrity	D99 Financial Analysis Validity
D97 Accounting Information Transparency	1		
D98 Financial Report Integrity		1	
D99 Financial Analysis Validity			1

C37 Customer Satisfaction	D100 Service Agreement Fulfillment	D101 Customer Requirement Fulfillment	D102 Customer Loyalty
D100 Service Agreement Fulfillment	1		
D101 Customer Requirement Fulfillment		1	
D102 Customer Loyalty			1

C38 External Service Performance	D103 Market Share	D104 External Income Ratio
D103 Market Share	1	
D104 External Income Ratio		1

C39 Operational Efficiency	D105 Payment Efficiency	D106 Collection Efficiency	D107 Reimbursement Review Efficiency	D108 Report Preparation Efficiency
D105 Payment Efficiency	1			
D106 Collection Efficiency		1		
D107 Reimbursement Review Efficiency			1	
D108 Report Preparation Efficiency				1

C40 Management and Decision Efficiency	D109 Fund Management Efficiency	D110 Budget Management Efficiency	D111 Tax Management Efficiency	D112 Risk Management Efficiency	D113 Decision Execution Efficiency
D109 Fund Management Efficiency	1				
D110 Budget Management Efficiency		1			
D111 Tax Management Efficiency			1		
D112 Risk Management Efficiency				1	
D113 Decision Execution Efficiency					1

C41 Information Transfer Efficiency	D114 FSSC Communication Efficiency	D115 FSSC–Business Unit Communication Efficiency	D116 Data Summarization Efficiency	D117 Data Update Efficiency
D114 FSSC Communication Efficiency	1			
D115 FSSC–Business Unit Communication Efficiency		1		
D116 Data Summarization Efficiency			1	
D117 Data Update Efficiency				1

C44 Market Adaptation	D120 Market Demand Awareness	D121 External Customer Development	D122 Competitor Monitoring
D120 Market Demand Awareness	1		
D121 External Customer Development		1	
D122 Competitor Monitoring			1

C45 Digital Ecosystem Construction	D123 Supply Chain Digital Resource Integration	D124 Digital Resource Complementarity with Competitors	D125 Industry–University–Research Cooperation	D126 Shared Database Creation
D123 Supply Chain Digital Resource Integration	1			
D124 Digital Resource Complementarity with Competitors		1		
D125 Industry–University–Research Cooperation			1	
D126 Shared Database Creation				1

C46 Disaster Risk Management	D127 Budget Emergency Management	D128 Capital Risk Early Warning	D129 Material Control
D127 Budget Emergency Management	1		
D128 Capital Risk Early Warning		1	
D129 Material Control			1

C47 Work Arrangement	D130 Emergency Support Team Establishment	D131 Remote Work Implementation
D130 Emergency Support Team Establishment	1	
D131 Remote Work Implementation		1

Appendix 6

Questionnaire on Digital Maturity of FSSCs in Chinese State-owned Enterprises

Dear Enterprise Leader,

Greetings!

This questionnaire aims to investigate the level of digital maturity in your enterprise's FSSC. It consists of two sections: Section 1 collects basic information about the respondent, and Section 2 evaluates the indicators for assessing digital maturity.

Please complete the questionnaire based on your understanding of the digitalization of FSSC in your enterprise, as well as your daily work experience and practical observations. The survey is anonymous, and all collected information will be used solely for academic research and kept strictly confidential.

I sincerely appreciate your valuable time and your kind support for my research.

Section 1 Basic Information of Respondent

1. Your highest level of education:

- A. Associate Degree
- B. Bachelor's Degree
- C. Master's Degree
- D. Doctoral Degree

2. Your age:

- A. 25 years old or younger
- B. 26–35 years old
- C. 36–45 years old
- D. 46–55 years old
- E. Over 55 years old

3. Your current position:

- A. Top Manager
- B. Middle Manager
- C. Staff

4. Your department:
 - A. Financial Shared Service Center (FSSC)
 - B. Traditional Finance Department

5. Are you directly involved in the digitalization of the FSSC?
 - A. Yes
 - B. No

6. Which areas or functions are you responsible for in the digitalization projects?

Section 2 Evaluation Indicator System

This Section aims to evaluate the digital maturity of FSSC in your enterprise using the Fuzzy Comprehensive Evaluation (FCE) method. In this evaluation indicator system, each indicator is assigned a score on a five-point scale (1–5) corresponding to the five digital maturity levels defined in the developed model:

Score	Level	Description
1	Initial	Basic awareness; no formal digital practices
2	Repeatable	Partial digitalization; limited standardization
3	Defined	Established standards and digital procedures
4	Managed	Integrated digital systems and coordinated management
5	Optimizing	Continuous improvement and intelligent digital operations

A higher score indicates a higher level of digital maturity. Please tick (✓) the option that best reflects the actual situation of your FSSC in each indicator table provided.

Evaluation Indicator System				Score				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
A1 Strategy and Organization	B1 Strategy	C1 Digital Strategy Goal	D1 Actual Situation Alignment					
			D2 Business Strategy Alignment					
			D3 Customer Value Maximization					
		C2 Digital Strategy Planning	D4 Long Term Strategic Development					
			D5 Transformation Model Selection					
			D6 Resource Allocation Plan					
	B2 Culture	C3 Digital Thinking	D7 Data-driven Culture Construction					
			D8 Risk Appetite					
		C4 Innovation and Change	D9 Innovative Idea Implementation					
	B3 Talent	C5 Digital Talent	D10 Digital Talent Ratio					
			D11 Digital Application Proficiency					
			D12 Adaptation and Adjustment					
		C6 Talent Training	D13 Accounting Training					
			D14 Business Training					
			D15 Digital Technology Training					
		C7 Talent Security	D16 Talent Appraisal System Establishment					
			D17 Promotion Channel Provision					
			D18 Talent Incentive Mechanism Construction					
	B4 Structure	C8 Digital Leadership	D19 Job Rotation Implementation					
			D20 Leadership Position					
		C9 Organizational Restructuring	D21 Leadership Engagement					
			D22 Role and Responsibility					
			D23 Flat Organization					
			D24 Decentralized Functional Structure					

Evaluation Indicator System				Score				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
A2 Infrastructure	B5 Technology	C10 Digital Technology Basis	D25 IoT Application					
			D26 Big Data Application					
			D27 Cloud Computing Application					
			D28 Blockchain Application					
			D29 AI Application					
		C11 Digital Infrastructure	D30 Equipment Digitalization					
	B6 Network	C12 Internet Construction	D31 Internet Access					
			D32 Internet Performance					
		C13 Internal Network Construction	D33 Internal Network Access					
			D34 Internal Network Performance					
	B7 Capital	C14 Digital Capital Investment	D35 Software and Hardware Investment					
			D36 System Upgrade and Maintenance Investment					
			D37 Digital Talent Training Investment					
			D38 Organizational Restructuring Investment					
D39 Process Re-engineering Investment								
A3 Process Management	B8 Process Re-engineering	C15 System Establishment	D40 Quality Assessment System					
			D41 Efficiency Supervision System					
			D42 Operation Management System					
		C16 Continuous Optimization	D43 Feedback Mechanism					
			D44 Process–Operation Alignment					
		C17 Standardization	D45 Procurement and A/P Standardization					
	D46 Sales and A/R Standardization							
	D47 Expense Reimbursement Standardization							
			D48 General Ledger and Reporting Standardization					

Evaluation Indicator System				Score					
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5	
		C18 Automation and Digitalization	D49 Procurement and A/P Automation						
			D50 Sales and A/R Automation						
			D51 Expense Reimbursement Automation						
			D52 General Ledger and Reporting Automation						
	B9 Process Integration	C19 Vertical Integration	C20 Horizontal Integration	D53 Financial Process Coordination					
				D54 Financial–Business Process Alignment					
		C21 Management Integration	D55 Business Operation Support						
			D56 Centralized Fund Management						
			D57 Comprehensive Budget Management						
		B10 Information Systems	C22 Process Support	C23 System Integration	D58 Integrated Tax Management				
	D59 Unified Risk Management								
	D60 Connection Stability								
	C24 Safety and Security			D61 User-friendly Operation					
				D62 Successful Process Execution					
				D63 FSSC System Integration					
				D64 FSSC–Business System Integration					
				D65 Access Control					
				D66 Firewall Installation and Update					
	A4 Data Management	B11 Data Acquisition	C25 IoT Data Collection	D67 Vulnerability Scan and Report					
				D68 Fault Restoration					
			D69 System Maintenance						
		C26 Real-time Data Connection	D70 RFID Asset Identification Integrity						
			D71 RFID Data Entry Accuracy						
			D72 Supply Chain Connection						

Evaluation Indicator System				Score				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
A5 Digital Performance			D73 Business Travel Platform Connection					
			D74 Tax Sharing Center Connection					
	B12 Data Application	C27 Heterogeneous Data Storage	D75 Data Storage Capacity					
			D76 Data Storage Performance					
		C28 Heterogeneous Data Processing	D77 Data Processing Timeliness					
			D78 Data Processing Quality					
		C29 Data Analysis on Financial Cloud	D79 Cloud Platform Architecture					
			D80 Computing Speed					
			D81 Data Mining Breadth and Depth					
			D82 Model Establishment and Prediction					
		C30 Data Visualization	D83 Usage Frequency					
			D84 Clarity and Conciseness					
	D85 Adaptability							
	B13 Data-driven Decision-making	C31 Decision-making Support System	D86 Decision-making Compliance					
			D87 Decision-making Effectiveness					
		C32 Intelligent Decision Support System	D88 Human-Computer Interaction					
			D89 Decision-making Intelligence					
	B14 Data Security	C33 Data Encryption	D90 Data Storage Encryption					
			D91 Data Transmission Encryption					
		C34 Data Assurance	D92 Data Backup and Recovery					
D93 Audit and Report								
B15 Effectiveness	C35 Financial Performance	D94 Cost Benefit Ratio						
		D95 Net Profit Growth Rate						
		D96 Current Ratio						

Evaluation Indicator System				Score				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
		C36 Service Quality	D97 Accounting Information Transparency					
			D98 Financial Report Integrity					
			D99 Financial Analysis Validity					
		C37 Customer Satisfaction	D100 Service Agreement Fulfillment					
			D101 Customer Requirement Fulfillment					
			D102 Customer Loyalty					
		C38 External Service Performance	D103 Market Share					
			D104 External Income Ratio					
		B16 Efficiency	C39 Operational Efficiency	D105 Payment Efficiency				
	D106 Collection Efficiency							
	D107 Reimbursement Review Efficiency							
	D108 Report Preparation Efficiency							
	C40 Management and Decision Efficiency		D109 Fund Management Efficiency					
			D110 Budget Management Efficiency					
			D111 Tax Management Efficiency					
			D112 Risk Management Efficiency					
	C41 Information Transfer Efficiency		D113 Decision Execution Efficiency					
D114 FSSC Communication Efficiency								
D115 FSSC–Business Unit Communication Efficiency								
D116 Data Summarization Efficiency								
A6 External Environment	B17 Government	C42 Policy Support	D117 Data Update Efficiency					
		C43 Financial Support	D118 Access to Policy Information					
	B18 Ecosystem	C44 Market Adaptation	D119 Government Funding Acquisition					
			D120 Market Demand Awareness					

Evaluation Indicator System				Score				
KPAs	First-level Indicators	Second-level Indicators	Third-level Indicators	1	2	3	4	5
			D121 External Customer Development					
			D122 Competitor Monitoring					
		C45 Digital Ecosystem Construction	D123 Supply Chain Digital Resource Integration					
			D124 Digital Resource Complementarity with Competitors					
			D125 Industry–University–Research Cooperation					
			D126 Shared Database Creation					
	B19 External Disaster	C46 Disaster Risk Management	D127 Budget Emergency Management					
			D128 Capital Risk Early Warning					
			D129 Material Control					
		C47 Work Arrangement	D130 Emergency Support Team Establishment					
			D131 Remote Work Implementation					