PIONEER
ACADEMIC PUBLISHING LIMITED

Journal of Progress in Engineering and Physical Science
ISSN 2709-4006
www.pioneerpublisher.com/jpeps
Volume 4 Number 5 October 2025

The Construction and Empirical Study of a Brand Marketing Information Technology Maturity Model for Small and Medium-Sized Enterprises

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doi:10.56397/JPEPS.2025.10.08

Abstract

Small and medium-sized enterprises (SMEs) face the dilemma of "vague stage positioning and low transformation efficiency" in brand marketing information technology (IT). 45% of these enterprises suffer from resource misallocation due to the lack of a unified evaluation standard. This paper, with the resource constraints of SMEs as the core premise, integrates the CMMI grading logic and the DTMF dimension framework to construct a four-stage maturity model ("Basic - Growth - Optimization - Excellence") that includes six first-level indicators (such as "data collection and integration") and 18 second-level indicators. Through stratified surveys of 192 SMEs across six major regions in China from September 2023 to March 2024 (40.1% in fast-moving consumer goods, 30.2% in catering, and 29.7% in retail), the model's scientific validity was verified through reliability and validity tests (overall Cronbach's $\alpha = 0.89$, KMO = 0.82). The empirical results show that the average maturity score of enterprises is 48.6 points (Growth stage), with "intelligent decision-making application" (2.1 points) and "resource coordination ability" (2.3 points) being the core weaknesses. Enterprises in the fast-moving consumer goods sector, those with a size of 50-100 employees, and those in the East China region have relatively higher maturity scores. This study provides SMEs with a "self-assessment - improvement" tool and offers empirical references for governments to formulate differentiated transformation subsidy policies.

Keywords: small and medium-sized enterprises (SMEs), brand marketing information technology, maturity model, four-stage classification, indicator system, empirical study, digital transformation, Delphi method, stratified sampling, industry differences, transformation path

1. Introduction

1.1 Policy and Industry Background

The digital transformation of SMEs has become a core driver for global economic recovery. In China, the "14th Five-Year Action Plan for the Digital Transformation of SMEs" clearly proposes to promote the transformation of SMEs from "having basic digital capabilities" to "achieving high-quality digital operations" by 2025. Local policies, such as the digital transformation subsidy details for SMEs in

Shanghai, further specify that "clarifying the transformation stage" is a prerequisite for obtaining subsidies. However, there is a significant gap in the field of brand marketing information technology: 72% of SMEs list it as a key area for transformation, with an average annual investment of 128,000 yuan in 2023, yet only 32% can accurately quantify the return on investment (ROI). Data from the China Association of SMEs show that the marketing ROI of enterprises without a clear transformation stage is only 1:2.1, far lower than that of enterprises with a clear positioning at 1:3.5. More critically, 85% of SMEs have an annual marketing information technology budget of less than 200,000 yuan, and 70% lack a dedicated IT team (Brown, S., & Davis, L., 2024). Existing evaluation tools designed for large enterprises are completely unfeasible to implement, leading enterprises into the dilemma of "blind investment with no results."

1.2 Literature Review

Existing maturity models set the threshold as "exclusive to large enterprises," with million-level IT investments directly excluding SMEs. In the marketing process, only "data collection frequency" is retained as a facade, while the entire chain of decision-making, placement, and iteration is left unattended. Moreover, the samples are uniformly selected from the same industry or region, which makes them unsuitable for other areas. What's worse, the topic of brand information technology revolves around "tools," with everyone competing to see who has more dazzling AI copywriting, yet no one reminds enterprises to set the pace before joining the game. As a result, data silos have not been dismantled, and high-priced tools have already been implemented first, with 30% of the budget becoming sunk costs.

1.3 Research Definition

SMEs are defined according to the "Regulations on the Classification Standards for SMEs" as "consumer goods, catering, and retail enterprises with less than 100 employees or annual revenue of less than 20 million yuan." These enterprises have the most urgent brand marketing needs and the most limited resources. Brand marketing information technology focuses on the entire marketing process of "data collection - decision-making - placement - monitoring," excluding non-marketing links such as production and supply chain, which aligns with the core needs of enterprises. The research objectives are to construct a brand marketing information technology maturity model suitable for SMEs, verify the model's effectiveness through empirical studies, and propose phased transformation suggestions. The research methods include literature research to lay the theoretical foundation, the Delphi method to determine the weights of indicators, questionnaire surveys to collect data, and statistical analysis to test reliability and validity, ensuring that the results are both theoretically rigorous and practically feasible.

2. Maturity Model Construction

2.1 Basis for Model Construction

2.1.1 Theoretical Basis

The model is based on the "graded improvement" logic of the Capability Maturity Model Integration (CMMI) and the "dimensional decomposition" approach of the Digital Transformation Maturity Framework (DTMF), with adjustments to fit the constraints of SMEs. The "progressive capability layering" of CMMI provides a paradigm for stage division, which is simplified in this study to "Basic - Growth - Optimization - Excellence" stages, in line with the transformation law of enterprises from initial attempts to full maturity. The "multi-dimensional evaluation" concept of DTMF guides the design of indicators but excludes high-investment indicators such as "enterprise-level data centers" and "full-chain custom development" — these indicators require million-level investments, far exceeding the average annual marketing information technology budget of less than 200,000 yuan for SMEs. Instead, practical indicators such as "low-cost tool adaptability" and "lightweight data integration capability" are added to ensure the implementation of the theory and match the resources of enterprises.

2.1.2 Design Principles

The model follows the logic of "scientificity - practicality - adaptability". Scientificity is reflected in the high consistency between indicators and the entire brand marketing process, with weights determined through the Delphi method to avoid subjective assignment. Practicality focuses on operability, with all second-level indicators being quantifiable, such as "multi-platform data coverage rate = number of connected platforms / number of commonly used platforms," allowing enterprises to self-assess without professional capabilities. Adaptability targets the pain points of SMEs, avoiding technical barriers such as "code development" and "data modeling," and incorporating "cost control" into the indicators in combination with budget constraints to guide rational investment.

2.2 Four-Stage Maturity Division

The four-stage division is centered on the progressive capabilities of enterprises, with characteristics, tools, and scores all fitting actual operational scenarios. The Basic stage (1-30 points) is the starting period of transformation, with data scattered across a single platform, decisions made based on experience, no dedicated personnel or fixed monitoring processes, and typical tools being WeChat Index and free public opinion tools, covering only basic data collection needs. The Growth stage (31-60 points) achieves data integration across 2-3 platforms, with some decisions relying on data, supported by 1-2 part-time staff conducting monthly monitoring, relying on lightweight data integration tools and advanced Excel functions. The Optimization stage (61-85 points) realizes real-time synchronization of data across all platforms, with core decisions aided by AI, full-time staff conducting weekly iterations, and the application of AI decision-making systems and data visualization tools. The Excellence stage (86-100 points) integrates marketing with CRM/ERP systems, achieving full-process automation, with professional teams responsible for real-time iterations and industry benchmarking, using full-chain automation systems and data platforms.

Table 1.

Level	Typical Tools
Basic Level (1-30 points)	WeChat Index, Free Sentiment Analysis Tools
Growth Level (31-60 points)	Lightweight Data Integration Tools, Advanced Excel Functions
Optimization Level (61-85 points)	AI Decision-making Systems, Data Visualization Tools
Excellence Level (86-100 points)	Full-Chain Automation Systems, Data Platform

2.3 Indicator System and Weights

2.3.1 Indicator System (Six First-Level Indicators and 18 Second-Level Indicators)

The indicator system is based on the logic of "basic capability - core application - support and guarantee", covering six first-level indicators and 18 second-level indicators. "Data collection and integration" (20%) is the foundation, with sub-indicators such as "multi-platform data coverage rate," "data timeliness," and "data standardization degree," addressing issues of data sources, timeliness, and usability. "Intelligent decision-making application" (20%) is the core, including "AI tool usage rate," "decision data support rate," and "decision iteration efficiency," which directly affect marketing effectiveness. "Resource coordination ability" (15%) and "effect monitoring and iteration" (15%) are process guarantees, with the former measuring internal and external resource linkage and the latter ensuring traceable and optimizable marketing. "Organizational support" (15%) and "cost control" (15%) are long-term supports, with the former focusing on personnel and training and the latter guiding rational investment.

2.3.2 Weight Determination (Delphi Method)

The weights were determined through three rounds of the Delphi method, with a panel of experts consisting of two university professors, two industry association experts, and one CEO, balancing theory and practice. The first round of consultation adjusted the indicator structure, the second round scored to calculate weights and coefficient of variation, and the third round coordinated differences. Ultimately, all indicators had a coefficient of variation <0.1, indicating good consistency of opinions. "Data collection and integration" and "intelligent decision-making application" had the highest weights (both 20%), forming the "dual pillars" of enterprise digital capabilities, while the remaining four indicators each accounted for 15%, creating a balanced structure of "basic - core - support" to comprehensively evaluate the overall capabilities of enterprises.

3. Empirical Analysis

3.1 Survey Design and Sample

The survey was designed based on the maturity indicator system constructed in Chapter 2 to ensure the representativeness and effectiveness of the data. The survey questionnaire was divided into three parts: the enterprise information section collected background data such as industry, size, and region, laying the foundation for subsequent difference analysis; the core scoring section used a Likert 5-point scale (1 = completely disagree to 5 = completely agree) to score the actual performance of the 18 second-level indicators, directly supporting the calculation of maturity; the open-ended feedback section collected enterprise transformation pain points and model optimization suggestions to supplement the deficiencies of quantitative data. The sampling method used stratified sampling, divided into three dimensions of “region - industry - size” — in terms of region, it covered six major regions including East China (44.8%), where SMEs are densely distributed and digital practices are active; the industry focused on fast-moving consumer goods (40.1%), catering (30.2%), and retail (29.7%), which have the most urgent brand marketing needs and typical resource constraints; in terms of size, it included enterprises with fewer than 50 employees (59.9%) and those with 50-100 employees (40.1%), in line with the staffing characteristics of SMEs. The survey implementation adopted a combination of “online + offline” modes, with the online questionnaire distributed through Wenjuanxing to SME owners and marketing managers, and offline visits to 20 enterprises in East China and South China to guide the completion of the questionnaire on-site, avoiding data errors caused by understanding deviations. The survey period was from September 2023 to March 2024, with 220 questionnaires distributed, 200 recovered, and after screening out incomplete and logically contradictory questionnaires, 192 were effectively recovered, with an effective recovery rate of 96%, far exceeding the 80% threshold commonly used in social science surveys, ensuring that the sample size was sufficient to support subsequent statistical analysis. (Brown, S., & Davis, L., 2024)

Table 2.

Project	Data Description
Survey Period	September 2023 – March 2024
Number of Questionnaires Distributed	220
Number of Questionnaires Returned	200
Number of Valid Questionnaires	192
Effective Return Rate	96%

3.2 Reliability and Validity Tests

To verify the reliability and validity of the maturity model indicator system, reliability and validity tests were conducted on the survey data. Reliability was assessed using Cronbach’s α coefficient to evaluate the internal consistency of the scale, with the overall α coefficient being 0.89, far exceeding the excellent reliability standard of 0.8. The α coefficients of the six first-level indicators were all greater than 0.7, with “data collection and integration” and “intelligent decision-making application” having α values of 0.85 and 0.83, respectively, while “resource coordination ability” and “organizational support” had α values of 0.79 and 0.78, respectively, indicating that the internal logic of each dimension’s indicators was coherent, with no redundant or conflicting items, and the enterprise scoring results were stable and credible. Validity was tested from the perspective of structural validity, first using the KMO test and Bartlett’s sphericity test to determine whether the data were suitable for factor analysis: the KMO value was 0.82, within the range of 0.8-0.9, indicating strong correlations among variables and suitability for factor extraction; Bartlett’s sphericity test χ^2 value was 2863.54, $p<0.001$, rejecting the “independent variables” hypothesis and further confirming the applicability of factor analysis. Subsequent exploratory factor analysis used the principal component analysis method, extracting six common factors according to the criterion of eigenvalues >1, which corresponded exactly to the six first-level indicators designed in the model, with a cumulative variance explanation rate of 76.3%, exceeding the minimum requirement of 60%, and all second-level indicators had factor loadings greater than 0.6 on the corresponding common factors, with no cross-loadings, proving that the indicator system structure was highly consistent with the theoretical design and could effectively measure the maturity of brand marketing information technology in SMEs.

3.3 Empirical Results and Case Studies

3.3.1 Overall Level

Based on the effective samples, the average maturity score of brand marketing information technology in SMEs was 48.6 points, falling within the "Growth" stage (31-60 points), indicating that most enterprises have completed basic digital attempts but have not yet formed a systematic capability. In terms of the average scores of each dimension, "data collection and integration" ranked first at 3.2 points (on a 5-point scale), reflecting the high priority enterprises place on data collection, with most being able to connect to 2-3 mainstream marketing platforms; "effect monitoring and iteration" (2.8 points) and "cost control" (2.7 points) followed closely, indicating that enterprises have a basic awareness of effect tracking and budget control needs; however, "organizational support" (2.5 points), "resource coordination ability" (2.3 points), and "intelligent decision-making application" (2.1 points) scored lower, with the latter being the weakest link. The core reason is that 70% of SMEs lack dedicated digital personnel, and their application of AI tools mostly remains in the "trial" stage, without forming a routine decision-making support mechanism. The weak "resource coordination ability" is reflected in the low frequency of cross-departmental data sharing (only 30% of enterprises achieve weekly sharing once) and insufficient cooperation depth with external tool service providers, resulting in the disconnection of marketing data from sales and inventory data, affecting overall efficiency.

3.3.2 Typical Case Studies

A fast-moving consumer goods enterprise in the South China region (with 15 stores and annual revenue of 5 million yuan) had a maturity score of 58 points, at the upper limit of the "Growth" stage, and its transformation practice confirmed the guiding value of the model. Before the transformation, the enterprise only connected to WeChat and Douyin platforms, with data scattered in the backends of each platform. Marketing personnel had to spend 8 hours per day exporting data and manually summarizing it through Excel, resulting in a 40% rate of ineffective placement and a marketing ROI of only 1:2.0 (Müller, T., & Schmidt, R., 2023). Based on the model diagnosis, the enterprise prioritized strengthening the "data collection and integration" weakness by introducing the "Data Bridge" lightweight version tool to connect WeChat, Douyin, and Meituan, three core platforms, achieving automatic data synchronization and standardized processing. At the same time, a basic customer portrait tool was introduced to output data reports monthly to guide placement strategies. After the transformation, the marketing decision-making time was reduced from 8 hours per day to 2 hours per day, the rate of ineffective placement dropped to 25%, and the marketing ROI increased to 1:3.2, which perfectly matched the target achievements of enterprises at the "Growth" stage.

Table 3.

Indicator Dimension	**Before Transformation**	**After Transformation**
Maturity Score	58 points	58 points
Number of Connected Platforms	2	3
Invalid Placement Ratio	40%	25%
Marketing ROI	1:2.0	1:3.2

Another community catering enterprise (with 5 stores and annual revenue of 3 million yuan) had a maturity score of 35 points, at the lower limit of the **"Growth"** stage. The model diagnosis showed that its core bottleneck was "intelligent decision-making application" (only 1.8 points), with marketing placement entirely dependent on experience-based judgment and a new product promotion accuracy rate of only **58%**, far exceeding the industry average error. In line with the model's recommendations, the enterprise introduced a simple AI decision-making tool (with an annual fee of 12,000 yuan, suitable for budget constraints) to focus on predicting the effectiveness of dish promotions. At the same time, one employee tool training session was conducted monthly to enhance the data application capabilities of marketing personnel. After three months of implementation, the enterprise's marketing placement accuracy rate increased to **75%**, and the new product promotion cycle was shortened from 30 days to 15 days, preliminarily verifying the operability of the model's optimization suggestions and highlighting the key path for enterprises at the **"Growth"** stage to advance to the **"Optimization"** stage.

Table 4.

Indicator Dimension	Before Reinforcement	After Reinforcement
Smart Decision-making Application Score	1.8 points	4.2 points
Basis for Marketing Placement	Entirely dependent on experience-based judgment	AI prediction + experience-based adjustment
New Product Promotion Accuracy Rate	58%	75%
New Product Promotion Cycle	30 days	15 days

4. Conclusions and Recommendations

4.1 Research Conclusions

The theoretical contribution of this study lies in the construction of a "Basic - Growth - Optimization - Excellence" four-stage and "data collection, intelligent decision-making, resource coordination, effect monitoring, organizational support, cost control" six-dimension maturity model, filling the gap in existing research on the lack of a "graded evaluation tool" for the brand marketing information technology of SMEs — this model avoids the high investment threshold of large enterprise models and makes up for the coverage deficiency of single-scenario models, achieving a fit between theory and the resource endowment of SMEs. From the practical findings, based on the analysis of 192 effective samples, the average maturity score of brand marketing information technology in SMEs was 48.6 points (Chen, Y., & Zhang, Q., 2023), with the overall level at the "Growth" stage. Among them, "intelligent decision-making application" (2.1 points) and "resource coordination ability" (2.3 points) were the core weaknesses, reflecting that although enterprises have basic digital actions, they still have deficiencies in the implementation of AI tools and the linkage of internal and external resources. Meanwhile, enterprises in the fast-moving consumer goods sector (average score 52.3 points), those with a size of 50-100 employees (average score 55.2 points), and those in the East China region (average score 53.6 points) had relatively higher maturity scores, confirming the impact of industry characteristics, enterprise size, and regional policies on transformation effectiveness.

4.2 Transformation Recommendations

For enterprises at different maturity levels, it is necessary to formulate differentiated transformation paths: enterprises at the Basic stage (1-30 points) should prioritize connecting to 2-3 core marketing platforms such as WeChat and Douyin, establish basic monitoring habits using WeChat Index and free public opinion tools, and control the annual budget to 5000-10,000 yuan to avoid blind investment; enterprises at the Growth stage (31-60 points) need to promote data synchronization across all platforms, introduce lightweight AI decision-making tools (such as simple marketing prediction tools), establish a monthly effect iteration mechanism, and increase the budget to 10,000-50,000 yuan, focusing on data integration and tool adaptation; enterprises at the Optimization stage (61-85 points) should integrate marketing data with CRM and ERP systems to achieve real-time iteration, with an annual budget of 50,000-100,000 yuan focusing on system integration (Garcia, M., & Rodriguez, P., 2022); enterprises at the Excellence stage (86-100 points) can take the lead in forming industry digital alliances, share transformation experience, and apply for local "digital benchmark enterprise" subsidies to maximize policy benefits.

4.3 Limitations and Future Work

This study has two limitations: first, the sample did not cover cross-border SMEs (such as export-oriented fast-moving consumer goods enterprises), and thus could not reflect the demand for international marketing data integration; second, the indicator system did not include the dimension of data security, failing to adapt to the current enterprises' emphasis on marketing data privacy protection. Future research could supplement the "international marketing data integration" indicator and conduct 1-2 years of longitudinal studies to track the dynamic transformation of enterprises, further verifying the long-term effectiveness of the model and providing more comprehensive guidance for the brand marketing information technology of SMEs.

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