Chinese Business Review, July-Sept. 2025, Vol. 24, No. 3, 99-108
doi: 10.17265/1537-1506/2025.03.002

State-Owned Enterprises IPD R&D Management Optimization Using Data-Driven Decision-Making Models

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In the rapidly evolving technological landscape, state-owned enterprises (SOEs) encounter significant challenges in sustaining their competitiveness through efficient R&D management. Integrated Product Development (IPD), with its emphasis on cross-functional teamwork, concurrent engineering, and data-driven decision-making, has been widely recognized for enhancing R&D efficiency and product quality. However, the unique characteristics of SOEs pose challenges to the effective implementation of IPD. The advancement of big data and artificial intelligence technologies offers new opportunities for optimizing IPD R&D management through data-driven decision-making models. This paper constructs and validates a data-driven decision-making model tailored to the IPD R&D management of SOEs. By integrating data mining, machine learning, and other advanced analytical techniques, the model serves as a scientific and efficient decision-making tool. It aids SOEs in optimizing R&D resource allocation, shortening product development cycles, reducing R&D costs, and improving product quality and innovation. Moreover, this study contributes to a deeper theoretical understanding of the value of data-driven decision-making in the context of IPD.

Keywords: state-owned enterprises, IPD R&D management, data-driven decision-making, R&D optimization, innovation

Introduction

Background and Context

In the current era of rapid technological advancement, state-owned enterprises (SOEs) play a crucial role in national economic development and technological innovation. However, they face fierce market competition and the increasing complexity of technological innovation, which pose significant challenges to traditional R&D management models. The Integrated Product Development (IPD) model, with its emphasis on cross-functional teamwork, concurrent engineering, and data-driven decision-making, has garnered attention for its ability to enhance R&D efficiency and product quality. Yet, the unique characteristics of SOEs, such as their large scale, complex organizational structures, and diverse business areas, present challenges in the effective implementation of IPD. Meanwhile, the rise of big data and artificial intelligence technologies offers new opportunities for optimizing IPD R&D management through data-driven decision-making models.

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Research Objectives and Significance

This paper aims to construct and validate a data-driven decision-making model tailored to the IPD R&D management of SOEs. By integrating data mining, machine learning, and other advanced analytical techniques, we seek to provide SOEs with a scientific and efficient decision-making tool that addresses the limitations of traditional experience-based decision-making. This tool will help SOEs optimize R&D resource allocation, shorten product development cycles, reduce R&D costs, and improve product quality and innovation. Additionally, this study contributes to the existing literature by offering new insights into the application of data-driven decision-making in the specific context of SOEs, thereby enriching the theoretical foundations of IPD R&D management.

Research Questions and Methods

The research questions explored in this paper include:

(1) What are the key factors influencing R&D management decisions in SOEs, and how can these factors be effectively measured and analyzed using data-driven approaches?

(2) How can data-driven decision-making models be integrated with the IPD framework to optimize R&D processes in SOEs?

(3) What challenges do SOEs encounter when implementing data-driven decision-making models in IPD R&D management, and what strategies can be employed to overcome these challenges?

To address these questions, this paper employs a combination of literature review and quantitative modeling. The literature review examines existing studies on IPD and data-driven decision-making to establish a theoretical foundation. Through the development of quantitative models and algorithms, we analyze the collected data to provide decision-making support for R&D management. This approach allows us to identify patterns and trends in the data, which in turn helps in formulating effective strategies for optimizing R&D processes in SOEs.

Literature Review

IPD R&D Management

IPD is a systematic approach to product development that emphasizes the integration of cross-functional teams, concurrent engineering, and customer-focused innovation. Originating in the 1990s, IPD has been widely adopted in industries such as electronics, automotive, and aerospace, demonstrating significant advantages in improving R&D efficiency and product quality. The IPD process typically includes several stages: concept development, planning, product development, testing and verification, and product launch. Throughout these stages, cross-functional teams collaborate closely to ensure that all aspects of the product, from design to production, are considered simultaneously. This approach helps to identify and resolve potential issues early in the development process, reducing the need for costly design changes and rework.

However, the implementation of IPD in SOEs faces several challenges. The hierarchical organizational structures and bureaucratic processes common in SOEs can impede the rapid flow of information and decision-making, which are critical for the success of IPD. Additionally, the diverse business areas and complex product lines of SOEs require a more flexible and adaptable IPD framework that can accommodate varying R&D needs and priorities. Furthermore, the assessment and incentive mechanisms in SOEs may not fully align with the collaborative and innovative requirements of IPD, potentially affecting the motivation and performance of R&D teams.

Data-Driven Decision-Making Models

Data-driven decision-making refers to the process of making decisions based on the analysis of large volumes of data using statistical and machine learning techniques. In recent years, with the advancement of big data technologies, data-driven decision-making has gained widespread attention and application across various industries. By collecting, storing, and analyzing massive amounts of data generated during business operations, organizations can uncover hidden patterns, trends, and relationships, providing valuable insights for decision-making.

In the context of R&D management, data-driven decision-making models can be applied to various aspects, such as project selection, resource allocation, risk assessment, and performance evaluation. For example, by analyzing historical R&D project data, organizations can identify factors that influence project success and develop predictive models to assess the potential of new projects. Similarly, data-driven approaches can optimize the allocation of R&D resources by matching resource availability with project requirements based on data analysis. These applications of data-driven decision-making models help organizations enhance the scientific and rational basis of R&D management decisions, improve R&D efficiency, and reduce risks.

Data-Driven Decision-Making Model for IPD R&D Management

Key Data Dimensions for IPD R&D Management

In the context of SOEs, several critical data dimensions are relevant to IPD R&D management decisions. These include:

(1) Market demand data: Information on market size, growth trends, customer needs, and competitive landscape helps organizations identify potential market opportunities and guide product development directions.

(2) Technological trend data: Data on technological advancements, emerging technologies, and industry standards enable organizations to stay updated on the latest technological developments and incorporate promising technologies into their R&D projects.

(3) Project performance data: Historical and real-time data on R&D project progress, cost, quality, and timeline provide insights into project execution and help identify bottlenecks and issues.

(4) Resource utilization data: Data on human, financial, and material resource allocation and utilization efficiency help organizations optimize resource allocation and improve resource utilization rates.

(5) Supply chain data: Information on suppliers, partners, and logistics can help organizations enhance supply chain management, reduce supply chain risks, and ensure the smooth progress of R&D projects.

Data-Driven Decision-Making Model Framework

The data-driven decision-making model for IPD R&D management in SOEs is illustrated in Table 1. The model encompasses several key layers designed to facilitate the transformation of raw data into actionable insights for R&D decision-making.

Table 1

Data-Driven Decision-Making Model Framework

Modeling framework	Detailed content
Data collection layer	Collects data from various sources, including internal enterprise systems (e.g., ERP, PDM, CRM) and external data sources (e.g., market research reports, industry databases).
Data storage and management layer	Stores and manages the collected data using data warehousing and data lake technologies, ensuring data quality, security, and accessibility.

Table 1 to be continued

Data analysis layer	Employs data mining, machine learning algorithms, and statistical analysis techniques to analyze the stored data and extract valuable information and knowledge.
Decision support layer	Based on the analytical results, provides decision support for IPD R&D management, including project prioritization, resource allocation, risk assessment, and performance evaluation.
Visualization and interaction layer	Presents the decision-making results to managers and R&D personnel through intuitive visualization dashboards and interactive interfaces, facilitating the communication and application of decision-making information.

Model Training and Validation

To ensure the effectiveness of the data-driven decision-making model, it is essential to conduct model training and validation using historical R&D data from SOEs. The specific steps include (see Figure 1):

(1) Data preprocessing: Clean and preprocess the collected historical data to address issues such as data missing values, outliers, and inconsistencies, ensuring data quality.

(2) Feature selection and extraction: Select and extract relevant features from the preprocessed data based on the research objectives and decision-making requirements. Techniques such as principal component analysis (PCA) and feature importance ranking can be employed to reduce data dimensions and improve model performance.

(3) Model selection and training: Choose appropriate machine learning algorithms (e.g., decision trees, neural networks, support vector machines) based on the nature of the data and decision-making problems. Train the models using the selected algorithms and the extracted feature data, optimizing model parameters to enhance model accuracy and generalization ability.

(4) Model validation and evaluation: Validate and evaluate the trained models using cross-validation and other techniques. Assess model performance using metrics such as accuracy, precision, recall, and F1-score. Iterate the model training and validation process until satisfactory performance is achieved.

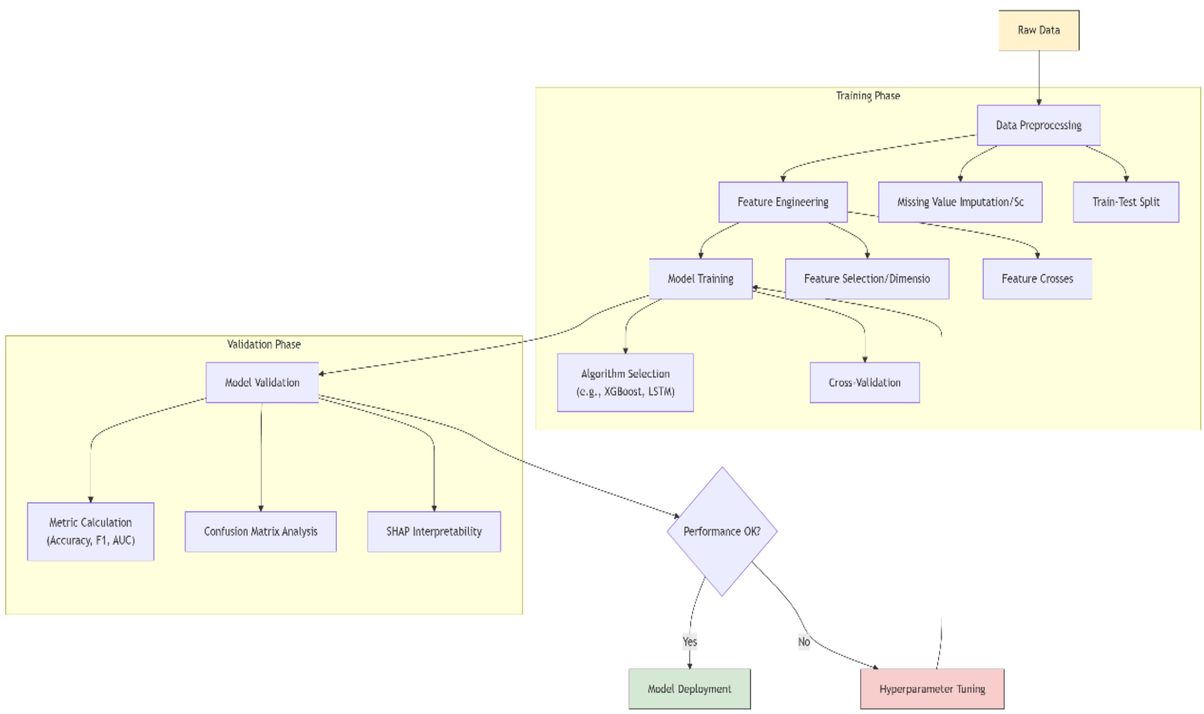

Figure 1. Model training and validation flowchart.

Data Collection and Analysis

Data Collection Methods

To support the data-driven decision-making model for IPD R&D management, we employed the following data collection methods:

(1) Internal data extraction: Extracted relevant data from the enterprise resource planning (ERP) system, product data management (PDM) system, and customer relationship management (CRM) system of the case SOE. These data included R&D project information, resource allocation data, project progress data, and financial data.

(2) Questionnaire surveys: Designed and distributed questionnaires to R&D personnel, managers, and other relevant stakeholders within the SOE to collect their perceptions and evaluations of IPD R&D management. The questionnaire covered aspects such as teamwork, communication effectiveness, and innovation capability.

(3) Interviews: Conducted in-depth interviews with senior management, R&D project managers, and technical experts to gather qualitative insights into the challenges and opportunities of IPD R&D management. The interviews provided valuable contextual information and expert opinions that supplemented the quantitative data.

Data Preprocessing and Integration

The collected data were heterogeneous and existed in various formats. To ensure data consistency and usability, we performed the following data preprocessing and integration steps (see Figure 2):

(1) Data cleaning: Removed duplicate records, corrected data entry errors, and addressed missing values through imputation or deletion.

(2) Data transformation: Standardized data formats and units of measurement, and normalized data values to facilitate data analysis.

(3) Data integration: Combined data from different sources into a unified data warehouse using data integration tools and techniques. This step ensured that data from various systems and sources were integrated seamlessly, providing a comprehensive view of the R&D management process.

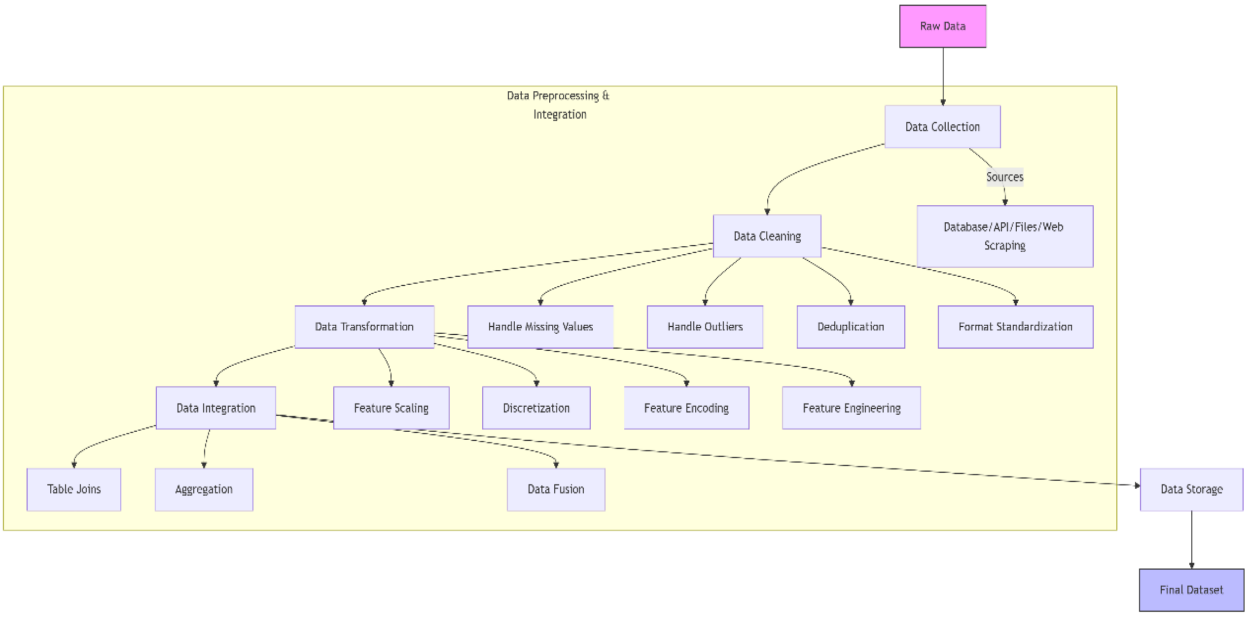

Figure 2. Data preprocessing and integration flowchart.

Data Analysis Techniques

We employed a variety of data analysis techniques to uncover patterns and insights from the collected data (see Figure 3 and Table 2):

(1) Descriptive statistics: Calculated basic statistical measures such as mean, median, standard deviation, and correlation coefficients to describe the central tendency, dispersion, and relationships of the data. This provided an initial understanding of the data distribution and characteristics.

(2) Data visualization: Created visualizations such as charts, graphs, and heatmaps to present the data in an intuitive manner. These visualizations helped identify trends, patterns, and outliers in the data, providing a clearer picture of the R&D management status.

(3) Predictive analytics: Utilized machine learning algorithms such as linear regression, decision trees, and neural networks to build predictive models. These models forecasted R&D project performance indicators (e.g., project duration, cost overruns, defect rates) based on historical data, offering insights into potential future outcomes and aiding in proactive decision-making.

(4) Cluster analysis: Applied clustering algorithms to group R&D projects based on similarities in features such as technical complexity, market demand, and resource requirements. This analysis helped identify common characteristics and patterns among projects, enabling tailored management strategies for different project clusters.

(5) Text mining: Analyzed textual data from questionnaire responses and interview transcripts using text mining techniques. This involved extracting keywords, sentiment analysis, and topic modeling to uncover latent opinions, suggestions, and concerns from the respondents, providing qualitative insights into the R&D management process.

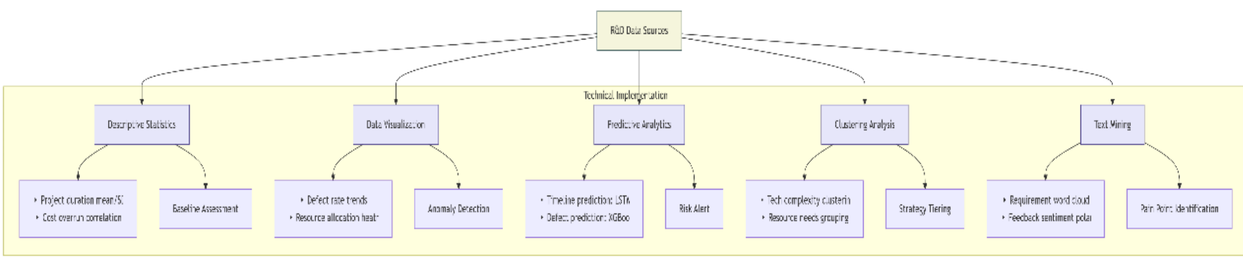

Figure 3. Example diagram of data analysis techniques.

Table 2

Technology-Business Alignment Table

Analytic technique	R&D management application	Typical output	Business value
Descriptive stats	Historical project performance baseline	Cost/time distribution report	Establish process capability baseline
Data visualization	Monitor KPI fluctuations	Real-time dashboard (e.g. defect rate)	Identify resource bottlenecks
Predictive analytics	New project delay risk assessment	Risk scorecard (probability + key factors)	Enable proactive mitigation
Clustering analysis	Differentiated management strategies	Project grouping matrix (high/medium/low priority)	Optimize resource allocation
Text mining	User requirement analysis	Sentiment trend + TOP3 frequent needs	Guide product iteration

Challenges in Implementing Data-Driven Decision-Making Models in IPD R&D Management of SOEs and Strategies

Data Quality and Security Issues

(1) Data quality problems: In SOEs, data are often scattered across various departments and systems, with inconsistent data formats and definitions. This heterogeneity can lead to data quality issues such as incomplete, inaccurate, and duplicate data, which affect the accuracy and reliability of data-driven decision-making models.

(2) Data security concerns: R&D data in SOEs often involve trade secrets and sensitive information. Ensuring data security during the collection, storage, and analysis processes is critical. Data breaches or unauthorized access can result in significant losses for the enterprise.

(3) Strategies:

- Establish a comprehensive data governance framework that includes data standardization, data cleaning, and data validation processes to improve data quality.
- Implement strict data security measures, such as data encryption, access control, and user authentication, to protect data from breaches and unauthorized access.
- Strengthen the training of employees on data management and security awareness to ensure compliance with data security policies and procedures.

Model Adaptability and Update Issues

(1) Model adaptability challenges: The business environment and R&D processes of SOEs are dynamic, with changes in market demands, technological advancements, and organizational strategies. Data-driven decision-making models need to adapt to these changes to maintain their effectiveness. However, the complexity of SOEs' R&D management makes it difficult for models to quickly respond to such changes.

(2) Model update and maintenance difficulties: As new data become available and business requirements evolve, data-driven decision-making models require regular updates and maintenance to ensure their accuracy and reliability. This process demands significant human, material, and financial resources, and the complexity of SOEs' R&D management further complicates model updates and maintenance.

(3) Strategies:

- Adopt flexible and modular model architectures that allow for easy adjustments and updates to individual model components in response to changes in business needs.
- Establish a dedicated model maintenance team or collaborate with external data science experts to regularly monitor and update the models. Implement a continuous improvement mechanism that leverages feedback from model applications to enhance model performance.
- Invest in advanced data analysis tools and platforms that can automate certain aspects of model updates and maintenance, reducing the resource requirements for these tasks.

Personnel and Organizational Culture Change Issues

(1) Resistance to change: The implementation of data-driven decision-making models in SOEs requires changes in the work processes and decision-making habits of R&D personnel and managers. Traditional decision-making approaches in SOEs often rely on experience and intuition. Transitioning to a data-driven decision-making paradigm may encounter resistance from employees due to unfamiliarity with the new methods or concerns about the impact on their work.

(2) Shortage of data analytics talent: Data-driven decision-making models rely on professionals with expertise in data analysis, such as data scientists and data analysts. However, SOEs may face a shortage of such talent, which can hinder the effective implementation of data-driven decision-making models.

(3) Strategies:

- Strengthen training and education initiatives to enhance employees' understanding and acceptance of data-driven decision-making concepts and methods. Provide practical training opportunities to help employees develop data analysis skills and become familiar with the use of data-driven decision-making tools.
- Foster a corporate culture that values data and innovation, encouraging employees to actively explore and apply data-driven approaches in their work. Establish incentive mechanisms to recognize and reward employees who successfully implement data-driven decision-making practices.
- Collaborate with universities and research institutions to recruit and develop data analytics talent. Additionally, consider outsourcing certain data analysis tasks to external specialized agencies to supplement internal capabilities during the transition period.

Integration with Existing R&D Management Systems

(1) System integration complexity: SOEs typically have well-established R&D management systems and processes. Integrating data-driven decision-making models with these existing systems without causing conflicts or disruptions is a complex task. Differences in data formats, interfaces, and business logic between systems can pose challenges to seamless integration.

(2) Process reengineering requirements: The implementation of data-driven decision-making models may require modifications to existing R&D management processes. However, the inertia of established processes within SOEs can make it difficult to implement such changes, potentially leading to resistance from employees and managers.

(3) Strategies:

- Conduct a thorough analysis of the existing R&D management systems and processes to identify potential integration points and conflicts with the data-driven decision-making models. Develop detailed integration plans that address data format conversion, interface development, and business process coordination to ensure smooth system integration.
- Adopt a gradual approach to process reengineering, starting with small-scale pilot projects to demonstrate the benefits of the new processes. Use these successes to build momentum for broader changes and provide adequate training and support to help employees adapt to the new workflows.
- Establish cross-functional teams comprising personnel from R&D, information technology, and management departments to oversee the integration process and ensure effective communication and collaboration across departments.

Conclusions and Future Outlook

Research Summary

This paper presents a data-driven decision-making model designed to optimize Integrated Product Development (IPD) R&D management in state-owned enterprises (SOEs). The model incorporates advanced techniques such as data mining and machine learning to provide comprehensive decision support for R&D management tasks like project prioritization, resource allocation, risk assessment, and performance evaluation.

The framework of the model is composed of multiple layers, including data collection, storage, analysis, decision support, and visualization. This structure ensures that the model can effectively handle large volumes of data from various sources and convert them into actionable insights for R&D decision-making.

Through the application of this model, SOEs can significantly enhance their R&D efficiency and product innovation capabilities. The model helps identify potential issues in the R&D process and provides solutions to address these challenges. Additionally, it enables more efficient use of R&D resources, ensuring that they are directed towards projects with the highest potential for success and innovation.

Overall, the implementation of the data-driven decision-making model offers a robust approach for SOEs to optimize their IPD R&D management processes. It equips these enterprises with a powerful tool to navigate the complexities of modern R&D management and enhance their competitiveness in the market.

Research Contributions

(1) Theoretical contributions: This study enriches the theoretical foundations of IPD R&D management by introducing data-driven decision-making models into the specific context of SOEs. The proposed model framework and analytical methods provide new perspectives and approaches for academic research on R&D management in SOEs. Furthermore, the findings contribute to the literature on data-driven decision-making by demonstrating its application and value in the IPD R&D management of SOEs.

(2) Practical implications: The research offers SOEs practical guidance on optimizing their IPD R&D management processes. By adopting data-driven decision-making models, SOEs can enhance the scientific and rational basis of R&D management decisions, improve R&D efficiency and product innovation capability, and strengthen their competitiveness in the market. The case study provides a concrete example of how SOEs can successfully implement such models, offering valuable insights and lessons for other enterprises facing similar challenges.

Future Research Directions

(1) Model enhancement and optimization: Future research can further refine and optimize the data-driven decision-making model by incorporating more advanced machine learning algorithms and deep learning techniques. This will improve the model’s predictive accuracy and adaptability to complex R&D scenarios. Additionally, exploring the integration of other data analysis methods, such as big data analytics and artificial intelligence, with the existing model framework can enhance the model’s functionality and performance.

(2) Cross-industry and cross-enterprise comparative studies: Conducting comparative studies across different industries and enterprises can provide a more comprehensive understanding of the application of data-driven decision-making models in IPD R&D management. By analyzing the differences and similarities in the implementation of these models across various contexts, researchers can identify generalizable patterns and industry-specific best practices, offering more targeted guidance for enterprises in different sectors.

(3) Longitudinal research on implementation effects: This study primarily focused on the short-term effects of implementing data-driven decision-making models in SOEs. Future research can adopt a longitudinal approach to investigating the long-term impacts of these models on R&D performance and enterprise development. This will help to assess the sustainability of the model’s benefits and identify potential issues that may arise over time, enabling the development of more effective strategies for continuous improvement.

(4) Integration with other management models: Exploring the integration of data-driven decision-making models with other R&D management models, such as agile development and lean R&D, can provide enterprises

with more comprehensive and integrated management solutions. Research on how these models can complement and reinforce each other in the context of IPD R&D management can contribute to the advancement of R&D management practices in SOEs and other organizations.

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