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Digital Cost Control and Financial Decision Support in the Intelligent Textile Industry

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Article

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ABSTRACT

For the intelligent textile industry, whose manufacturing processes integrate electronic components into textile substrates, significant cost control and financial decision-making challenges exist. These challenges arise from high supply chain complexity, rapid technological iteration, and market uncertainty. Traditional cost management systems, designed for conventional textile production, are ineffective in this hybrid manufacturing environment, leading to distorted cost information and flawed financial strategies. This paper proposes a data-driven, dual closed-loop integrated management framework tailored for the intelligent textile industry. The first loop establishes a dynamic cost control model for the entire textile product life cycle by integrating Life Cycle Cost (LCC), Target Cost (TC), and real-time activity-based costing (RT-ABC). This model is intended to provide precise, real-time cost data directly from the textile manufacturing floor. The second loop features an agile financial decision support system (FDSS) that utilizes this granular production data to power advanced models, such as real options valuation for R&D projects and dynamic pricing for textile products. By systematically linking real-time manufacturing costs with strategic financial planning, the framework is designed to transform cost data into forward-looking insights. This research proposes a conceptual framework to explore how digital technologies could potentially address critical cost dilemmas in textile R&D, supply chain, and hybrid textile-electronics manufacturing, aiming to enhance the competitive advantage of enterprises in the modern textile industry. A conceptual case study illustrates the framework's application and potential.

KEYWORDS

smart textiles, textile industry, cost control, financial decision support system, intelligent manufacturing

INTRODUCTION

The deep integration of Cyber-Physical Systems (CPS) with traditional manufacturing is leading to a new industrial revolution [1]. The textile industry, as an important sector, is seeking new growth curves through intelligent transformation. Smart textiles, which integrate sensing, communication, computing, and energy modules, upgrade single-function clothing into wearable intelligent terminals, and have huge market potential in areas such as health monitoring, sports science, and human-computer interaction [2]. However, behind the prosperity of this emerging industry lies a common set of management anxieties faced by enterprises. Unlike the large-scale and standardized production mode of traditional textiles, smart textiles exhibit typical "four-high" characteristics: high R&D investment, high technological iteration, high supply chain complexity, and high market uncertainty [3,4].

These industrial characteristics directly impact the core of enterprise management—cost and decision-making [5]. The traditional cost accounting system—built on stable production and clear cost drivers—becomes ineffective in the context of smart textiles. Firstly, the cost structure has undergone a fundamental shift. The costs of electronic components, software algorithms, and data services have significantly increased, and traditional methods for calculating material and labor costs cannot accurately allocate these costs [6]. Secondly, the value chain has been restructured, evolving from a linear supply chain to a complex ecological network that includes technology suppliers, software developers, and data analysis service providers. The points of cost occurrence and the responsible entities have become blurred. More importantly, the rapid changes in market demand and the rapid iteration of technology require enterprises to have extremely high cost flexibility and decision-making agility. Delayed monthly or quarterly cost reports have become the "rearview mirror" for decision-making rather than the "navigation instrument".

Although the academic community has begun to pay attention to this issue, the existing research is clearly fragmented. On the one hand, technological research focuses on material innovation and functional realization [7]; on the other hand, management research mostly applies general digital systems, such as enterprise resource planning (ERP) and manufacturing execution systems (MES), to the textile industry [8,9], or conducts theoretical discussions on financial decision support systems (FDSS) [10]. There are few studies that can truly delve into the "texture" of the intelligent textile industry and propose a systematic solution that connects the entire chain of "data acquisition–cost control–financial decision-making".

Based on this, the core research objective of this paper is to construct a data-driven "cost control–financial decision-making" dual closed-loop integrated management framework specifically for the intelligent textile industry. This framework aims to utilize digital technology to break through the "black box" of cost information, to form a virtuous cycle based on dynamic cost control and to enable agile financial decision-making, thereby providing theoretical support and practical paths for intelligent textile enterprises to establish sustainable competitive advantages in fierce competition.

THE COST CHALLENGES IN THE SMART TEXTILE INDUSTRY AND THE DIGITAL SOLUTION

The Three Key Challenges in Cost Management

Intelligent textile enterprises are confronted with three interrelated dilemmas in terms of cost management.
Challenge 1: "Cost Lock-in" in R&D. Approximately 80% of a smart textile product's life-cycle cost is determined during the design phase. Decisions on technical routes, materials, and software architecture have profound cost impacts, yet R&D teams often prioritize technical implementation over cost efficiency, locking in high costs from the start.
Challenge 2: The "Cost Swamp" in Manufacturing. The hybrid manufacturing process, combining textile and electronics assembly, features complex cost drivers. Hidden "cost swamps" include losses of tiny electronic components, defect rates from integration, and process coordination delays. Traditional cost systems, using simple allocation bases like labor hours, distort product costs and fail to identify these sources of waste.
Challenge 3: "Cost Risk Spillover" in the Supply Chain. The multi-industry supply chain is vulnerable to price fluctuations and supply instability of core electronic components, driven by the global semiconductor market. Upstream risks, like chip shortages, quickly cascade downstream, threatening enterprise costs and delivery schedules. Enterprises often lack tools to dynamically assess and mitigate these external risks.

The Breakthrough Approach of Digital Technologies

Digital technologies enable end-to-end data visibility, breaking down barriers between the physical and information worlds to make costs transparent and predictable.

Solving R&D "Cost Lock-in" with Digital Twin and Big Data

To counter the lack of cost foresight in R&D, a digital twin of the product can be created, modeling material properties, process flows, and supply chain parameters. R&D teams can run "what-if" simulations to evaluate the cost and performance trade-offs of different design choices (e.g., imported vs. domestic fibers). A big data platform provides accurate input parameters for these simulations by analyzing historical project, market, and supplier data, transforming cost estimation from guesswork to data-driven prediction.

Eliminating the Manufacturing "Cost Swamp" with IoT and MES

To capture the "invisible costs" in complex manufacturing, Internet of Things (IoT) sensors are deployed on production equipment and integrated with an MES. This allows for the real-time, automatic capture of granular resource consumption data for every process, including equipment hours, energy use, and material consumption. This data granularity enables real-time activity-based costing (RT-ABC), which can accurately trace previously hidden costs to specific products or processes, allowing for immediate intervention.

Mitigating Supply Chain "Cost Risk Spillover" with Big Data and AI

- To manage supply chain volatility, a big data platform acts as a "risk radar", analyzing external market data (e.g., semiconductor price indices, geopolitical news) alongside internal ERP and supply chain management (SCM) data. AI-powered machine learning models can then predict price trends of core components or issue early warnings for potential supplier delays. This allows enterprises to shift from reactive to proactive risk management, for example, by strategically stocking up before a predicted price increase or certifying alternative suppliers.

Conceptual Data Architecture

A robust data architecture is essential for this framework.

- Data Collection & Ingestion Layer

  Data is sourced from heterogeneous systems, including high-frequency time-series data from IoT sensors, process data from MES, and business data from ERP/SCM systems. A mix of streaming and batch ingestion is used to meet different timeliness needs. Data ingestion latency is monitored, with alerts triggered if it exceeds a predefined threshold (e.g., sub-minute latency targets) to ensure real-time capability.
- Data Storage & Processing Layer

  A unified data lake stores raw data from all sources. A crucial Extract, Transform, Load (ETL) process cleans, normalizes, and validates the data. This includes specific strategies for data loss handling (e.g., interpolation for missing values) and a two-level anomaly detection mechanism using both statistical methods and machine learning models to identify data errors. Real-time computing engines (e.g., Apache Flink) process streaming data for RT-ABC, while batch computing engines handle less urgent, complex analyses.

- Analysis & Application Layer

  This layer hosts the two loops. The first loop (cost control) runs the RT-ABC model, which consumes real-time cost data for immediate feedback. The second loop (decision support) contains the FDSS models (e.g., real options, Monte Carlo simulation), which use the high-quality data from the data platform to generate insights for decision-makers via visual dashboards.

THE FIRST CLOSED-LOOP: CONCEPTUALIZATION OF THE DYNAMIC COST CONTROL MODEL

To achieve effective cost management, this paper has constructed a three-stage, integrated dynamic cost control model. This model is driven by data flow and closely links the cost management activities at the strategic, design, and operational levels, forming the first closed-loop feedback system (Figure 1).

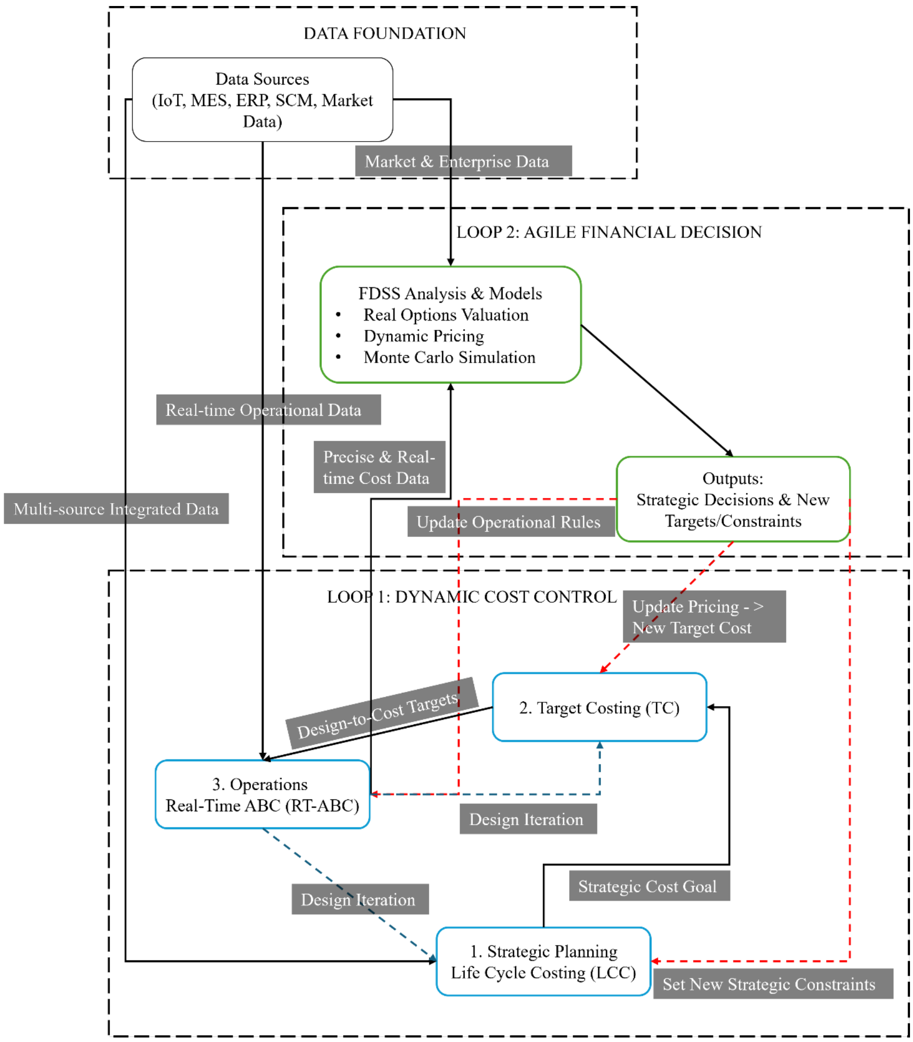

Figure 1. Dynamic Cost Control Closed-Loop Model

Stage One: Strategic Planning Based on Life Cycle Cost (LCC)

During the project initiation and concept design phases, the LCC method should be introduced. Enterprises should not only focus on the current research and development and manufacturing costs, but also estimate the total cost of the product from “cradle to grave”, including research and development, procurement, production, marketing, user use, after-sales maintenance, and final waste recycling costs.

Application Points: The decision-making level utilizes the LCC model to conduct macroeconomic evaluations for different product concepts or technology platforms. For instance, for an intelligent temperature-controlled jacket, Scheme A employs a high-cost but long-lasting graphene heating film, while Scheme B uses a low-cost but periodically replaceable carbon fiber heating sheet. The LCC takes into account the initial investment, user replacement costs, and potential maintenance expenses, helping enterprises select the scheme with the lowest total cost in the long run, thereby establishing a top-level cost strategy.

Furthermore, this LCC model has high scalability and can further integrate environmental, social, and governance (ESG) costs to form a sustainable LCC. For instance, energy consumption data collected through IoT devices can be used to calculate the carbon footprint cost during the product manufacturing process; by tracing the source of raw materials through the SCM system, one can assess whether it complies with social responsibility standards and incorporate the risk costs of compliance or non-compliance into consideration. This will enable the top-level strategic decisions of enterprises to no longer be limited to a single financial goal, but shift toward a more long-term competitive strategy that integrates economic benefits with social and environmental benefits.

Stage Two: Design Guidance Based on Target Cost (TC)

Once the strategic direction is determined, the TC process should be initiated immediately. The core concept of TC is *cost design is driven by market pricing*, and its formula is: TC = Market Forecasted Selling Price - Target Profit. More formally, this is expressed as $TC_{product} = P_{market} - \Pi_{target}$. This total TC is then decomposed into major functional components (e.g., sensing module, textile matrix), such that $TC_{product} = \sum_{i=1}^{n} TC_{component}$, providing specific cost constraints for each design team.

Key points for application:

- Market-driven pricing: Firstly, through market research, competitor analysis, and assessment of consumer value perception, a competitive future selling price is determined.
- TC breakdown: The total TC is decomposed into individual components by using the method of value

engineering (VE), based on functional modules (such as sensing module, communication module, energy module, and textile matrix).

Cross-functional team collaboration: Form a project team consisting of personnel from R&D, procurement, manufacturing, and finance. During the design process, the estimated costs are constantly compared with the target costs. If the cost exceeds the limit, the team must push back the cost within the target range through technological innovation (such as using new materials instead), optimizing the design (such as reducing unnecessary components), or collaborating with suppliers to reduce prices. TC places cost control upfront, avoiding the passive situation after the design is finalized.

Stage Three: Process Control Based on RT-ABC

After the product enters the production operation stage, the RT-ABC model is used for detailed cost accounting and control. This addresses the problem that the traditional ABC method is difficult to implement due to high data collection costs and long accounting cycles. Indeed, modern MES and ERP systems provide a solid foundation for real-time data collection. However, their standard cost modules often fail to fully adapt to the particularities of intelligent textile manufacturing. The superiority of the RT-ABC model in this framework is mainly reflected in its targeted dynamic modeling and unique feedback loop design.

Key points for application:

- Real-time data collection: Through MES and IoT devices, automatically and in real time, collect the actual resources consumed by each operation (such as soldering, sewing, testing) including equipment working hours, electricity, operator working hours, and auxiliary materials.
- Dynamic cost drivers: Cost drivers are no longer static and estimated ratios, but dynamic variables based on real-time data. The key innovation of this model lies in its ability to identify and handle the unique mixed process cost drivers specific to intelligent textiles. For instance, it not only tracks the traditional equipment operation time, but also dynamically analyzes how factors such as sensor mounting accuracy (which directly affects the defect rate), firmware burning duration, and sewing thread density interact to influence the overall cost. This goes beyond the general cost drivers typically provided by standard systems. To operationalize the RT-ABC model, the following key elements are formally defined:
  - Activity Cost Pools (j): A set of core operations identified as major cost consumption units. For intelligent textiles, this includes j∈ [Welding, Sewing, Firmware Burning, Functional Testing, ...]

- Resource Drivers (d): Quantifiable factors that represent the consumption of resources by each activity pool. These include not only traditional drivers like $d \in$ [Operator Hours, Machine Hours, Power Consumption (kWh)] but also unique drivers for this industry, such as a yield correction factor that accounts for material losses of microelectronic components.

Real-time Calculation Formula: The actual cost of a production batch (Cbatch) at any given time (t) is intended to be calculated in real-time. The following formula illustrates the general cost accumulation logic proposed in this framwork:

$$C_{batch}(t) = \sum_{j \epsilon J} \sum_{d \epsilon D} (R_{d,j}(t) \times P_d)$$

where $R_{d,j}(t)$ is the cumulative consumption of resource driver d by activity j up to time t, captured by IoT/MES systems, and Pd is the standard price or rate for resource driver d.

Deviation Threshold: The preset threshold for triggering an alert is mathematically defined. An alert is triggered if the real-time actual cost exceeds the operation-level TC by a certain percentage (δ). Let TCop be the TC allocated to a specific operation. An alert is issued if:

$$C_{op}(t) > TC_{op} \times (1 + \delta)$$

where δ is a dynamically adjustable parameter (e.g., 5%), which can be tightened as process control matures.

- Data Latency Indicator: The real-time nature of the system is quantitatively defined by a strict data latency indicator, aiming to support near-real-time feedback under appropriate data integration conditions. This guarantees that alerts are timely enough for effective intervention. For instance, the functional testing of a certain batch of products is more complex, and the time consumed by the testing equipment and the working hours of engineers will automatically increase. Consequently, the cost of this batch of products will also be higher.
- Difference analysis and feedback: The RT-ABC system can calculate the difference between actual cost and TC in real time, and trace it back to specific operations or materials. The core advantage lies in that the system breaks down and assigns the TC set during the design stage to each specific operation. When

the real-time cost deviates from the preset threshold of the operation-level TC, the system will immediately issue a warning instead of conducting a summary analysis at the end of the month. This instant deviation detection and warning mechanism is the key to achieving active process control, and is much more agile than the periodic reporting of traditional ERP systems. When the difference exceeds the preset threshold, the system issues a real-time alert, which constitutes a multi-level, guiding feedback loop for the model: The production manager can immediately adjust the production process (feedback on operations); if the system discovers through data correlation analysis that the high defect rate stems from design flaws (such as too small component spacing causing welding short circuits), the information will be automatically pushed to the R&D team for iterative design (feedback on design); if it is confirmed that the inability to achieve the cost target is due to an improper strategic positioning, the information will be reported to the management for review of the strategy (feedback on strategy). This closed-loop feedback mechanism, which connects operational cost data in real time and automatically with design and strategic goals, is the unique feature of this framework. It transforms the cost system from a passive “scorecard” into an active “navigator” embedded throughout the entire value chain.

Through the interlocking of these three stages and the data-driven feedback, the enterprise has established a cost control loop that can learn independently and continuously optimize itself.

THE SECOND LOOP: AGILE FINANCIAL DECISION SUPPORT MODEL

Accurate and dynamic cost data is the foundation for high-quality financial decisions, but it is not the end goal. Enterprises need to convert the data into insights to support critical financial decisions. This is where the value of the second loop–the agile FDSS–lies. This system takes the output of the aforementioned cost model as the core input and drives a series of advanced decision-making models. The practical applicability of these models depends significantly on data availability, parameter estimation quality, and the organizational maturity of the enterprise.

Valuation of R&D Projects Based on Real Options

The research and development projects of intelligent textiles are highly uncertain. The traditional net present value (NPV) method often fails to recognize potential innovative projects due to an excessively high risk discount rate [11]. The real options method quantifies the value of management flexibility (such as delaying investment, phased investment, and abandoning the project), making it more suitable for evaluating high-risk projects [12].

FDSS Application:

- Input: The estimated investment for each stage by LCC, the set cost targets for TC, and market forecast data.
- Model: The FDSS incorporates the Black-Scholes option pricing model or the binomial tree model. The R&D project is regarded as a call option, the investment cost is the exercise price, and the future cash flows after the project's success are the value of the underlying asset. The application of these option pricing models is predicated on key assumptions, namely high uncertainty in project outcomes and the presence of managerial flexibility to adapt or abandon the project based on new information. To ensure the model's validity, the FDSS provides a structured approach for estimating its critical parameters:
  - Underlying Asset Value (S): This is the present value of all expected cash inflows after a successful project launch. It is derived from market forecasts and user data, discounted at a rate that reflects the project's systematic risk.
  - Exercise Price (K): This represents the planned capital expenditure required to commercialize the project, such as the investment in production lines and marketing, as estimated by the LCC module.
  - Time to Expiration (T): This is explicitly defined as the project's R&D decision window. For instance, it could be the 2-year period before a major capital commitment for mass production is required, representing the time management has to defer the investment decision.
  - Volatility (σ): This is the most critical parameter and is derived directly from our framework's simulation capabilities. The FDSS uses the Monte Carlo model to run thousands of simulations based on the probability distributions of key cost drivers (e.g., component price fluctuations from the supply chain risk model) and market drivers (e.g., product adoption rates). The standard deviation of the resulting distribution of the underlying asset value (S) is then used as the volatility input. This data-driven approach is more robust than relying solely on historical data from dissimilar products.
  - Risk-Free Interest Rate (r): As a standard financial practice, this is based on the yield of government bonds corresponding to the option's expiration time (T).

- Output: The calculated project value by the system = traditional NPV + option value. A project with a negative NPV but a high option value (meaning it appears to be a loss at present but creates huge possibilities for the future) may also be worth investing in. FDSS provides decision-makers with a more comprehensive perspective, avoiding strategic short-sightedness.

Dynamic Pricing and Profitability Analysis

The value of smart textiles lies not only in the hardware, but also in the data and services it carries. Therefore, the pricing strategy should also be multi-dimensional and dynamic.

FDSS Application:

- Input: The precise unit costs provided by RT-ABC, the user profile data from the customer relationship management (CRM) system, and the price data of market competitors.
- Model: The FDSS incorporates multiple pricing models.
    - Cost-plus pricing: Based on the precise costs calculated by RT-ABC, set the minimum selling price to ensure the basic profit.
    - Value-based pricing: Differentiated pricing is implemented based on users' willingness to pay for different features (such as monitoring accuracy, battery life, comfort level).
    - Penetration/Skimming pricing: Based on the product life cycle stage and market strategy, simulate the changes in sales volume and profits under different pricing scenarios.
- Subscription-based pricing: For intelligent textiles that offer continuous data services, FDSS can help calculate the long-term profitability of models such as "free hardware + service charges" or "low-priced hardware + subscription fees."
- Output: FDSS generates an interactive dashboard where decision-makers can adjust the price parameters and immediately observe the impact on predicted profits, market share, and return on investment, thereby choosing the optimal pricing strategy.

Quantification of Supply Chain Risks and Optimization of Decision-Making

FDSS Application:

- Input: External supplier quotations, historical delivery time data, global component price index, geopolitical risk rating.
- Model: Using Monte Carlo simulation, thousands of simulations are conducted to assess the probability and impact of risk events such as supply chain disruptions and price fluctuations. The rigor of Monte Carlo simulation depends on the accurate definition of the probability distribution of key risk variables

[13]. For instance, the delivery time of suppliers can be modeled using the triangular (PERT) or the log-normal distribution based on historical data; the price fluctuations of core components can be modeled as a geometric Brownian motion process, with the drift rate and volatility parameters being estimated from historical price indices. FDSS will conduct 10,000 sampling iterations based on these distributions to generate the probability distribution of total costs, rather than a single point estimate.

- Output: FDSS no longer merely recommends the supplier offering the lowest price; instead, it provides a ranking based on a risk-adjusted total cost. For instance, Supplier A offers a 5% lower price, but simulations indicate that there is a 20% probability of delayed delivery, which could result in a 10% loss in sales. FDSS quantifies this expected loss, assisting decision-makers in making a trade-off between cost and supply chain resilience.

These two closed loops are closely coupled through data flow: The cost control loop is dedicated to doing it right and keeping the cost low, providing a solid and reliable data foundation for financial decisions; the financial decision loop uses these data for forward-looking analysis, guiding the allocation of resources and strategic direction of the enterprise. The decision results of this loop, in turn, become new targets and constraints for the next round of cost control.

Measuring Financial Agility: Proposed Metrics

Time-Based Metrics: Measuring the Speed and Responsiveness of Decisions

Decision Cycle Time: The total time spent from identifying external market events (such as competitors' price cuts, supply chain disruption warnings) or internal cost anomalies (from the first loop's warnings) to the output of the FDSS optimized decision plan (such as new pricing strategies, adjusted production plans). Benchmark: Compared with the traditional decision-making cycle that relies on monthly/quarterly financial reports (usually several weeks or months).

Insight Generation Time (time to insight): The time required from the output of the RT-ABC system from the first loop's new cost data to the update of the relevant financial forecasting model by FDSS (such as project valuation, profitability analysis) and the generation of new insights in the second loop.

Quality and Breadth Metrics: Measuring the Depth and Robustness of Decisions

Scenario Analysis Breadth: The number of "what-if" simulation analyses that decision-makers can conduct using FDSS within a given decision time window (such as within one day). Agile systems can support more dimensions of scenario exploration (for example, testing 5 pricing strategies and 3 supply options simultaneously), while traditional methods may only be able to analyze one or two.

Forecast Accuracy: Calculating the prediction error (such as mean absolute percentage error (MAPE)) by comparing the profit predictions made by FDSS based on real-time data and advanced models with the actual financial results after the fact, and comparing it with the prediction accuracy based on historical data and traditional methods.

Economic Value Metrics: Measuring the Final Financial Contribution of the Decision

Management Flexibility Return on Investment: Directly quantifying the value brought by the real option model. This is the difference between the total project value (NPV + option value) calculated by FDSS and the NPV calculated by traditional methods. This difference represents the incremental value created by the system when evaluating projects with high uncertainty, due to the full consideration of management flexibility.

Risk-Adjusted Return on Investment: Comparing the investment decisions made using FDSS (embedded Monte Carlo risk simulation) with the final ROI of decisions made without using risk quantification tools. The agile system should be able to achieve higher risk-adjusted returns through more accurate risk identification and hedging.

Evolution toward Autonomous Decision-Making

It is worth noting that the FDSS described in this framework serves as the foundation for achieving higher-level intelligent decision-making. With the maturity of artificial intelligence models (particularly reinforcement learning algorithms), this system has the potential to evolve toward partially autonomous decision-making. For example, in decision-making scenarios that occur frequently in daily operations and have clear rules to follow (such as dynamic safety inventory adjustments based on real-time costs and inventory levels, automatic switching of suppliers for small quantities of raw materials, etc.), the system can, within preset risk thresholds, upgrade from providing decision suggestions to generating approved decision instructions or even automatically executing decisions. This will greatly liberate the managers' energy, allowing them to focus more on handling highly complex strategic issues.

The Coupling Mechanism: Closing the Outer Loop

To specifically illustrate this coupling mechanism, the following presents several examples of how decision outcomes are transformed into new goals:

From dynamic pricing to the update of TC: When the second-loop FDSS, after analysis through the dynamic pricing model, decides to adopt a more aggressive penetration pricing strategy to seize the market, this new market predicted selling price will be directly fed back as an instruction back into the first closed-loop TC calculation formula (TC = market predicted selling price - target profit). This will generate a more challenging new TC for the R&D and manufacturing teams, thereby driving the next round of design optimization and cost reduction activities.

From project valuation to LCC constraints: When real option analysis identifies a research and development project with extremely high future value but also very high current costs, the decision outcome of FDSS may be to approve the project while attaching a clear strategic constraint, such as "the total cost of ownership (TCO) for this product must be 20% lower than that of the previous generation product." This instruction will become a new strategic constraint in the LCC assessment stage of the first loop, guiding the team to choose the technical path with lower maintenance costs and greater durability in the initial stage.

From supply chain risks to adjustments of operational rules: When Monte Carlo simulation indicates that a certain low-price supplier has a high risk of supply disruption, the decision made by FDSS might be "diversify the procurement of key components, and the share allocated to a single supplier should not exceed 60%." This decision outcome will be transformed into a specific business rule and directly updated in the SCM and ERP systems, thereby directly constraining the procurement behavior within the cost control loop at the operational level.

CONCEPTUAL ILLUSTRATION BASED ON A HYPOTHETICAL SCENARIO

The following scenario is purely hypothetical and serves only to illustrate the logical relationships within the framework. It is important to note that this section aims to clarify the specific application process and decision-making logic of the aforementioned dual-loop framework through a hypothetical case, rather than through rigorous empirical verification of its effectiveness. Due to the limitations in obtaining real data, this case is constructed based on reasonable industry assumptions, and the results should be regarded as exploratory. To visually demonstrate the effectiveness of this framework, the following case is set: Fictional SmartTex Corp. plans to develop an intelligent seat cushion for monitoring fatigue among long-distance drivers.

Decision scenario: The company is confronted with two technical options, A and B.

- Option A: Utilize a pressure sensor array combined with a heart rate sensor. This option offers high monitoring accuracy, but the cost of the sensors and algorithms is relatively high.
- Option B: Utilize only a pressure sensor array, and infer the fatigue state by analyzing body posture changes through AI algorithms. This option has low hardware costs, but requires significant investment in algorithm development and training, and there is a risk of recognition failure.

Analysis using the dual closed-loop framework:

For the sake of clarity in this conceptual illustration, we define the following parameters: (1) Let P_{market} be the hypothetical market entry price based on consumer willingness-to-pay; (2) Let R_{margin} (e.g., 30%) be the standard target gross profit margin; (3) Let C_{LCC} represent the estimated life-cycle cost, where $C_{LCC}(A)$ and $C_{LCC}(B)$ denote the costs for Scheme A and Scheme B, respectively.

TC Specification: The target manufacturing cost is derived as $TC = P_{market} \times (1 - r_{margin})$.

RT-ABC Simulation: The simulation indicates that the projected cost for Scheme A ($C_{mfg}(A)$) exceeds TC_{target}, whereas the projected cost for Scheme B ($C_{mfg}(B)$) falls within the target range.

Preliminary conclusion: Scheme B demonstrates a theoretical cost advantage.

Initiate the second closed-loop (financial decision-making):

Traditional NPV Analysis: Under traditional financial metrics, Scheme A yields a marginal or slightly negative Net Present Value (NPV_A). Due to the higher perceived technical risk associated with the AI algorithms in Scheme B (requiring a higher discount rate), its calculated NPV (NPV_B) is significantly lower than NPV_A. Based solely on this static analysis, the less risky Scheme A would be the preferred choice.

Quantitative Valuation: The Real Options module recalculates the value by incorporating the platform option. Assuming a representative volatility factor (σ) for future cash flows, the option value of Scheme B ($V_{option}(B)$) is projected to be substantial due to its high scalability. In contrast, Scheme A's option value ($V_{option}(A)$) remains limited due to its specificity. Consequently, the Total Strategic Value ($V_{total} = NPV + V_{option}$) for Scheme B surpasses that of Scheme A ($V_{total}(B) > V_{total}(A)$), may potentially reverse the initial investment decision.

Final Decision and Efficiency: The company ultimately selects Option B based on the dual-loop analysis. During the subsequent development, the TC process continuously monitors R&D costs against the derived TC_{target}. This decision logic is designed to facilitate a successful market entry. More importantly, the core AI algorithm would theoretically lay the technical foundation for future product lines (e.g., sedentary alerts), thereby potentially achieving sustainable development advantages that traditional cost methods might have overlooked.

In future practical applications, it is necessary to conduct sensitivity analyses on key assumptions (such as the success rate of algorithm development, future service revenue, etc.) to test the robustness of the decision-making results under different scenarios. The summary of performance comparison is shown in Table 1.

Table 1. Conceptual Comparison of Management Approaches

Dimension	Traditional Management Model	Dual Closed-Loop Framework Model
Cost Information	Delayed, vague, static	Relatively real-time, more precise, and dynamic
Project Evaluation	Based on static NPV, inclined to avoid risks	Based on real options, balancing risks and opportunities
Decision Basis	Experience + historical financial statements	Data + model simulation + forward-looking insights
Expected Management Effect	High cost control risks may lead to missed strategic opportunities.	It is expected to achieve controllable cost processes and enhance the opportunities for value discovery.

CONCLUSIONS

This study addresses the unique challenges of the intelligent textile industry and designs and demonstrates a data-driven “cost control–financial decision-making” dual closed-loop integrated management framework. The core contribution of this framework lies in deeply integrating multiple theories and models: it combines the strategic forward-looking nature of LCC, the design guidance of TC, and RT-ABC process control, together with forward-looking financial decision-making models such as real options and Monte Carlo simulation. Through a unified digital platform, these tools are constructed into an organic, self-optimizing interlinked management system, aiming to drive enterprise management to transform from the traditional passive response to the advanced paradigm of real-time prediction and intervention.

However, the practical application of this framework still faces significant challenges in reality. From a technical perspective, the successful operation of the system requires overcoming the interoperability issues of heterogeneous systems (such as IoT, MES, and ERP), and establishing a robust data governance system including data cleaning and verification rules to ensure data quality. At the organizational management level, implementing this framework requires enterprises to undergo profound cultural transformation, shifting from the traditional departmental model to a cross-functional collaborative working model. This may trigger resistance from employees and require enterprises to provide systematic employee training.

Furthermore, the main limitation of this study lies in the fact that its case analysis is based on simulated data rather than real longitudinal enterprise data. This study limits its scope to the theoretical construction of the management framework and does not provide empirical evidence for its operational effectiveness. Future research should validate the proposed model through longitudinal case studies and large-sample quantitative analysis to test its robustness in real-world industrial environments. Secondly, based on the preliminary integration of ESG cost accounting and the partially autonomous decision-making concept presented in this paper, more specific quantitative models and algorithms can be developed. Finally, extending this management framework from a single enterprise to the entire industrial chain to achieve cost and value synergy at the ecosystem level will be another highly valuable research direction.

Author Contributions

Sujuan Wang designed, collected and analyzed the data, and drafted the manuscript. Sujuan Wang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Sujuan Wang 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.

Conflict of Interest

The author declares no conflict of interest.

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Availability of Data and Materials

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

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