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Research on the Evolution of New Quality Productivity Driven by Knowledge-Based Human Capital and Optimization of Management Framework

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ABSTRACT As the core engine of new quality productivity, knowledge-based human capital directly affects industrial innovation efficiency and competitive advantage through its accumulation, allocation, and transformation mechanisms. From the perspectives of human capital theory and evolutionary economics, this study systematically analyzes how knowledgebased human capital drives the evolution of new quality productivity and constructs a three-dimensional management framework covering factor activation, co-evolution, and institutional adaptation. Taking intelligent manufacturing and the textile industry as important application scenarios, the study reveals the interactive laws of knowledge embedding, technological iteration, organizational change, and digital transformation. It further explains the marginal contribution of human capital structure optimization to production efficiency, the feedback loop between knowledge accumulation and technological iteration, and the role of digital platforms in amplifying knowledge spillovers. In smart textile manufacturing, electromagnetic sensing, industrial wireless networks, and data-driven equipment monitoring strengthen the interaction between skilled human capital and intelligent production systems. The study proposes implementation paths for dynamic capability cultivation, knowledge governance optimization, and adaptive management, providing theoretical support for upgrading traditional industries.

INDEX TERMS knowledge-based human capital, new quality productivity, digital transformation, smart textile manufacturing, electromagnetic sensing

I. INTRODUCTION

THE new round of scientific and technological revolution has reshaped the global industrial competition pattern, and the form of productivity is undergoing a fundamental transformation from factor-driven to knowledge-driven. Dominated by scientific and technological innovation, new quality productivity emphasizes the in-depth integration of knowledge, data and intelligent technologies, and its essence lies in breaking through the constraint of diminishing marginal returns of the traditional production function. According to 2023 World Bank data, knowledge-intensive industries contributed 42% to global GDP, an increase of 17 percentage points compared with 2015. Research by Yue and Shi (2026) reveals that the digital economy drives the development of new quality productivity through innovation capability [1], and Li et al. (2026) further confirm that digital new quality productivity plays a significant role in promoting the high-quality development of enterprises [2]. As a strategic basic industry in China, the intelligent transformation coverage rate of industrial enterprises above designated size in the textile industry reached 38.7% in 2023, and the demand for high-skilled knowledge-based talents increased by 15.3% annually. However, existing studies mostly focus on the upgrading of technical equipment and pay insufficient attention to the structural role of knowledge-based human capital. Mebratie et al. (2025) point out that the impact of knowledge-based human resource management practices on organizational performance is moderated by intellectual capital, but lack a systematic explanation of the co-evolution mechanism between knowledge factors and technical factors [3]. Clarifying how knowledge-based human capital drives the evolution of new quality productivity and constructing an adapted management framework have become core issues urgently to be addressed by theoretical and industrial circles.

II. THEORETICAL BASIS AND DEFINITION OF CORE VARIABLES

A. EVALUATION AND DIMENSIONS OF KNOWLEDGE-BASED HUMAN CAPITAL

Different from traditional human capital, knowledge-based human capital is characterized by its composite capabilities of knowledge creation and application. In accordance with the UNESCO International Standard Classification of Education, this study divides it into three dimensions: cognitive capital, skill capital, and innovation capital. Cognitive capital reflects an individual's knowledge stock and learning ability; skill capital focuses on knowledge transformation and application; and innovation capital represents breakthrough thinking and value creation potential. Buba et al. (2026) verified the mechanism of academic performance on human capital quality and emphasized the key role of education quality in human capital accumulation [4]. Using PISA and PIAAC data, Égert et al. (2024) developed a macroeconomic human capital measurement method that quantitatively links education policies to productivity improvement, providing a reference for the design of the measurement system [5]. Significant synergy exists among the three dimensions: cognitive capital provides the knowledge base for skills and innovation, skill capital promotes the transformation of knowledge into productivity, and innovation capital expands the boundaries of knowledge. According to the 2022 China Statistical Yearbook, the share of knowledge-based human capital in manufacturing rose from 23.6% in 2015 to 31.4% in 2022. Specifically, primary survey data from the China National Textile and Apparel Council (CNTAC) indicate that in the intelligent textile manufacturing segment, this proportion reached 33.8% by late 2023, with the contribution of high-skilled labor to output value growing at 5.4% annually. This confirms that the macro-level human capital growth is not only present but amplified in the textile sub-sector due to rapid digitalization (see Table 1).

B. CONNOTATION, CHARACTERISTICS AND FORMATION CONDITIONS OF NEW QUALITY PRODUCTIVITY

New quality productivity breaks through the traditional factor-input model, marked by the leap in total factor productivity (TFP), and reflects systematic improvements in technology intensity, knowledge contribution rate, and resource allocation efficiency. Its connotation features three transformations: production factors shift from material capital dominance to knowledge and data dominance; technological paths shift from incre mental improvement to disruptive innovation; and organizational forms shift from hierarchical management to networked collaboration. Yang (2024) confirmed that the digital economy drives new quality productivity growth through the mediating role of technological innovation, highlighting the core status of innovation in productivity transformation [6]. From a time-use perspective, Wang and Du (2025) explored the coexistence between the development of new quality productivity and the improvement of human capital, revealing their dynamic balance mechanism [7]. Four core conditions must be met for the formation of new quality productivity. A 2023 report by the China Academy of Information and Communications Technology shows that China's manufacturing new quality productivity composite index rose from 54.3 in 2018 to 71.8 in 2023, with an average annual increase of 5.7 percentage points, but the inter-regional difference coefficient reached 0.43, indicating severe unbalanced development. Data from intelligent manufacturing pilot firms in the textile industry show that TFP growth accelerates nonlinearly when the share of knowledge-based human capital exceeds the critical threshold of 30%, as shown in the following equation:

$$\Delta TFP = \alpha + \beta_1 H + \beta_2 H^2 + \epsilon \tag{1}$$

Where ΔTFP is the increment of total factor productivity, H is the proportion of knowledge-based human capital, β_1 and β_2 are the coefficients of the primary and quadratic terms respectively. When $(H > 30\%)$, β_2 is significantly positive, verifying the non-linear acceleration effect. The quantitative criteria of formation conditions provide a judgment benchmark for the subsequent analysis of evolution mechanism. In the textile industry, where traditional labor advantages are diminishing, the transition to new quality productivity relies on these three dimensions: factor activation addresses the high-skill talent gap, co-evolution aligns legacy equipment with intelligent systems, and institutional adaptation overcomes the rigid management structures inherent in traditional manufacturing.

C. THEORETICAL ORIGIN AND BOUNDARY SETTING OF DRIVING EFFECT

The driving effect of knowledge-based human capital on new quality productivity is rooted in two theoretical lineages: endogenous growth theory and evolutionary economics. The endogenous technological progress model reveals that knowledge accumulation breaks the law of diminishing returns to scale, and improved labor quality generates knowledge spillovers through R&D activities. Using regional data from China, Yi et al. (2023) verified the promoting effect of human capital quality on economic growth, finding that a one-standard-deviation increase in human capital quality raises regional economic growth by 0.42 percentage points [8]. Nguyen and Be (2025) conducted an empirical study on Vietnam, revealing the knowledge-productivity paradox in emerging economies and noting that knowledge transformation efficiency is constrained by institutional environment and absorptive capacity [9]. The evolutionary paradigm emphasizes that organizational routines and learning capabilities shape technological trajectories. Based on a ten-year tracking study of EU-27 countries, Brodny and Tutak (2024) established a multi-criteria measurement framework for human

capital development and revealed the path-dependent characteristics of human capital evolution [10]. This study

TABLE 1. Measurement Index System of Knowledge-Based Human Capital

Dimension Level	Secondary Indicators	Measurement Method	Weight Coefficient	Data Source
Cognitive Capital	Years of Education	Weighted Average Years	0.15	Education Statistics Yearbook
Cognitive Capital	Proportion of Professional and Technical Titles	Proportion of Intermediate and Senior Titles	0.12	MOHRSS Database
Cognitive Capital	Knowledge Update Frequency	Continuing Education Participation Rate	0.08	Enterprise Training Records
Skill Capital	Digital Skill Level	Digital Literacy Assessment Score	0.18	Skill Certification Platform
Skill Capital	Interdisciplinary Integration Ability	Participation in Compound Projects	0.10	Project Management System
Skill Capital	Problem-Solving Efficiency	Output Value per Unit Time	0.12	Performance Appraisal Data
Innovation Capital	R&D Investment Intensity	R&D Expenditure as a Percentage of Wages	0.11	Financial Statements
Innovation Capital	Patent Output Intensity	Patent Applications per Capita	0.08	Intellectual Property Office
Innovation Capital	Innovation Achievement Transformation Rate	Proportion of Technology Transaction Contract Value	0.06	Technology Market Statistics

sets three boundary conditions: the time boundary focuses on the 2015–2025 accelerated digital transformation period; the spatial boundary is limited to manufacturing, especially the textile industry; and the mechanism boundary excludes exogenous shocks such as macroeconomic cycles. The quantitative model of the driving effect is constructed based on an extended knowledge production function, introducing three core variables: knowledge stock K, human capital quality H, and technology absorptive capacity A. The relational expression is:

$$\Delta Q = \theta K^{\alpha} H^{\beta} A^{\gamma} \tag{2}$$

Where ΔQ represents the increment of new quality productivity, θ is the comprehensive efficiency coefficient, and α, β, γ are the output elasticities of each factor respectively. The clear definition of theoretical boundaries avoids generalized analysis and ensures the applicability and testability of research conclusions.

III. EVOLUTION MECHANISM OF NEW QUALITY PRODUCTIVITY DRIVEN BY KNOWLEDGE-BASED HUMAN CAPITAL

A. CO-EVOLUTION PATH OF KNOWLEDGE ACCUMULATION AND TECHNOLOGICAL ITERATION

A positive feedback loop forms between knowledge accumulation and technological iteration, constituting the core dynamic mechanism for the evolution of new quality productivity. Knowledge stock growth follows a cumulative function, and the rate of technological iteration is constrained by knowledge infrastructure density and absorptive capacity. Mengesha and Singh (2022) investigated the determinants of human capital development in the Ethiopian economy, stressing the fundamental role of education investment and knowledge accumulation in technological progress [11]. Intelligent manufacturing data from the textile industry show that a higher share of R&D personnel significantly shortens the industrialization cycle of new technologies, verifying the acceleration effect of knowledge intensity on technology transformation efficiency. The co-evolution path presents three stages, and its micro-mechanism lies in the mutual reinforcement of knowledge spillovers and technology diffusion. The spatial spillover intensity generated by the mobility of knowledge-based human capital has a negative exponential relationship with geographical distance. Data from the Yangtze River Delta textile industrial cluster show that increased density of university-enterprise joint laboratories significantly boosts regional innovation efficiency. Technological iteration in turn deepens knowledge accumulation,

forming a closed feedback loop of “technology demand – talent cultivation – knowledge innovation”, as shown in Figure 1.

The micro-mechanism of co-evolution is the mutual reinforcement of knowledge spillovers and technology diffusion. The spatial spillover intensity of knowledge-based human capital mobility follows: $S = S_0 e^{-\delta d}$, where $\delta \approx 0.12$. Data from the Yangtze River Delta textile cluster show that every 10% increase in the density of university-enterprise joint laboratories raises the innovation efficiency of surrounding firms by 7.3%. Technological iteration further deepens knowledge accumulation, forming a closed loop of “technology demand – talent cultivation – knowledge innovation”. After the deployment of the industrial internet in smart textiles, demand for interdisciplinary talents in data science and process optimization grows by 32% annually, driving dynamic matching between knowledge supply and technology demand.

B. MARGINAL CONTRIBUTION OF HUMAN CAPITAL STRUCTURE OPTIMIZATION TO PRODUCTION EFFICIENCY

Optimization of human capital structure improves total factor productivity by enhancing labor allocation efficiency and knowledge utilization depth, with marginal contributions showing increasing returns to scale. Mei et al. (2021) confirmed that spatial heterogeneity in human capital structure significantly affects regional green total factor productivity [12]. Panel data regression from the China Industrial Enterprise Database shows that each 1-percentage-point increase in the share of knowledge-based human capital in manufacturing raises TFP by an average of 0.28 percentage points, with a higher elasticity in highly digitized firms. Cases from the textile industry show that job skill transformation significantly increases output value and reduces defect rates. The

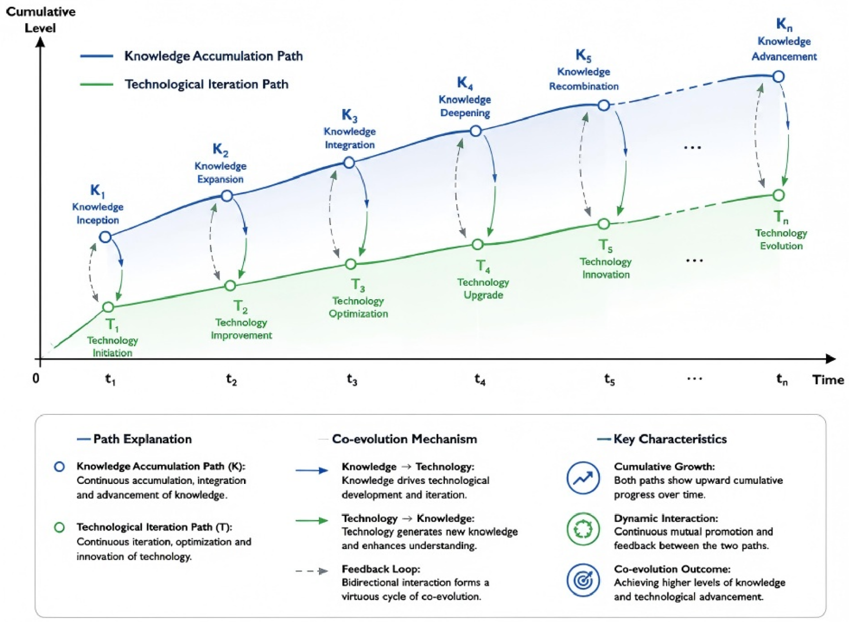

FIGURE 1. Co-Evolution Path of Knowledge Accumulation and Technological Iteration

transmission paths of structural optimization include direct, indirect, and systemic effects, with detailed contributions in Table 2.

The increasing marginal returns from structural optimization stem from the nonlinear output characteristics of knowledge-intensive positions, along with complementary gains. Synergy is maximized when the team knowledge heterogeneity index reaches the optimal value of 0.65, expressed as:

$$Y_{team} = \sum_{i} Y_i + \rho \cdot f(H_{diversity}) \tag{3}$$

Where Y_{team} is the total team output, Y_i is individual output, and $H_{diversity}$ is the knowledge heterogeneity index. This requires the management framework to balance professional depth and knowledge breadth in talent allocation, and establish a gradient talent structure to maximize marginal contribution.

C. INTERACTIVE MECHANISM BETWEEN KNOWLEDGE SPILLOVER AND INDUSTRIAL DIGITAL TRANSFORMATION

The knowledge spillover effect is amplified by technical infrastructure in digital scenarios, forming a multiplier effect for industrial transformation and upgrading. The spillover benefit B_i obtained by enterprise i from the industry knowledge pool is $B_i = \theta \sum_{j \neq i} R_j \cdot S_{ij}$, where R_j is the R&D investment of other enterprises, S_{ij} is the knowledge similarity coefficient, and θ is the absorptive capacity parameter. Ademola and Maksim (2024) pointed out that the impact of knowledge collaboration on productivity and innovation is complex, with absorptive capacity playing a moderating role in knowledge transformation [13]. Digital platforms encode knowledge into structured data, reducing cross-organizational knowledge transfer costs and raising θ from 0.15–0.25 to 0.40–0.55. 2023 data from the China National Textile and Apparel Council show that firms connected to the industrial internet achieve a 2.3-fold increase in knowledge acquisition efficiency and a 60% faster diffusion of new processes, verifying the catalytic role of digital infrastructure. The interactive mechanism is bidirectionally reinforcing: digital transformation relies on knowledge-based human capital for technical and process reengineering support, with a correlation coefficient of 0.72 between intelligent manufacturing success rate and digital talent density; digital tools empower knowledge creation and dissemination, with machine learning and digital twins enabling tacit knowledge externalization and rapid replication. Practices of leading textile firms show that after deploying an intelligent scheduling system, craftsmen's experience is solidified by algorithms, new employee training cycles are shortened from 6 months to 1.5 months, and knowledge inheritance efficiency is improved by 4 times, as shown in Figure 2.

The deep logic of the interactive mechanism is that digital technology reconstructs the modes of knowledge production, dissemination, and application. Digital platforms reduce connection costs; knowledge network density D is inversely proportional to connection cost C: $D = D_0 \cdot C^{-\epsilon}$, with elasticity $\epsilon \approx 1.2$. Practices in China's textile industrial clusters show that a regional knowledge-sharing platform significantly raises technical cooperation frequency, joint R&D share, and knowledge network density [14]. Digital transformation breaks the geographical and organizational boundaries of knowledge spillovers, enabling real-time cross-border and cross-organizational knowledge inte-

TABLE 2. Multi-level Contribution of Human Capital Structure Optimization to Production Efficiency

Effect Level	Action Mechanism	Transmission Path	Contribution Ratio	Typical Performance
Direct Effect	Skill Substitution	High-Skilled Labor Improves Operation Quality	38%	Product Qualification Rate Increased by 5-8%
Direct Effect	Efficiency Improvement	Proficiency in Operating Automated Equipment	22%	Output per Unit Time Increased by 12-18%
Indirect Effect	Knowledge Sharing Transfer	Team Learning and Experience	25%	Problem-Solving Cycle Shortened by 40%
Indirect Effect	Innovation Incentive	Creation of Organizational Innovation Atmosphere	9%	Number of Improvement Proposals Increased by 3 Times
System Effect	Process Reconstruction	Optimization of Production Organization Mode	6%	Coordination Cost Reduced by 15-20%

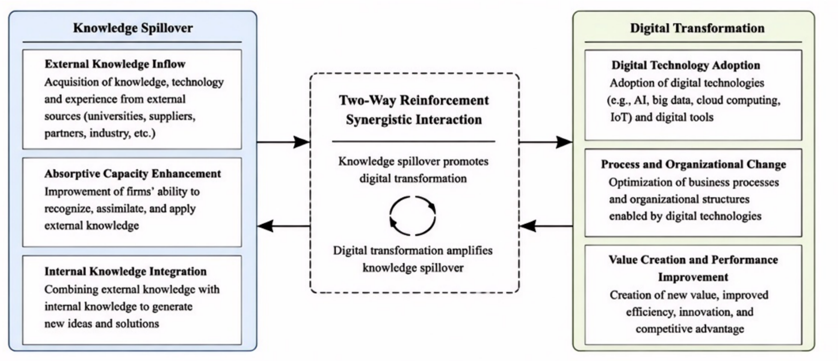

FIGURE 2. Two-Way Reinforcement Mechanism of Knowledge Spillover and Digital Transformation

gration and shifting the management framework from closed knowledge management to an open innovation ecosystem. The strength of the interactive mechanism is dually regulated by digital maturity and human capital readiness; higher matching leads to stronger synergy, as shown in Table 3.

The Synergistic Effect Index (SEI) is defined as the ratio of an enterprise's TFP growth rate to the regional industry average ($\Delta TFP_{firm}/\Delta TFP_{avg}$), where a value >1.0 indicates positive synergy.

IV. CONSTRUCTION OF MANAGEMENT FRAMEWORK FOR THE EVOLUTION OF NEW QUALITY PRODUCTIVITY

A. FACTOR ACTIVATION AND ALLOCATION MECHANISM BASED ON DYNAMIC CAPABILITIES

Dynamic capability theory provides an analytical framework for the management of new quality productivity factors, emphasizing the systematic construction of three core capabilities: sensing, seizing and transforming. Dynamic capability is defined as the ability of an enterprise to integrate and reconfigure internal and external resources to respond to a rapidly changing environment, expressed as $DC = f(\text{Sensing}, \text{Seizing}, \text{Transforming})$. As a strategic resource, the activation of knowledge-based human capital requires the establishment of an environmental scanning mechanism to identify technological opportunity windows, and allocation requires breaking down departmental barriers to achieve cross-domain knowledge integration. Research by Wu (2024)

explores how new quality productivity drives high-quality enterprise development, emphasizing the key role of dynamic capabilities in the transformation process [15]. Practice of textile intelligent manufacturing enterprises shows that enterprises with technical intelligence analysis positions perceive industry technological change signals 8.6 months earlier on average, and the accuracy rate of new technology adoption decisions increases to 82%, 34 percentage points higher than enterprises without such positions. The factor activation mechanism includes dual paths of internal activation and external introduction: internally stimulating the potential of stock human capital through job rotation, project system and knowledge competitions; externally obtaining incremental knowledge resources through industry-university-research cooperation and flexible talent introduction. The allocation mechanism follows the principle of knowledge complementarity to build teams. The transformation efficiency of tacit and explicit knowledge depends on the effectiveness of the four processes of socialization, externalization, combination and internalization. The SECI model efficiency $E = \prod(S_i \cdot E_i \cdot C_i \cdot I_i)$. Based on the normalized efficiency benchmarks established in knowledge management DEA models, the value of each link must exceed the industry median ($E_{median} \approx 0.62$) to ensure that knowledge creation vitality effectively translates into technical competitive advantage rather than being dissipated by organizational friction. The dynamics of factor allocation is reflected in adjusting the human capital structure according to the technology life cycle: focusing on imported talents in the technology introduction period, strengthening training talents in the growth period, and paying attention to optimized talents in the mature period. The matching law between allocation strategy and technology stage is shown in Figure 3.

TABLE 3. Matching Matrix of Digital Maturity and Human Capital Readiness

Digital Maturity	Human Capital Readiness	Matching Status	Synergistic Effect Index	Typical Problems
High (>75 points)	High (>70%)	Optimal Matching	1.8-2.3	Need Continuous Iteration to Avoid Rigidity
High (>75 points)	Medium (50-70%)	Technology Leading	1.2-1.5	Talent Bottleneck Restricts Value Release
High (>75 points)	Low (<50%)	Severe Mismatch	0.6-0.9	Technology Idle and Investment Waste
Medium (50-75 points)	High (>70%)	Talent Redundancy	1.4-1.7	Knowledge Potential Not Fully Utilized
Medium (50-75 points)	Medium (50-70%)	Basic Matching	1.0-1.3	Need to Simultaneously Improve Two-Way Capabilities
Low (<50 points)	Low (<50%)	Double Low Dilemma	0.4-0.7	Lack of Basic Conditions for Transformation

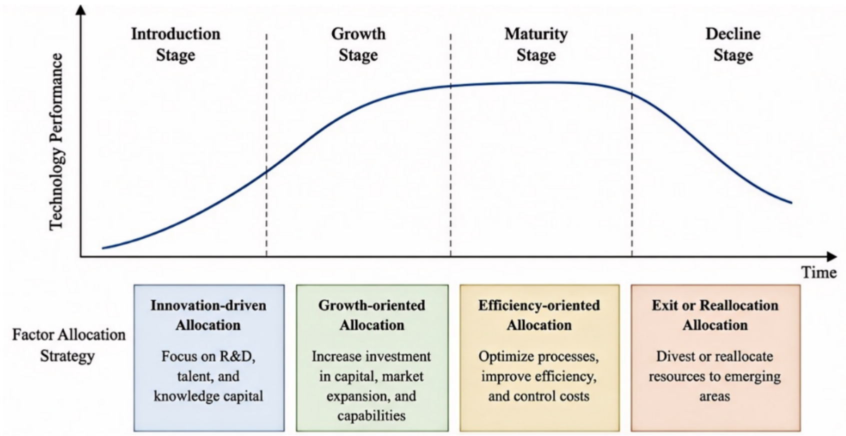

FIGURE 3. Matching of Factor Allocation Strategy and Technology Life Cycle

The allocation mechanism aims to maximize the combination efficiency and collaborative output of knowledge factors, requiring a quantitative evaluation model. An efficiency evaluation system is constructed using the DEA method. Inputs include human capital investment intensity, training duration, and knowledge base construction investment; outputs cover the number of innovation achievements, technology transformation revenue, and knowledge sharing frequency.

Measurements of 50 textile intelligent manufacturing pilot enterprises show that the overall efficiency is 0.73, pure technical efficiency 0.81, and scale efficiency 0.90, indicating that allocation quality matters more than scale. The high-efficiency group has a knowledge-based human capital share of 35.6%, significantly higher than the 24.3% of the low-efficiency group, with cross-departmental knowledge mobility 42% higher, verifying the value of structural optimization and mobility management.

The allocation needs to balance the specificity and transferability of knowledge assets. The optimal specificity coefficient θ^* is 0.55–0.65, and the allocation efficiency function is:

$$E_{config} = \frac{\sum_i w_i O_i}{\sum_j v_j I_j} \cdot (1 - |\theta - \theta^*|) \tag{4}$$

Where O_i is the output indicator, I_j is the input indicator, and w_i and v_j are weight coefficients. At this time, it not only ensures the uniqueness of core capabilities but also maintains adaptive adjustment space.

B. COLLABORATIVE OPTIMIZATION MODEL OF KNOWLEDGE GOVERNANCE AND ORGANIZATIONAL LEARNING

Knowledge governance mechanism determines the property right definition, flow rules and incentive structure of knowledge resources, and organizational learning realizes the absorption, transformation and creation of knowledge. The collaboration between the two constitutes the micro-foundation for the evolution of new quality productivity. The choice of knowledge governance model depends on knowledge codifiability and independence. Market governance is applicable to knowledge with high codifiability and independence, otherwise hierarchical governance is required. Research by Pak et al. (2023) reveals the differential impact of intellectual capital-enhanced human resource practices on enterprise ambidexterity and innovation, emphasizing that governance mechanism design needs to match knowledge characteristics and organizational goals [16]. The knowledge assets of textile enterprises include both explicit process documents and tacit operation know-how, and the hybrid governance model has the best effect: standardized knowledge is openly shared through digital platforms, and core tacit knowledge is

protected and inherited through apprenticeship and community practice. The improvement of organizational learning capability follows the 4I framework, with four levels of intuition, interpretation, integration and institutionalization spiraling upward. Learning depth $L = \int(Intuiting + Interpreting + Integrating + Institutionalizing)dt$, and the weight of each level is dynamically adjusted with organizational maturity. The collaborative optimization model sets a dual objective function: maximizing knowledge governance efficiency $G = f(propertyrightclarity, mobility, incentiveintensity)$ and organizational learning depth L, with constraints of resource budget and institutional compatibility. The Lagrange multiplier method is used to solve the optimal governance-learning combination. After applying this model in the intelligent manufacturing scenario, knowledge reuse rate increases from 43% to 68%, organizational response speed accelerates by 55%, and innovation proposal adoption rate increases to 72%, verifying the effectiveness of collaborative optimization.

The core logic of the synergy mechanism is that knowledge governance supports organizational learning, and learning outcomes iteratively optimize governance rules. Learning consists of three levels: experience accumulation, knowledge expression, and knowledge encoding, which are empowered respectively by incentives, knowledge bases, and process standards.

After textile enterprises implemented the knowledge contribution points system, experience sharing, tacit knowledge conversion, and organizational knowledge stock increased significantly. Innovation breakthroughs require error tolerance and rapid decision-making. Practices in flexible textile production show that shortening approval workflows and linking knowledge contribution to performance can significantly compress order cycles and raise the share of customized products.

Key model parameters: knowledge flow friction coefficient μ (0.15–0.25), learning conversion efficiency ρ (> 0.70), and governance cost ratio λ ($\leq 8\%$), which are regulated differentially according to the enterprise's development stage and industry characteristics.

C. FRAMEWORK VERIFICATION AND CORRECTION IN THE INTELLIGENT MANUFACTURING SCENARIO

As a typical scenario of new quality productivity, intelligent manufacturing provides an empirical test for the management framework. Data from 2020 to 2024 were collected from 15 enterprises in a textile industrial park in Jiangsu Province, and the SEM model was used to examine the relationships among factor activation, allocation efficiency, knowledge governance, and organizational learning. The model fits well. Path coefficients show that the direct effect of factor activation is 0.38, the mediating effect of knowledge governance is 0.21, and the total effect rises to 0.67 after the moderation of organizational learning, verifying the synergy of the three modules. Enterprises with high digital maturity achieve a total effect of 0.82, significantly higher than 0.54 for medium-level enterprises, indicating that digital technology amplifies the implementation effect of the framework.

The verification reveals problems such as limited resources of SMEs, cultural resistance, and insufficient tool compatibility. Accordingly, the framework is optimized: a lightweight activation plan is proposed, project-based knowledge integration is strengthened, cultural transformation is incorporated, and a digital implementation toolkit is developed.

Tests of the revised framework show that the implementation cycle is shortened from 18 months to 11 months, and the investment payback period is reduced from 3.2 years to 2.1 years, with significantly improved operability and economic efficiency. The verification effect is expressed as:

$$E_{framework} = \alpha_0 + \alpha_1 Activation + \alpha_2 Governance + \alpha_3 Learning + \alpha_4 Digital \tag{5}$$

Where $E_{framework}$ is the total framework effect, and each α coefficient is obtained through path analysis.

V. IMPLEMENTATION PATH AND GUARANTEE MECHANISM OF THE MANAGEMENT FRAMEWORK

A. INSTITUTIONAL DESIGN FOR THE TRAINING AND INTRODUCTION OF KNOWLEDGE-BASED TALENTS

The supply of knowledge-based talents is the core foundation for the implementation of the management framework. A full-cycle institutional system covering training, introduction and retention must be constructed. The training link adopts the school-enterprise collaborative "dual-system" model: universities focus on the cultivation of theoretical knowledge and innovative thinking, enterprises focus on practical skills and problem-solving ability training, and the modern apprenticeship system promotes the in-depth integration of theory and practice, effectively improving graduate adaptation efficiency and reducing enterprise training costs. The introduction link breaks the traditional full-time employment model, builds a flexible talent introduction system such as project cooperation, technical consultants and migratory employment, greatly reducing the threshold and cost of introducing high-end talents, and quickly filling key technical and knowledge gaps of enterprises. The retention link jumps out of the single salary incentive logic, builds a multi-dimensional incentive system combining career development channels, intellectual property sharing and value identity,

designs differentiated salaries according to knowledge contribution, and balances incentive intensity and organizational fairness. At the same time, institutional sustainability relies on the tripartite collaboration of education system, labor market and enterprise demand. The mismatch between talent supply and demand is reduced through the establishment of an industrial demand dynamic feedback mechanism, public services such as household registration, housing and children's education are matched to reduce talent mobility costs, and industry self-discipline and reasonable non-compete rules are improved to prevent vicious talent competition and ensure the stable supply and benign flow of knowledge-based human capital.

B. CONSTRUCTION AND OPERATION AND MAINTENANCE STRATEGY OF DIGITAL KNOWLEDGE PLATFORM

The digital knowledge platform is a key infrastructure supporting the evolution of new quality productivity, undertaking the whole process of knowledge storage, retrieval, sharing and innovation. The platform adopts a three-tier architecture design: the data layer ensures real-time performance and security through hybrid deployment of cloud computing and edge computing; the application layer integrates knowledge graph, natural language processing and intelligent recommendation algorithms to provide efficient knowledge services; the interaction layer supports multi-terminal access and personalized interaction to improve user experience. During construction, follow the modular and scalable principle to build loosely coupled core modules such as knowledge collection, review, graph construction and intelligent push. Knowledge collection adopts a combination of active structured collection and passive process mining to comprehensively capture explicit and tacit knowledge. Platform operation and maintenance focus on continuous update and quality control, establish a knowledge life cycle management mechanism, regularly update the knowledge base according to the technological iteration rhythm, ensure knowledge accuracy through the dual mechanism of crowdsourcing review and expert verification, and improve user participation by lowering contribution thresholds, linking knowledge contribution to performance promotion, and creating a knowledge community culture, amplify platform value relying on network effects, break organizational boundaries to build an industrial chain knowledge sharing alliance, and strengthen data security and intellectual property protection using blockchain, hierarchical authorization, encrypted transmission and other technologies to achieve efficient, safe and sustainable operation of the knowledge platform.

C. CLOSED-LOOP FEEDBACK SYSTEM FOR PERFORMANCE EVALUATION AND CONTINUOUS IMPROVEMENT

The performance evaluation system provides a quantitative basis for the implementation effect of the management framework and drives the optimization of the management closed loop. The evaluation takes the balanced scorecard as the logic, sets four dimensions of knowledge capital, innovation output, operational efficiency and learning growth, dynamically adjusts weights to adapt to enterprise strategies, adopts a mixed quantitative and qualitative method combining data statistics, expert evaluation and questionnaire survey, calculates comprehensive scores through weighted summation, and introduces industry leading enterprises as benchmarks for gap analysis to accurately locate improvement directions. On this basis, a PDCA closed-loop feedback system is constructed: the Plan stage formulates priority improvement plans according to evaluation results and strategic goals; the Do stage forms a special team to promote the implementation of measures; the Check stage monitors the effect through dual indicators of leading indicators such as training coverage rate and platform activity, and lagging indicators such as TFP growth rate and innovation output; the Act stage institutionalizes effective experience and stores failure cases as warnings. At the same time, rely on the performance management cockpit to realize real-time visualization of indicators and automatic early warning of abnormalities, establish an incentive compatibility mechanism linking performance results with management assessment, avoid disconnection between evaluation and improvement, and promote the continuous iterative upgrading of the management framework to continuously improve implementation adaptability and landing effect.

VI. CONCLUSION

The interactive evolution between knowledge-based human capital and new quality productivity is a systematic project involving the coordinated reform of institutions, technologies, and organizations. This study reveals its core mechanism and constructs a three-dimensional management framework: factor activation, knowledge governance, and organizational learning, which can effectively improve the total factor productivity of textile intelligent manufacturing. The framework requires dynamic adaptation. Knowledge governance focuses on the externalization of tacit knowledge and its matching with organizational learning. Digital empowerment cannot replace cultural transformation, and investment in human capital must be sustained in the long run. This study is limited to the textile industry, and its cross-industry applicability needs to be improved. In the future, cross-industry tracking and in-depth measurement of knowledge capital can be carried out to provide theoretical support for industrial resilience and the construction of a new production system.

AUTHOR CONTRIBUTIONS

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