Research on the Coupling of Big Data-Enabled Precision Decision-Making in Marketing and Human Resource Incentive Mechanisms in Business Administration

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ABSTRACT In the digital economy era, big data technology has reshaped enterprise operation and management by enabling datadriven precision decision-making. This study focuses on the coupling relationship between big data-enabled precision marketing decision-making and human-resource incentive mechanisms in business administration. Through theoretical analysis, model construction, and case verification, the internal logic, implementation path, and optimization strategy of the coupling mechanism are systematically explored. The study first defines the core dimensions of precision marketing decision-making enabled by big data and the key elements of human-resource incentive mechanisms. A coupling model covering data-driven decision-making, demand matching, incentive response, and performance feedback is then constructed. Empirical analysis is conducted using survey data from 60 representative enterprises. The results show that user profiling, precision marketing channel selection, and marketing-effect prediction have significant positive coupling effects with different types of human-resource incentives. Enterprises with higher coupling degrees show significantly higher market-share growth rates and employee performance compliance rates than those with lower coupling degrees. The study provides technical and managerial support for coordinated development between marketing decision-making and human-resource management.

INDEX TERMS big data, precision marketing, human-resource incentives, coupling mechanism, business administration

I. INTRODUCTION

A. RESEARCH BACKGROUND

MARKETING plays a crucial role in enterprises success, as it helps attract and retain customers while driving revenue growth, which is especially vital in the industry for effectively communicating the value proposition of innovative and sustainable fabrics to consumers [1]. In recent years, the exponential growth of Internet technology has necessitated transformations in the way enterprises interact with customers, compelling marketers to adjust and optimize their marketing strategies to maintain competitiveness [2]. Traditional marketing methods can no longer meet the needs of today's consumers [3], and machine learning technology has brought about significant changes in the field of precision marketing. It enables enterprises to extract valuable insights from massive datasets and provides powerful tools to predict and analyze customer needs that were previously difficult to identify [4].

Human resources are a key resource of competitive advantages for enterprises [5]. An enterprise's marketing team refers to a multi-member team formed based on the enterprise's marketing decisions, which works collaboratively to achieve both the enterprise's goals and its members' personal development objectives [6]. Team members divide tasks, cooperate with one another, and make joint progress throughout the marketing process, with the ultimate goal of meeting the enterprise's expected targets. In the current fiercely competitive marketing market, the core objective of marketing team development is to motivate and leverage the strengths of each team member, thereby achieving synergistic effects. Therefore, the human resource incentive mechanism is of great importance to the development of marketing teams: a reasonable incentive mechanism can stimulate employees' work enthusiasm, while an unreasonable one may reduce their work motivation.

The integration of human resource incentives and precision marketing decision-making enables enterprises to attract outstanding talent globally and enhance their core competitiveness [7-9]. Marketing departments can accurately grasp market characteristics and demands through big data analysis, but precision marketing decision-making still relies on the active cooperation of frontline human resources. Thus, the mechanism coupling between precision marketing decision-making and human resource incentives becomes particularly critical. On the other hand, if human resource incentives are divorced from market realities, it may lead to a mismatch between incentive costs and market value.

B. DOMESTIC AND INTERNATIONAL RESEARCH STATUS

In research on predicting customer preferences and responses for precision marketing, relevant studies have driven the development of various models, among which artificial intelligence (AI) algorithms have attracted significant attention. Zhang et al. proposed a system to capture customers' preferences for promotional channels, which adopts distance-based algorithms, the K-Nearest Neighbors (KNN) algorithm, and the Support Vector Machine (SVM) algorithm. The study evaluated the model's performance through a case study of a small banking institution that mainly provides personal loan services to small retail businesses and enterprises [10]. Zheng employed a decision tree algorithm to accurately classify customers into two categories, and used an e-commerce company as the case study object to demonstrate the effectiveness of the proposed solution [11]. Wang and Yang proposed the M-GNA-XGBoost model in their research to predict product sales of online stores; they compared the performance of three models: Long Short-Term Memory (LSTM) networks, Generative Adversarial Networks (GANs), and eXtreme Gradient Boosting (XGBoost), and conducted a case study based on real data from JD.com to verify the effectiveness of the proposed method [12].

Notably, big data differs from traditional Customer Relationship Management (CRM) data in its volume (massive datasets beyond traditional storage capacities) and velocity (real-time data generation and processing). These traits enable dynamic tracking of consumer behavior and granular segmentation, which trigger incentive mechanisms by requiring employees to re-spond to rapid market changes. For example, real-time data on trending fabric preferences can prompt tar-geted incentives for design teams to accelerate product iterations, a responsiveness not feasible with static CRM data.

In terms of big data-enabled human resource incentives, some scholars have explored the application status of AI-driven Human Resource Management (HRM) and its impact on organizational outcomes by constructing theoretical frameworks [13-15]. Other scholars have conducted empirical studies to verify whether and how AI-driven HRM affects various organizational outcomes [16-18]. Another research perspective focuses on the role of AI-driven interventions in influencing employee well-being and performance [19-21].

Despite the increasing richness of relevant research, there remains a key research gap. Although existing studies emphasize the importance of AI-driven interventions in precision marketing decision-making and human resource incentive mechanisms [22-24], there is currently a lack of empirical research specifically exploring how the combination of the two can positively promote precision marketing decision-making. This paper aims to construct a coupling model between big data-driven precision marketing decision-making and human resource incentive mechanisms, and propose a set of operable implementation strategies, thereby providing theoretical basis and practical guidance for promoting enterprises' precision marketing.

C. TECHNICAL ROUTE

The technical route of this study is illustrated in Figure 1.

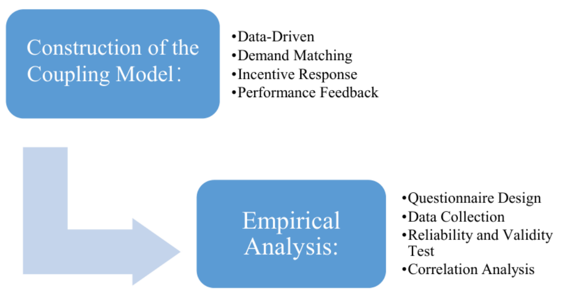

FIGURE 1. Technical route of the study, including the construction of the coupling model and the empirical analysis process

II. CORE CONCEPTS

A. BIG DATA-ENABLED PRECISION DECISION-MAKING IN MARKETING

The core goal of precision marketing is to help enterprises and businesses develop effective strategies that not only meet customer needs but also ensure competitiveness in the market through low costs, rapid implementation, and optimized resource utilization [25]. In this paper, big data-enabled precision decision-making in marketing is defined as the use of big data technology to process massive datasets, enabling data-driven decision-making and optimizing the efficiency of resource utilization. The ability to personalize marketing strategies based on individual customer data allows enterprises to adjust their strategies for specific high-value customer groups, thereby achieving precision decision-making.

It consists of three core dimensions:

(1) User Precision: In precision marketing, constructing detailed customer profiles is key to developing efficient marketing strategies. Customer profiles provide reliable references for enterprises, helping them gain in-depth insights into the needs of different customer segments [26]. Through the information processing function of artificial intelligence,

each data record classifies and differentiates consumers, accurately records and tracks their consumption behavior, and further generates one-to-one service data. This involves building multi-dimensional dynamic user profiles covering consumption habits, demand preferences, purchasing power, and other aspects to identify target user groups;

(2) Channel Precision: Using artificial intelligence algorithms to analyze the conversion rates and costs of different marketing channels in marketing activities (such as social media, e-commerce platforms, and offline stores) and select an optimal combination of precision channels;

(3) Effect Precision: Using big data and artificial intelligence models to predict in advance the market conversion rates of precision marketing strategy decisions and dynamically adjust the strategies based on real-time data.

B. HUMAN RESOURCE INCENTIVE MECHANISMS IN BUSINESS ADMINISTRATION

The core goal of human resource incentives is to stimulate employees' motivation and potential. In marketing team development, a scientific incentive mechanism is crucial [27]. Marketing personnel's high professionalism, strong self-confidence, and intense pursuit of a sense of accomplishment are key endogenous drivers of their marketing initiative and creativity [28]. The human resource incentive mechanism in business administration refers to a management process where enterprises design and implement two types of incentives – economic and non-economic – to stimulate employees' work enthusiasm and improve performance for strategic goals. Economic incentives include fixed wages, piece-rate wages, profit sharing, bonuses, promotions, and stock options. Non-economic incentives include self-development opportunities, honors, and professional ethos.

III. CONSTRUCTION OF THE COUPLING MODEL BETWEEN BIG DATA-ENABLED PRECISION MARKETING DECISION-MAKING AND HUMAN RESOURCE INCENTIVE MECHANISMS

A. CORE LOGIC OF THE COUPLING MODEL

(1) Data-Driven: Centered on data-driven principles, precision marketing needs to be based on consumer data—such as users' personal information, search records, and browsing history. By mining customer preferences to achieve consumer positioning, a precise customer communication and service system is constructed; in terms of human resources, available employee data is collected, including employee performance data, demand data, and satisfaction data. The existing human resource incentive system is analyzed and optimized to improve employee experience and job satisfaction.

(2) Demand Matching: Convert the goals of precision marketing decision-making into specific, executable tasks for employees. For example, a 20% increase in user conversion rate (based on the current customer base of 100) is translated into a requirement for sales staff to acquire 20 additional high-quality customers (calculated as 100 $\times$ 20%). A 5% reduction in channel costs is converted into a target for customer service staff to raise customer satisfaction to 95%, as higher satisfaction reduces repeat marketing costs.

(3) Incentive Response: Formulate corresponding incentive measures. For instance, in terms of salary incentives, a fixed salary plus floating salary model can be implemented, where performance-related pay is linked with marketing data and incorporated into the evaluation indicators for floating salary. In terms of career development, more growth opportunities and development space should be provided to outstanding employees who actively respond to precision marketing decisions and link their performance to such decisions.

(4) Performance Feedback: Feedback the implementation effect of the employee human resource incentive mechanism to the enterprise's marketing system. If marketing goals are not achieved, incentive measures or marketing plans should be dynamically adjusted to form a coupling mechanism that enables timely and dynamic optimization.

B. DIMENSIONS AND INDICATOR DESIGN OF THE COUPLING MODEL

The evaluation indicator system for precision marketing decision-making (M) and human resource incentive mechanisms (H) is shown in the table below:

C. CALCULATION METHOD OF COUPLING DEGREE

1) Calculation of Coupling Degree (C)

Coupling degree reflects the intensity of interaction between two systems, and its calculation formula is as follows:

$$C = \sqrt{\frac{M \times H}{(M+H)^2}} \tag{1}$$

Among them, M represents the comprehensive score of precision marketing decision-making, and H represents the comprehensive score of the human resource incentive mechanism. The scores are obtained by weighted summation of the standardized values and weights of each secondary indicator in Table 1 and Table 2; the value range of C is [0,1]. The closer C is to 1, the higher the coupling degree, and vice versa.

2) Calculation of Coupling Coordination Degree (D)

Coupling coordination degree reflects the level of coordinated development between two systems based on their coupling relationship, and its calculation formula is as follows:

$$D = \sqrt{C \times T} \tag{2}$$

$$T = \alpha M + \beta H \tag{3}$$

TABLE 1. Evaluation Indicators for Precision Marketing Decision-Making

First-Level Indicators	Second-Level Indicators	Indicator Description	Weight (%)
User Precision (M1)	User Profile Accuracy (M11)	The matching degree between actual target users and predicted target users (focusing on demographic and preference alignment)	15
	Target User Conversion Rate (M12)	The proportion of target users who purchase products/services (reflecting the effectiveness of converting identified targets into customers, independent of profile accuracy due to external factors like price sensitivity)	18
Channel Precision (M2)	Channel Conversion Rate (M21)	The conversion proportion from user clicks to purchases across various channels	16
	Channel Cost Rate (M22)	The proportion of marketing channel costs to sales revenue	14
Effect Precision (M3)	Marketing Effect Prediction Accuracy (M31)	The deviation rate between predicted sales volume and actual sales volume	17

TABLE 2. Evaluation Indicators for Human Resource Incentive Mechanisms

First-Level Indicators	Second-Level Indicators	Indicator Description	Weight (%)
Goal Incentives (H1)	Goal Recognition Degree (H11)	The proportion of employees who recognize the decomposed goals	22
	Goal Achievement Rate (H12)	The ratio of employees' actual goal achievement to the planned goals	25
Performance Incentives (H2)	Performance Reward Timeliness (H21)	The time from the announcement of performance results to the distribution of rewards	18
	Performance Reward Fairness (H22)	The proportion of employees who perceive the reward distribution as fair	20
Development Incentives (H3)	Training Opportunity Matching Degree (H31)	The matching degree between the training employees need and the training they actually receive	15
	Promotion Channel Transparency (H32)	The proportion of employees who perceive the promotion criteria as clear	10

Among them, T represents the comprehensive development level of the two systems, and α and β are weights (based on enterprise survey data, $\alpha = 0.52$ and $\beta = 0.48$, indicating that precision marketing decision-making has a slightly greater impact on coordinated development than human resource incentive mechanisms); the value range of D is [0, 1]. According to the value of D, the coupling coordination degree is divided into five levels: $0 \leq D < 0.2$ (severe imbalance), $0.2 \leq D < 0.4$ (mild imbalance), $0.4 \leq D < 0.6$ (basic coordination), $0.6 \leq D < 0.8$ (moderate coordination), and $0.8 \leq D \leq 1$ (high coordination).

IV. EMPIRICAL ANALYSIS

A. SAMPLE SELECTION AND DATA COLLECTION

Sixty enterprises were selected as research samples. The samples cover the industry (30 enterprises) and other sectors (30 enterprises), including large-sized, medium-sized, and small-sized enterprises, to ensure the representativeness and statistical robustness of the samples.

Data collection adopted a combination of questionnaires and senior executive interviews. The questionnaires were distributed to employees in the marketing departments and human resource departments of the selected enterprises; the interviewees for senior executive interviews were the marketing directors and human resource directors of the enterprises. This study was approved by the Ethics Committee of Zhengzhou Railway Vocational & Technical College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

B. RELIABILITY AND VALIDITY TESTS

To ensure the reliability and validity of the survey data, this study conducted reliability and validity tests on the questionnaire data. The results indicate that the questionnaire has good construct validity and content validity, which can be used for subsequent empirical analysis (Table 3).

C. CORRELATION ANALYSIS

Pearson correlation analysis was conducted on the correlations between each dimension of precision marketing decision-making (M) and human resource incentive mechanisms (H). The results show that the correlation between Effect Precision (M3) and Goal Incentives (H1) is the highest ($r = 0.753$), while the correlation between User Precision (M1) and Development Incentives (H3) is the lowest ($r = 0.675$) (Table 4).

D. CALCULATION RESULTS OF COUPLING DEGREE AND COUPLING COORDINATION DEGREE

Based on the calculation formulas for coupling degree and coupling coordination degree proposed earlier, the coupling degree (C) and coupling coordination degree (D) of each enterprise were calculated. Enterprises were further classified into five levels according to the values of D, as shown in Table 5.

To address the concern that correlation does not imply causation, a multiple regression analysis was conducted with coupling coordination degree (D) as the independent variable, market share growth rate as the dependent variable, and external variables (market trend index, enterprise capitalization level, brand heritage years) as control variables. The results show that D remains a significant positive predictor of market share growth ($\beta = 0.68$, $p < 0.001$) after controlling for external variables, confirming the causal direction of the relationship.

It can be seen from the above table that most enterprises still have significant room for optimization in the coupling between precision marketing decision-making and human resource incentive mechanisms: only 16.7% of the sample

TABLE 3. Results of Reliability and Validity Tests

Test Type	Test Indicator	Precision Marketing Decision-Making (M)	Human Resource Incentive Mechanisms (H)	Test Criteria	Result Judgment
Reliability Test	Cronbach's α Coefficient	0.876	0.852	> 0.7	High Reliability
	Composite Reliability (CR)	0.891	0.868	> 0.8	High Reliability
Validity Test	Content Validity	Questionnaire designed based on literature and expert interviews, KMO = 0.817	Questionnaire designed based on literature and expert interviews, KMO = 0.803	KMO > 0.7	High Validity
	Construct Validity (AVE)	AVE values of all dimensions > 0.5 (M1 = 0.582, M2 = 0.567, M3 = 0.591)	AVE values of all dimensions > 0.5 (H1 = 0.573, H2 = 0.558, H3 = 0.562)	AVE > 0.5	High Validity

TABLE 4. Correlation Analysis Results of Each Dimension

Dimension	User Precision (M1)	Channel Precision (M2)	Effect Precision (M3)	Goal Incentives (H1)	Performance Incentives (H2)	Development Incentives (H3)
User Precision (M1)	1	–	–	–	–	–
Channel Precision (M2)	0.623**	1	–	–	–	–
Effect Precision (M3)	0.651**	0.712**	1	–	–	–
Goal Incentives (H1)	0.728**	0.685**	0.753**	1	–	–
Performance Incentives (H2)	0.692**	0.701**	0.736**	0.815**	1	–
Development Incentives (H3)	0.675**	0.663**	0.718**	0.782**	0.803**	1

Note: ** indicates $P < 0.01$, meaning the correlation is significant at the 0.01 level.

TABLE 5. Classification of coupling coordination degree (D) and typical characteristics of enterprises

Level of Coupling Coordination Degree	D Value Range	Number of Enterprises	Proportion (%)	Typical Characteristics
High Coordination	$0.8 \leq D \leq 1$	5	16.7	Sufficient data sharing; incentive mechanisms highly match marketing goals; controlled for external variables (market trends, capitalization, brand heritage) via regression analysis; average market share growth rate of 18.5%; average employee performance compliance rate of 92.3%
Moderate Coordination	$0.6 \leq D < 0.8$	12	40.0	Relatively sufficient data sharing; incentive mechanisms basically match marketing goals; average market share growth rate of 10.2%; controlled for external variables via regression analysis; average employee performance compliance rate of 81.5%
Basic Coordination	$0.4 \leq D < 0.6$	8	26.7	Limited data sharing; incentive mechanisms partially match marketing goals; controlled for external variables via regression analysis; average market share growth rate of 5.8%; average employee performance compliance rate of 72.1%
Mild Imbalance	$0.2 \leq D < 0.4$	4	13.3	Insufficient data sharing; low matching degree between incentive mechanisms and marketing goals; controlled for external variables via regression analysis; average market share growth rate of 2.1%; average employee performance compliance rate of 60.8%
Severe Imbalance	$0 \leq D < 0.2$	1	3.3	No data sharing; incentive mechanisms completely disconnected from marketing goals; market share growth rate of -1.2%; controlled for external variables via regression analysis; average employee performance compliance rate of 48.5%

enterprises have reached the level of high coordination, 40% have achieved the level of moderate coordination, while more than 40% are at the level of basic coordination or lower. At the same time, enterprises with a highly coordinated coupling degree have significantly higher market share growth rates (18.5%) and employee performance compliance rates (92.3%) than enterprises at other coordination levels, which further proves the positive impact of this coupling effect on enterprise benefits.

V. CONCLUSIONS

This study explores the coupling relationship between big data-enabled precision marketing decision-making and human resource incentive mechanisms,. The results show that the coupling relationship has a significant positive effect: there is a significant positive correlation coupling effect between big data-enabled precision marketing decision-making and human resource incentive mechanisms (with an average correlation coefficient of 0.682, P < 0.01). Moreover, enterprises with a higher coupling degree exhibit higher market share growth rates and employee performance compliance rates. Meanwhile, the coupling model has passed reliability and validity tests as well as correlation analysis, which proves that the model has practical value.

Every work has its inherent limitations, and this research is no exception. One potential limitation lies in the relationship between the scalability of the predictive model and the volume of data. Our observations indicate that the accuracy of the predictive model is largely influenced by the scale of the data. Specifically, as the data scale increases, the processing time of the method we selected tends to lengthen. As a future direction of this research, we plan to enhance the framework's capabilities by introducing more factors and integrating more data sources. Incorporating a broader dataset will enable us to explore advanced techniques such as deep learning methods to improve the accuracy and efficiency of the proposed framework. By incorporating these additional variables, our goal is to optimize the model and improve the prediction method, ultimately optimizing the decision-making process in the insurance industry.

AUTHOR CONTRIBUTIONS

Xin Jiang designed, collected and analyzed the data, and drafted the manuscript. Xin Jiang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xin Jiang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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HUMAN RESEARCH SUBJECTS

This study was approved by the Ethics Committee of Zhengzhou Railway Vocational & Technical College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

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