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An Adaptability Index and Key Obstacle Identification Model for SMEs' Digital Transformation: Based on Perceived Utility Analytical Framework

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ABSTRACT

To address the dilemma of "daring not to transform, unwilling to transform, and unable to transform" faced by small and medium-sized enterprises (SMEs) in digital transformation, this paper applies perceived utility theory to construct a digital adaptability index measurement model for SMEs. The model defines positive utility as the weighted sum of belief values and attribute weights of perceived attributes, and negative utility as the product of perceived cost and cost weight. The net utility is defined as the adaptability index. Hierarchical thresholds are set to classify SMEs into three levels: high, medium, and low adaptability. Furthermore, based on importance-performance analysis (IPA), an obstacle identification model is constructed, where attribute weights serve as importance indicators and belief values serve as performance indicators. Key obstacles are identified and improvement priority scores are calculated to achieve ordered ranking. This paper aims to provide an operable model tool for the diagnosis and tiered intervention of digital transformation in SMEs.

KEYWORDS

Small and Medium-sized Enterprises; Digital Transformation; Perceived Utility; Digital Adaptability; Obstacle Identification.

1. INTRODUCTION

In the digital economy era, digital transformation has become a strategic necessity for the survival and development of enterprises. However, small and medium-sized enterprises (SMEs) generally face the dilemma of "daring not to transform, unwilling to transform, and unable to transform" (Xu & Zhang, 2026). Compared with large enterprises, SMEs have significant resource constraints in terms of capital, technology, talent, and management, making their transformation decisions more complex and risk-sensitive (Westerman et al., 2014). In practice, many SMEs remain hesitant about digital transformation, and even with policy support, the proportion actively initiating transformation remains low. This phenomenon raises a core question: How can we scientifically assess the intrinsic suitability of digital transformation from the perspective of enterprises' subjective perceptions, and then provide differentiated intervention strategies accordingly?

Regarding the issue of suitability for enterprise digital transformation, scholars have explored it from multiple perspectives. External environmental factors (e.g., industry competition pressure, policy incentives, supply chain coordination requirements) are considered important external forces driving transformation (Chen & Han, 2023); internal capability factors of enterprises (e.g., digital

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infrastructure, IT human capital, organizational change culture) are regarded as enabling conditions for successful transformation (Verhoef et al., 2021); and managerial cognition and attitudes (e.g., risk perception, benefit expectations) have also been shown to have a critical impact on transformation decisions (Chen et al., 2020). However, most of these studies adopt factor enumeration or regression analysis, rarely treating enterprises as rational decision-makers integrating perceived attributes and cost trade-offs, and lack a theoretical framework that can uniformly quantify positive and negative utilities.

In the fields of information systems and innovation diffusion, the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) framework have been widely used to explain enterprises' adoption behaviors of emerging technologies (Davis, 1989; Tornatzky & Fleischer, 1990). TAM emphasizes the decisive role of perceived usefulness and perceived ease of use in technology acceptance, while the TOE framework explains adoption decisions from three dimensions: technology, organization, and environment. However, these models are generally applicable to the adoption of a single technology and struggle to address digital transformation, which is a multi-attribute, multi-stage, and systemic organizational change. In recent years, some scholars have attempted to introduce utility theory into digital transformation research, arguing that enterprises compare expected utilities across multiple alternatives and choose the one with the maximum net utility (Zhu et al., 2006). Nevertheless, existing studies largely remain at the level of theoretical elaboration and lack operational utility measurement models. In particular, they fail to address the weighted synthesis of multi-attribute belief values and weights in positive utility, as well as the independent measurement and comparison of perceived costs in negative utility.

In addition, in the field of digital transformation evaluation, maturity models are the most mainstream approach, such as digital maturity models and industrial internet maturity assessments (Schumacher et al., 2016; Zhang & Bai, 2026; Wei et al., 2026). These models typically set several levels (e.g., initial, normative, integrated, optimized) and classify enterprises into corresponding levels based on their performance. The advantage of maturity models lies in their strong horizontal comparability, but their essence is an objective capability evaluation rather than a subjective adaptability judgment. An enterprise with objectively low maturity may, due to its resource endowment, strategic positioning, or risk preference, actually possess high "transformation suitability," and vice versa. This contradiction suggests the need to construct a new evaluation paradigm from the perspective of enterprise subject perception, namely digital adaptability, which measures the degree of match between an enterprise's subjective and objective conditions and the requirements of digital transformation, rather than merely its capability level.

Furthermore, in the field of management diagnosis, Importance-Performance Analysis (IPA) has been widely used for service quality evaluation and priority improvement identification (Martilla & James, 1977; Bao, 2025), and has been extended to scenarios such as information system service evaluation and digital service capability diagnosis (Du et al., 2016; Tang et al., 2025). Given the effectiveness of IPA in identifying priority improvements, applying it to identify key obstacle factors for enterprise digital transformation adaptability has certain theoretical and methodological advantages.

Therefore, to address the deficiencies in current research on digital adaptability of small and medium-sized enterprises (SMEs), this paper constructs a complete framework ranging from utility perception to adaptability measurement and then to key obstacle identification. Specifically, it includes the development of a digital adaptability index model, in which positive utility is defined as the weighted sum of attribute weights and belief values, negative utility is defined as the product of perceived cost and cost weight, and net utility serves as the adaptability index. Enterprises are classified into three levels: high, medium, and low adaptability. Furthermore, Importance-Performance Analysis (IPA) is applied, with attribute weights as importance indicators and belief values as performance indicators, to construct a four-quadrant diagram for identifying key obstacles, and improvement priority scores are proposed to achieve ordered ranking of obstacles.

2. A PERCEIVED UTILITY-BASED DIGITAL ADAPTABILITY INDEX MODEL FOR SMES

2.1. Model Assumptions and Data Acquisition Methods

Assume that the perceived attribute system for SMEs' digital adaptability consists of n perceived attributes. The specific attributes can be selected based on industry standards, expert opinions, or enterprise-specific evaluation objectives. To facilitate subsequent mathematical expressions, the perceived attributes are numbered sequentially, and the j-th perceived attribute is denoted as X_j, where $j = 1, 2, \cdots, n$. Meanwhile, assume that the target enterprise to be measured is numbered i.

For the target enterprise i, the belief value of perceived attribute (denoted as B_{ij}) and the perceived digital transformation cost (denoted as C_i) can be collected through questionnaire surveys, while the weight of perceived attribute (denoted as W_j) and the weight of perceived cost (denoted as W_c) can be determined using the Analytic Hierarchy Process (AHP). The specific methods are as follows:

(1)The date collection method for the belief value of perceived attribute B_{ij}

Based on the perceived attribute system, a structured questionnaire is designed. The questionnaire adopts a 5-point Likert scale, wherein each perceived attribute corresponds to one questionnaire item, inquiring about the degree of agreement of the enterprise respondent regarding the extent to which the attribute can be achieved. The response options are set as: 1 = strongly disagree, 2 = somewhat disagree, 3 = neutral, 4 = somewhat agree, 5 = strongly agree. The collected raw score is divided by 5 to convert it into a belief value B_{ij} having a value range of $[0, 1]$, wherein $B_{ij} = 1$ indicates the strongest belief of enterprise i with respect to the attribute X_j, and $B_{ij} = 0$ indicates the weakest belief. The questionnaire is distributed to management personnel of the target enterprise, including but not limited to enterprise principals, information technology supervisors, production supervisors, and other positions having decision-making authority or significant influence over digital transformation. To ensure data quality, at least five valid questionnaires are collected from the enterprise, and the average value of each questionnaire item is taken as the belief value B_{ij} of enterprise i.

(2)The date collection method for the perceived cost C_i

An independent perceived cost measurement module is provided in the questionnaire, measuring from three dimensions: financial cost, time cost, and human resource cost. The financial cost item inquires of the enterprise respondent about "the perceived extent of the financial investment required for digital transformation (including software and hardware procurement, system development, operation and maintenance expenses, etc.)". The time cost item inquires about "the perceived duration from initiation to effectiveness of digital transformation". The human resource cost item inquires about "the perceived extent of personnel effort, training costs, and talent acquisition costs required for digital transformation". Each item also adopts a 5-point Likert scale. The arithmetic mean of the scores of the three dimensions is taken, and then divided by 5 to convert it into a comprehensive perceived cost having a value range of $[0, 1]$. Similarly to the survey of belief values, the questionnaire is distributed to relevant personnel of the enterprise, and finally the arithmetic mean of the comprehensive perceived cost is taken as the perceived cost C_i of enterprise i.

(3)The date collection method for the attribute weight W_j

A judgment matrix is constructed using the Analytic Hierarchy Process (AHP). A total of m experts are invited to perform pairwise comparisons of the importance of the perceived attributes, using the

1-9 scaling method (where 1 indicates equal importance, 3 indicates moderate importance, 5 indicates strong importance, 7 indicates very strong importance, and 9 indicates extreme importance). A consistency check is performed on the judgment matrix constructed by each expert, and the consistency ratio is calculated by $CR = CI/RI$, wherein $CI = (\lambda_{\max} - n)/(n-1)$, $\lambda_{\max}$ is the maximum eigenvalue obtained, n is the number of perceived attributes, and RI is the random consistency index. When $CR < 0.1$, the judgment matrix is considered to have passed the consistency check. For each expert's judgment matrix that passes the consistency check, the eigenvector is calculated and normalized to obtain the attribute weight vector of the expert. Finally, the weight results of the experts are arithmetically averaged to obtain the final comprehensive attribute weight W_j, satisfying $\sum_{j=1}^{n} W_j = 1$.

(4)The date collection method for the cost weight W_c

Using the same Analytic Hierarchy Process (AHP), an independent module is provided in the expert questionnaire, and the experts are invited to compare the importance of the perceived cost with the perceived attributes in the perceived attribute system, so as to determine the weight coefficient of the perceived cost relative to each perceived attribute. After performing consistency checks and arithmetic averaging on the expert judgment results, the cost weight W_c is obtained, having a value range of $[0,1]$. This value reflects the relative importance of the cost factor in an enterprise's digital transformation decision under the chain-based transformation scenario. When W_c is larger, it indicates that the enterprise is more sensitive to cost perception, and the cost factor has a stronger negative impact on the suitability for digitalization. When W_c is smaller, it indicates that the enterprise pays more attention to the positive utility brought by the digital transformation.

2.2. Construction of the Digital Adaptability Index Measurement Model

Referring to the studies of Zhao et al. (2020) and Tong et al. (2023), this paper adopts the multi-attribute attitude model and utility theory to construct the digital adaptability index measurement model for small and medium-sized enterprises (SMEs). The model regards the decision of the enterprise i on digital transformation as a rational choice process based on utility maximization. The total utility of digital transformation perceived by the enterprise i is composed of two parts: the positive utility comes from the weighted sum of the belief values and attribute weights of enterprise i with respect to the perceived attributes, i.e., $\sum_{j=1}^{n}(B_{ij} \times W_j)$, which reflects the comprehensive value expected by enterprise i from digital transformation; the negative utility comes from the perceived cost of the input required for digital transformation by enterprise i, i.e., $W_c \times C_i$, which reflects the comprehensive cost expected to be borne by enterprise i. The net utility of digital transformation of enterprise i is the difference between the positive utility and the negative utility. The present invention defines the net utility as the digital adaptability index A_i of enterprise i, and the calculation formula is as follows:

$$A_i = \sum_{j=1}^{n}(B_{ij} \times W_j) - W_c \times C_i \tag{1}$$

In the Equation (1), i denotes the target enterprise i; j denotes the j-th perceived attribute X_j, with a value range of $j = 1, 2, \cdots, n$; B_{ij} is the belief value of enterprise i with respect to the perceived attribute X_j, having a value range of $[0,1]$; W_j is the weight of the perceived attribute

X_j, satisfying $\sum_{j=1}^{n} W_j = 1$; C_i is the perceived cost of enterprise i, having a value range of $[0,1]$; and W_c s the cost weight, having a value range of $[0,1]$.

Accordingly, the adaptability for digitalization index A_i has a value range of $[-W_c, 1]$. When the positive utility perceived by enterprise i is much greater than the negative utility, A_i approaches 1, indicating that enterprise i has high digital adaptability, is suitable for undertaking digital transformation, and a high expected success rate of transformation. When the negative utility perceived by enterprise i is greater than the positive utility, A_i is negative, indicating that enterprise i has low digital adaptability, insufficient suitability, and a low expected success rate of transformation.

Further, enterprise i may be classified into different adaptability levels according to the calculated value of A_i. Classification thresholds are set as θ_1 and θ_2, with $0 < \theta_2 < \theta_1 < 1$. The classification thresholds θ_1 and θ_2 can be set according to actual requirements of the transformation scenario. Therefore, enterprise i is classified into the following levels:

I. When $A_i \geq \theta_1$, enterprise i is determined to be at a high adaptability level, indicating that it has a strong willingness to transform and a high perceived utility, and is suitable for prioritized promotion;

II. When $\theta_2 \leq A_i < \theta_1$, enterprise i is determined to be at a medium adaptability level, indicating that it has a certain willingness to transform and requires targeted improvement of weak links;

III. When $A_i < \theta_2$, enterprise i is determined to be at a low adaptability level, indicating that its willingness to transform is insufficient or its perceived cost is excessively high, and basic support is required.

3. IPA-BASED KEY OBSTACLE IDENTIFICATION AND PRIORITY RANKING

To accurately identify the key obstacle factors restricting the digital adaptability of small and medium-sized enterprises (SMEs), this paper constructs an obstacle identification model for SMEs' digital adaptability based on the Importance-Performance Analysis (IPA) method. By integrating attribute weights and belief values, the model maps perceived attributes onto a four-quadrant diagram, thereby systematically diagnosing the core bottlenecks that require priority improvement.

The attribute weight W_j is used as the importance indicator I_{ij} of the perceived attribute X_j, i.e., $I_{ij} = W_j$. The belief value B_{ij} is used as the performance indicator P_{ij} of the perceived attribute X_j, i.e., $P_{ij} = B_{ij}$. The mean of importance $\overline{I}$ and the mean of performance $\overline{P}$ of all attributes are calculated as follows:

$$\overline{I} = \frac{1}{n}\sum_{j=1}^{n} I_{ij} = \frac{1}{n}\sum_{j=1}^{n} W_j = \frac{1}{n} \tag{2}$$

$$\overline{P} = \frac{1}{n}\sum_{j=1}^{n} P_{ij} = \frac{1}{n}\sum_{j=1}^{n} B_{ij} \tag{3}$$

In the Equation (2), since $\sum_{j=1}^{n} W_j = 1$, the mean of importance $\overline{I}$ is constantly equal to $\frac{1}{n}$, which depends solely on the total number n of perceived attributes.

According to the results obtained from Equations (2) and (3), using $\left(\overline{I},\overline{P}\right)$ as the origin, with the importance indicator I_{ij} as the horizontal axis (X-axis) and the performance indicator P_{ij} as the vertical axis (Y-axis), an importance-performance analysis four-quadrant diagram is constructed. Each perceived attribute is mapped onto the four-quadrant diagram according to its importance-performance coordinates $\left(I_{ij},P_{ij}\right)$, and an obstacle determination is made based on the quadrant in which it falls:

A. Quadrant I is the advantage zone, satisfying the conditions $I_{ij}\geq\overline{I}$ and $P_{ij}\geq\overline{P}$. The attributes in this quadrant have high importance and high performance, indicating that the enterprise has a high degree of recognition for these attributes, and that these attributes themselves are relatively important. Such attributes represent the strengths of the enterprise's adaptability for digitalization, should be maintained at the current level, and do not require key intervention.

B. Quadrant II is the over performance zone, satisfying the conditions $I_{ij}<\overline{I}$ and $P_{ij}\geq\overline{P}$. The attributes in this quadrant have low importance and high performance, indicating that the enterprise has a high degree of recognition for these attributes, but the importance of these attributes themselves is low. Such attributes may consume excessive resources or attention, and accordingly, investment therein may be appropriately reduced to reallocate resources to more important areas.

C. Quadrant III is the secondary improvement zone, satisfying the conditions $I_{ij}<\overline{I}$ and $P_{ij}<\overline{P}$. The attributes in this quadrant have low importance and low performance, indicating that the enterprise has a low degree of recognition for these attributes, but the importance of these attributes themselves is also low. Such attributes may serve as secondary directions for subsequent improvement and need not be prioritized for intervention.

D. Quadrant IV is the key improvement zone, satisfying the conditions $I_{ij}\geq\overline{I}$ and $P_{ij}<\overline{P}$. The attributes in this quadrant have high importance and low performance, indicating that the enterprise has a low degree of recognition for these attributes, but the importance of these attributes themselves is high. Such attributes are the key obstacle factors constraining the enterprise's adaptability for digitalization and should be taken as priority targets for improvement.

Further, all attributes falling into Quadrant IV are identified as key obstacle factors, and an improvement priority score is calculated to determine an improvement priority ranking among the key obstacle factors. The calculation formula for the improvement priority score is as follows:

$$Q_{ij}=\left(I_{ij}-\overline{I}\right)\times\left(\overline{P}-P_{ij}\right) \tag{4}$$

In the Equation (4), $I_{ij}-\overline{I}$ represents the degree to which the importance exceeds the mean, and a larger value indicates that the obstacle factor is more important; $\overline{P}-P_{ij}$ represents the gap by which the performance falls below the mean, and a larger value indicates a greater performance gap of the obstacle factor. The product of the two, denoted as Q_{ij}, comprehensively reflects the urgency of improvement of the obstacle factor. The larger the value of Q_{ij}, the higher the priority that should be given to improving the obstacle factor.

According to the result of Equation (4), all key obstacle factors are sorted in descending order of Q_{ij} to obtain a priority list of the obstacle factors. This list can be directly used to guide subsequent countermeasure formulation and resource allocation, with priority given to the obstacle factor having the largest Q_{ij} value.

In addition, for the improvement attributes in Quadrant III, although their importance is relatively low, if multiple attributes in Quadrant III continue to perform poorly in subsequent evaluations, or if the enterprise has sufficient resources, improvement may also be carried out as appropriate. For the over performance attributes in Quadrant II, it is recommended to assess whether there is a resource misallocation issue and to appropriately transfer resources to the attributes in Quadrant IV. For the advantage attributes in Quadrant I, they should be maintained and their changing trends should be monitored to prevent performance degradation due to changes in the external environment.

4. CONCLUSION

This paper addresses the common dilemma of "daring not to transform, unwilling to transform, and unable to transform" faced by small and medium-sized enterprises (SMEs) in their digital transformation decision-making, and constructs a perceived utility-based digital adaptability index and key obstacle identification model, as specified below:

(1) A quantitative measurement method for the digital adaptability index is proposed. The digital transformation decision of SMEs is modeled as a rational choice process based on utility maximization, where positive utility is defined as the weighted sum of belief values and attribute weights of perceived attributes, negative utility is defined as the product of perceived cost and cost weight, and net utility serves as the adaptability index. This index intuitively reflects the net value that an enterprise expects to gain from digital transformation, thereby compensating for the deficiency of existing maturity models that emphasize objective capabilities while neglecting subjective perception.

(2) A classification standard for enterprise adaptability is established. By setting classification thresholds, enterprises are divided into three adaptability levels: high, medium, and low. Enterprises with high adaptability have strong transformation willingness and high perceived utility, making them suitable for priority promotion; enterprises with medium adaptability have some willingness to transform and need targeted improvement of weak links; enterprises with low adaptability have insufficient willingness to transform or excessively high perceived costs, requiring basic support. This classification provides a clear operational basis for differentiated intervention.

(3) A key obstacle identification and priority ranking model based on the Importance-Performance Analysis (IPA) method is constructed. The model takes the weights of digital perceived attributes of SMEs as importance indicators and belief values as performance indicators. Through a four-quadrant diagram, perceived attributes are divided into the advantage zone, over performance zone, secondary improvement zone, and key improvement zone. For the key obstacle factors falling into the key improvement zone, improvement priority scores are calculated, thereby achieving effective identification and ordered ranking of the core obstacles that constrain the digital adaptability of enterprises.

The model constructed in this paper provides a new theoretical perspective for diagnosing digital transformation in SMEs. However, due to research design limitations, certain constraints remain. For instance, regarding the perceived attribute system, this paper does not preset a fixed set of attributes, which enhances the model's generality but may affect cross-sectional comparability. Future research could establish standardized attribute libraries for typical industries. In terms of data collection, questionnaire surveys and the analytic hierarchy process may introduce subjective biases; subsequent studies could incorporate objective enterprise operational data and natural language processing techniques for cross-validation. Overall, the model developed in this paper offers an operational diagnostic tool framework for digital transformation in SMEs and relevant government agencies, helping them formulate more targeted digital transformation strategies or intervention measures.

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