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The construction and implementation path of digital factory under the framework of high efficiency industrial automation system integration

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SUMMARY: *With the continuous deepening of digital transformation, manufacturing enterprises have put forward higher requirements for production collaboration, real-time response and fine control. Focusing on the construction and implementation path of the digital factory under the framework of high efficiency industrial automation system integration, this paper constructs an overall method covering target decomposition, system architecture design, multi-level data integration, collaborative control of industrial Internet and edge computing, digital twin and intelligent analysis and optimization, and phased promotion. In the verification of a discrete manufacturing workshop, 68 key devices and 214 sensing acquisition points are connected to the system. The success rate of device access is 98.6%, the average response time delay is 0.75 s, the success rate of scheduling is 96.0%, the first pass rate of products is increased to 97.1%, and the energy consumption per unit output value is reduced by 18.3%. The research shows that the path can enhance the ability of factory data penetration, business interaction and continuous optimization, and has practical reference significance for the digital upgrading of manufacturing enterprises.*

KEYWORDS: *digital factory; Industrial automation; System integration; Industrial Internet*

1 Introduction

The mode of manufacturing competition is shifting from single-point equipment efficiency competition to full-process, full-factor and full-link collaborative ability competition. Traditional factories rely on decentralized control, manual cohesion and experience scheduling to maintain operation, which is difficult to adapt to the practical requirements of flexible production, quality traceability, energy consumption optimization and rapid delivery in parallel. As technologies such as industrial Internet, edge computing, digital twin, machine vision and intelligent analysis continue to enter the production site, the digital factory is no longer just a simple superposition of equipment networking and information on the screen, but a systematic construction process formed around data penetration, business collaboration, state perception and intelligent decision-making. Especially under the support of high performance industrial automation system integration framework, the boundaries between production equipment, control unit, manufacturing execution system, enterprise resource planning system and operation and maintenance platform are being re-opened, and the factory operation is gradually shifting from "local automation" to "overall collaboration".

However, from the current construction practice, many enterprises still have a number of prominent problems in the promotion of digital factories. First, heterogeneous device protocols are complex, and the underlying data acquisition standards are not uniform, which

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leads to breakpoints in information transmission between device layer, control layer, production layer and management layer. Second, some system construction stays in the optimization of single module and lacks the overall design for business closed loop. Although some functions are launched quickly, it is difficult to form a coordination mechanism covering planning, production, detection, storage, energy consumption, and operation and maintenance. Third, the real-time perception ability is disconnected from the analysis and decision-making ability, and the amount of data collected in the field continues to grow, but the data quality management, edge side processing and high-value application transformation are insufficient, resulting in the phenomenon of "data is difficult to apply". Fourth, many implementation plans focus on technical stacking, and do not consider the phased construction path, investment rhythm and landing suitability enough, which affects the continuous promotion effect of digital factories.

Based on this, this paper focuses on the construction and implementation path of digital factory under the framework of high efficiency industrial automation system integration, focusing on the key links of construction goal decomposition, system architecture design, multi-level data integration, real-time perception and collaborative control, production optimization and phased implementation promotion, trying to build an implementation idea that takes into account both technical feasibility and engineering implementation. In order to provide more operational reference for the digital transformation of manufacturing enterprises.

2 Literature Review

2.1 Research status of integration of digital factory and industrial automation system

In recent years, the research on digital factory has significantly shifted from equipment access and information visualization to system collaboration and operation reconstruction. Early discussions focused more on automation equipment networking, control system transformation and production site data collection, while the research goal was relatively focused on improving the information transparency of local links. As the manufacturing scene becomes increasingly complex and the pace of product iteration accelerates, it is difficult to support the stable operation of the factory solely relying on a certain type of control system or a certain business module. Therefore, the digital factory is gradually understood as a comprehensive system covering production organization, process execution, quality tracking, equipment operation and management decision-making [1].

From the perspective of research orientation, industrial automation system integration is changing from connecting systems to making systems cooperate. In the new research framework, the factory is no longer divided into independent equipment units, control units and management modules, but is regarded as a composite system composed of people, machines, data and processes. Related research has begun to pay attention to role collaboration, information feedback and system resilience in the manufacturing field, emphasizing that the construction of digital factory should not only solve the underlying connection problem, but also take into account the dynamic coupling between operation subjects, business processes and decision-making mechanisms [2].

At the same time, the research on data closed-loop for plant operation status is also continuously advancing. Existing results show that the combination of iot perception, equipment status recognition and data analysis mechanism can open up the technical chain from on-site collection to early warning judgment to a certain extent, so that the factory operation no longer stops at post-hoc statistics, and can have stronger process identification ability [3]. On this basis, the research on the new generation intelligent manufacturing system further pointed out that the focus of factory construction is shifting from automatic function deployment to the shaping of the overall system capability, especially emphasizing the adaptability, sustainable evolution ability and collaborative operation efficiency of the system [4]. In general, the research on the integration of digital factory and industrial automation system has formed a relatively clear development context. However, how to truly organize multiple types of systems into a sustainable whole is still a problem that needs to be further studied.

2.2 Application progress of industrial Internet, digital twin and intelligent perception in factory construction

In the process of digital factory construction, industrial Internet, digital twin and intelligent perception have gradually become the three types of technologies with the most active application and the most obvious influence. In terms of digital twin, related research is no longer satisfied with establishing a static model, but tries to map information such as equipment status, process parameters, production line cycle time and resource consumption into the virtual space synchronously, and provides auxiliary support for production scheduling, state prediction and process adjustment by constructing a dynamic model corresponding to the physical plant [5]. This practice has changed the traditional factory management mode that relies on post-hoc statistics and empirical judgment, so that managers can observe system fluctuations in closer to real-time conditions and identify potential problems in advance.

In a wider industrial iot scenario, the role of digital twin is further amplified. Existing studies have summarized its development path from the aspects of application architecture, key technologies and tool system, and believed that digital twin is becoming an important link connecting the perception end, analysis end and decision-making end [6]. This means that it not only undertakes the role of visual expression, but also undertakes the function of state interpretation, process deduction and assistant decision-making. For the digital factory, this ability is particularly important, because the manufacturing site often has complex equipment types, close process relationships, and changeable operating conditions. If there is no virtual and real linkage model support, even if the data is collected, it is difficult to really transform into usable information.

The development of industrial Internet provides a more stable foundation for the landing of the above capabilities. Related research shows that the industrial Internet has gradually evolved from a single data transmission network to a comprehensive support platform integrating perception, communication, computing and control, which not only improves the access efficiency of devices, but also enhances the connection ability between different production factors [7]. In this context, the equipment data, process data and business data originally separated in the factory begin to have the conditions for connection, and the information flow mode at the production site has also changed from one-way upload to two-way interaction. Further research shows that driven by data and knowledge, smart factories can form stronger autonomous analysis and operation regulation capabilities, and the value of the factory system begins to be reflected in the overall response capability rather than the local automation level [8].

In addition to the progress at the network and model level, intelligent perception and edge processing on the field side are also continuously enhanced. For the manufacturing site, massive data is not naturally equivalent to high-value data. What really matters is whether the identification, screening and response can be completed quickly close to the production process. Existing studies discuss from the perspective of edge resource deployment, and show that the reasonable deployment of edge computing capabilities inside the factory can help reduce the pressure of centralized processing and improve the operating efficiency in low-latency scenarios [9]. In general, the industrial Internet strengthens the connection base, the digital twin improves the process modeling and state inference capabilities, and the intelligent perception and edge computing enhance the real-time processing level on the field side. The integration of the three is continuously promoting the evolution of the digital factory from the visible to the controllable.

2.3 Shortcomings of existing research in cross-system collaborative integration and implementation path design

Although related research has made much progress in connection technology, twin modeling, state awareness and autonomous analysis, if we turn to the actual construction process, it will be found that cross-system collaborative integration is still a weak link in the promotion of digital factory. Previous studies have pointed out that with the continuous coupling of production network and information network, risks faced by factory systems are no longer limited to single equipment failure or local communication anomaly, but will spread to the production process along the system connection relationship, thus affecting the operation continuity and overall availability [10].

From the perspective of engineering implementation, the existing research focuses more on integration, but not enough on how to land step by step. Although some achievements have begun to discuss the selection and integration of digital technologies from the perspective of data flow, enterprises still face a series of more specific problems in the actual promotion process, such as how to access old equipment, how to parallel new and old systems, how to unify data caliber, how to maintain interface standards, and how to extend local pilot to the whole process application [11]. These problems determine that the digital factory construction can not be achieved in one step, but must follow the promotion logic from point to line and from line to surface.

In addition, from the research of digital factory model and life-cycle information collaboration, existing results have realized the importance of the overall model, but in the real industrial environment, problems such as decentralized information environment, multiple participants and insufficient sharing mechanism are still common [12]. In other words, the data chain that can be formed through the theory is often cut off by the organizational structure, system heterogeneity, and management habits in the actual scenario. Because of this, the deficiency of the current research is not entirely in the technical means themselves, but in the lack of a mature cross-system collaboration method and phased implementation path. In order to improve the engineering guidance value of digital factory research in the future, it is necessary to put the depth of system integration, implementation rhythm control and continuous evolution mechanism into the same framework to discuss, so that the technical scheme and the factory construction process truly correspond.

3 Research Methods

3.1 Decomposition method of digital factory construction objectives and business scenarios

Digital factory construction often starts from the specific pressure of the production site: frequent order switching, uneven equipment operation rhythm, incomplete quality traceability chain, energy consumption data scattered in different systems, although the management has a large number of reports, it is difficult to form a timely and continuous scheduling judgment. Under the framework of high performance industrial automation system integration, the starting point of construction work should fall on target sorting and scene recognition. Only by clarifying the core problems that the factory hopes to solve, and then falling into the business links that can be calculated, collected and controlled, can the subsequent system design, data access and algorithm deployment have a clear direction.

Based on this idea, this paper summarizes the objectives of digital factory construction into five categories: production efficiency improvement, product quality stability, resource utilization optimization, reliable equipment operation and maintenance, and transparent management decision-making. A business scenario set is established around typical links such as order execution, process flow, equipment operation, quality inspection, warehousing and distribution, and energy monitoring. Let the set of plant construction targets be $G = \{g_1, g_2, \ldots, g_n\}$, the set of business scenarios is $S = \{s_1, s_2, \ldots, s_m\}$ Considering that the value density of different scenarios is different in the implementation stage, this paper introduces the scenario priority function:

$$Q_i = \frac{\lambda_1 F_i + \lambda_2 K_i + \lambda_3 U_i}{1 + \lambda_4 B_i} \tag{1}$$

where F_i represents the frequency of scenario occurrence, K_i represents the intensity of influence on key production links, U_i represents the potential of data utilization, and Bi represents the coefficient of implementation resistance. $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are the weight parameters. The higher the Q_i value, the more suitable the scene is as the first construction object. With the help of this index, high-value scenarios such as equipment failure warning, process beat balance, online quality identification and abnormal energy consumption monitoring can be preferentially screened out.

After the completion of scene screening, it is necessary to further judge the support degree of each scene to the overall construction goal. To this end, this paper constructs the target mapping strength model:

$$M_{ij} = \frac{r_{ij} \cdot \ln(1 + d_{ij})}{\sum_{j=1}^{n} r_{ij} \cdot \ln(1 + d_{ij})} \tag{2}$$

where, r_{ij} represents the correlation coefficient between scene s_i and target g_j, and d_{ij} represents the depth of data support that can be provided by the scene. By calculating M_{ij}, it can be clear whether a business scenario is more biased towards service efficiency, quality or operation and maintenance goals, so that the construction task continues to be refined to specific equipment, sections, control nodes and data interfaces. After this process, the construction object of digital factory no longer stays at the level of abstract concept, but is transformed into a distributable, measurable and iterative implementation unit.

After target disassembly and scene mapping, the core tasks of digital factory construction are transformed into business units that can be calculated, collected and implemented, and the construction focus is also changed from conceptual planning to key link identification and implementation sequence determination. The resulting scenario list can directly support the subsequent system architecture design and technical module configuration, and provide a method basis for promoting the construction of digital factories in stages.

3.2 Digital factory system architecture design method for the whole production process

After the completion of construction target identification and business scene decomposition, the system architecture design needs to further answer a more specific question: how to access the data generated by the production site, how to linkage the control logic, how to connect the business application, and how to return the decision results to the site. Around this chain, the digital factory architecture is divided into device perception layer, edge control layer, platform integration layer, application collaboration layer and decision optimization layer, and a unified data governance and security control mechanism is configured vertically. The design idea is directly oriented to the whole production process, which not only considers the real-time performance of equipment access and control response, but also takes into account the linkage relationship between manufacturing execution, quality management, warehousing logistics, energy consumption monitoring, operation and maintenance analysis and other business systems. Figure 1 shows the overall architecture of the digital factory system.

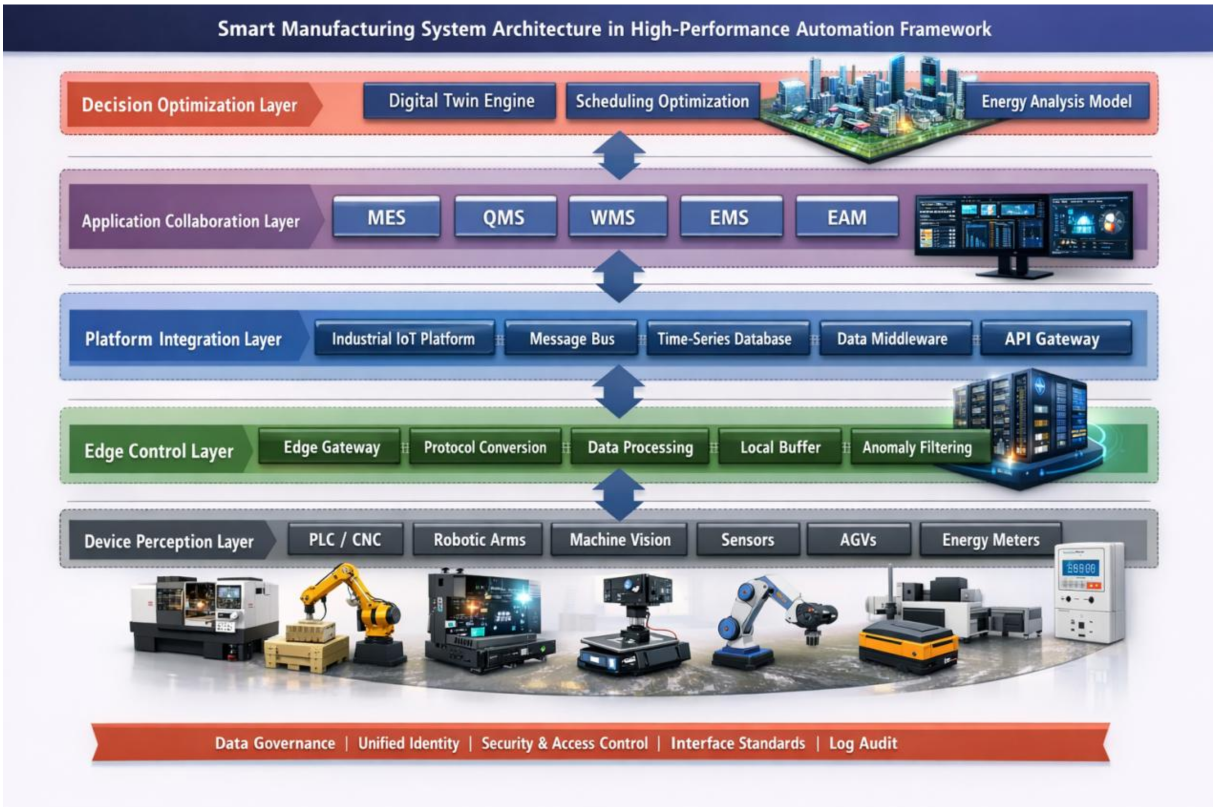

Figure 1: Digital factory system architecture diagram under the framework of high performance industrial automation system integration

From the bottom level, the device perception layer is responsible for collecting raw data from PLCS, CNC, robots, vision terminals, sensors, and energy metering devices, and maintaining a stable connection with field control objects. The edge control layer undertakes protocol parsing, data cleaning, local caching, feature extraction and proximal control tasks, which can preprocess high-frequency data and reduce the transmission and computing pressure of the central platform. The platform integration layer is the data hub of the whole architecture, which is composed of industrial Internet platform, message bus, time series database, master data management module and unified interface service, which is used to realize cross-system data aggregation, label management and service orchestration. The application collaboration layer corresponds to business modules such as MES, QMS, WMS, EMS, EAM, and undertakes functions such as plan execution, quality discrimination, inventory circulation, energy statistics, and equipment maintenance. In the decision optimization layer, digital twin, scheduling optimization, fault prediction and energy analysis models are introduced to convert the platform data into prediction results and control suggestions, which are then passed back to the application layer and control layer.

In order to measure the coverage degree of system architecture to production business, this paper defines the coverage rate of business architecture:

$$\Phi = \frac{\sum_{u=1}^{r} \sum_{v=1}^{s} a_{uv} w_u}{\sum_{u=1}^{r} w_u} \tag{3}$$

Among them, a_{uv} indicates whether the u-th business link is supported by the v-th system service node, and the support value is 1, otherwise it is 0. w_u represents the importance weight of this business link. The higher Φ is, the more complete is the support of the system architecture for the whole production process. The index can be used to determine whether the key links such as order scheduling, process execution, quality inspection, warehousing and distribution, and equipment operation and maintenance have been integrated into the unified architecture.

Considering that the digital factory emphasizes the end-to-end response ability, this paper further constructs the system total delay model:

$$T_{sys} = T_{acq} + T_{edge} + T_{net} + T_{app} + T_{fb} \tag{4}$$

where, T_{acq} is the on-site acquisition delay, T_{edge} is the edge-side preprocessing delay, T_{net} is the network transmission delay, T_{app} is the platform analysis and application decision delay, and T_{fb} is the instruction transmission and execution feedback delay. The formula can directly reflect the operating efficiency of the system architecture in the real-time perception and cooperative control scenario, and also provide a quantitative basis for the response performance evaluation of the subsequent experimental part.

The key of the architecture design method is to organize "equipment access, data aggregation, business collaboration, model decision, feedback execution" into a continuous link. Each layer not only assumes independent functions, but also maintains linkage with upper and lower layers through unified interface and event-driven mechanism, which avoids the separation of equipment system, management system and analysis system in traditional factories. Based on this architecture, the subsequent data integration, real-time control, and production optimization modules have clear deployment locations and interaction boundaries, and the method design of the subsequent sections in Chapter III can also be developed within the same architecture framework.

3.3 Data integration method for multi-level system collaboration

When the construction of digital factory advances to the stage of system interconnection, data problems are usually the first to be exposed. Field equipment continuously generates high-frequency status information, the control system saves operation parameters and alarm records, the execution system carries work orders, process and quality inspection information, and the management system corresponds to planning, cost, inventory and operation and maintenance arrangements. These data are scattered in different platforms with different coding rules, update times, and business implications. Without a unified data organization method, even if all layers of systems have been deployed, it is still difficult to form a stable collaborative relationship between the production site, the scheduling center and the management end. Based on this situation, this paper constructs a data integration method with unified identity, unified semantics and unified timing around the requirements of multi-level system collaboration, and organizes the data of device layer, control layer, execution layer and management layer into the same flow link.

When the method was implemented, the equipment number, production line number, work order number, batch number, process number and timestamp were uniformly coded, and the cross-level data master index z_i was established. On this basis, the original data is divided into four types: state data, control data, execution data and management data, and the mapping rules and synchronization frequency are configured respectively. Considering that the strength of data collaboration between different levels is not consistent, this paper defines the cross-layer data correlation function:

$$R_{uv} = \frac{\sum_{k=1}^{p} \eta_k \cdot \rho_k^{uv}}{\sum_{k=1}^{p} \eta_k} \tag{5}$$

Here, ρ_k^{uv} represents the association strength between the KTH type of data at level u and level v, and η_k represents the weight of this type of data in the business collaboration. The larger the R_{uv} value, the more suitable it is to establish a direct data linkage mechanism between the two-tier systems. For example, the correlation between the equipment layer and the control layer is usually high in the fault response scenario, and the correlation between the execution layer and the management layer is more obvious in the plan adjustment and resource allocation scenario. With the help of this index, the key data links that need to be opened can be prioritized, and the interface redundancy caused by invalid integration can be reduced.

After the data enters the platform, it is also necessary to deal with the problem of inconsistent acquisition frequency and fluctuating data quality. Therefore, this paper introduces the data currency credibility model:

$$E_i = \theta_i \cdot \frac{1}{1 + \exp[\kappa(\Delta t_i - \tau_i)]} \tag{6}$$

where, θ_i represents the data integrity coefficient, Δt_i represents the difference between the current time and the last update time of the data, τ_i represents the allowable delay threshold of this type of data, and κ is the adjustment parameter. The model is used to determine whether a piece of data is suitable for real-time scheduling, online warning or state analysis. High-frequency sensor data have stricter requirements on timeliness, while work order and inventory data emphasize more on consistency and integrity. Through this process, the probability of outdated data and abnormal data entering the upper analysis module can be reduced, and the stability of the multi-level collaboration process can be improved. The digital factory multi-level system integration objects and data content are shown in Table 1.

Table 1: Digital factory multi-level system integration objects and data content

Layer	Typical Systems or Objects	Main Data Content	Time Characteristics	Integration Method	Main Role
Device Layer	PLC, CNC, robots, sensors	Temperature, vibration, current, rotational speed, fault codes, equipment cycle time	Millisecond-level to second-level	OPC UA, Modbus TCP, edge data acquisition	Acquire real-time on-site status
Control Layer	SCADA, DCS, edge controllers	Setpoints, alarm records, interlock information, control feedback	Second-level	OPC UA, MQTT, industrial gateways	Support process control and abnormal response
Execution Layer	MES, QMS, WMS	Work orders, process parameters, quality inspection results, batch flow records, inventory changes	Second-level to minute-level	APIs, message buses, database synchronization	Support production execution and quality traceability
Management Layer	ERP, EMS, EAM	Production planning and scheduling, energy consumption statistics, maintenance plans, cost data	Minute-level to hour-level	ETL, ESB, service interfaces	Support business management and resource allocation

3.4 Real-time perception and cooperative Control Method Based on Industrial Internet and Edge Computing

The state change of the production site has the characteristics of continuity and sudden coexistence. Equipment vibration, current fluctuation, process deviation and beat imbalance are often accumulated and amplified in a short time. If the single path of "centralized uploading, unified processing and then issuing instructions" is still adopted, it is easy to cause problems such as response lag, network congestion and local anomaly amplification. In order to improve the on-site response ability of the digital factory, this paper combines the wide-area connection ability of the industrial Internet with the proximal processing ability of edge computing, and constructs a real-time closed loop of "perception acquisition, edge analysis, platform collaboration, control feedback". The industrial Internet platform is responsible for device access, message transmission and cross-system collaboration, and the edge node is responsible for high-frequency data caching, anomaly screening, feature extraction and local control decision. The two work together to complete the dynamic perception and rapid intervention of the production process. Figure 2 shows the flow of real-time sensing and cooperative control.

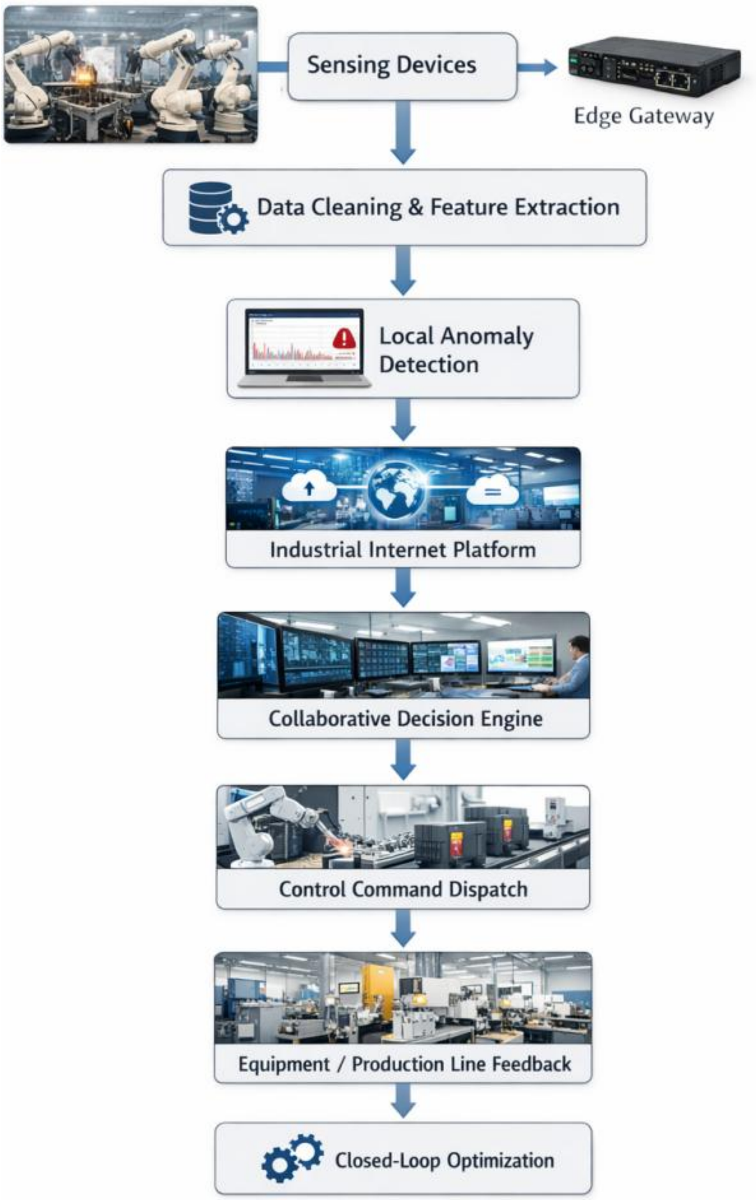

Figure 2: Flow chart of real-time sensing and cooperative control

In order to measure the response ability of the system to field changes, this paper defines the timeliness function of cooperative control:

$$H = \frac{\sum_{i=1}^{n} \omega_i \cdot \left(1 - \frac{t_i^r}{t_i^m}\right)}{\sum_{i=1}^{n} \omega_i} \tag{7}$$

Here, t_i^r represents the actual response time of type i events, t_i^m represents the allowed maximum response time, and ω_i represents the event importance weight. The closer H is to 1, the more the system can complete the sensing, analysis and control linkage within the specified time limit. For high-priority events such as abnormal equipment temperature rise, process beat drift and visual inspection defects, local control actions can be triggered by the edge side first, and then the results are uploaded to the platform for global coordination.

Considering that control instructions are also affected by network status and device load when propagated among multiple nodes, this paper further constructs the control stability index:

$$S_c = \frac{1}{n}\sum_{i=1}^{n} \frac{\chi_i}{1 + |u_i - \widehat{u_i}|} \tag{8}$$

where, χ_i represents the ith control execution success coefficient, u_i represents the target control quantity, and u^i represents the actual feedback quantity. This index can be used to evaluate the degree of agreement between command issuance and field execution during collaborative control. With the above method, high-frequency anomalies in the field can be identified at the edge node at the millisecond level, the middle platform is responsible for the cascading interaction and task redistribution of the production line, and the upper system combines quality, energy consumption and work order status to make comprehensive adjustment, so as to form a multi-level collaborative control mechanism covering equipment, production line and workshop.

3.5 Production optimization method integrating digital twin and intelligent analysis

Production optimization often occurs in the context of process parameter fluctuation, equipment load change and order structure adjustment at the same time. It is difficult to support continuous decision-making by static reports alone. Based on the above system architecture and data integration basis, this paper constructs a digital twin at the production line level and the workshop level, and maps equipment running status, process execution parameters, beat change, quality detection results and energy consumption records to the virtual space synchronously. Combined with timing prediction, anomaly identification and scheme evaluation model, the production process is online analyzed and rolling optimized. The digital twin is responsible for restoring "how the current production is running", and the intelligent analysis module answers "how to adjust the next time period to be better". Together, the two form a closed-loop optimization mechanism for the production site.

For model construction, let the state vector of the real production system at time t be x_t^r and the predicted state of the virtual twin system be x_t^v. In order to measure the consistency of virtual and real systems, this paper defines the twin fit index as follows.

$$D_t = 1 - \frac{\|x_t^r - x_t^v\|_2}{\|x_t^r\|_2 + \epsilon} \tag{9}$$

Here, ε is a tiny constant that prevents the denominator from being zero. The closer D_t is to 1, the more accurate the twin model is in describing the field state. Once the value continues to decrease, the system triggers the parameter recali-ation and model update to ensure that the subsequent optimization calculation is still based on the trusted state.

In the optimization decision-making level, this paper incorporates output efficiency, quality level, energy cost and downtime loss into the unified objective function, and constructs a comprehensive production optimization model:

$$\max Z = \alpha\frac{P_t}{P_{max}} + \beta\frac{Q_t}{Q_{max}} - \gamma\frac{E_t}{E_{max}} - \delta\frac{L_t}{L_{max}} \tag{10}$$

where, P_t represents output per unit cycle, Q_t represents qualified rate, E_t represents energy consumption per unit output, L_t represents downtime or beat loss, and $\alpha, \beta, \gamma, \delta$ are weight parameters. According to the real-time acquisition data and twin simulation results, the platform evaluates different scheduling schemes, process parameter combinations and equipment load distribution schemes in parallel, screens the optimal selection strategies under the current constraints, and then returns the adjustment suggestions to the execution layer and control layer to provide method support for the improvement of production line efficiency, quality improvement and energy consumption reduction in the subsequent experimental part.

3.6 The phased construction and implementation promotion method of digital factory

The construction of digital factory involves equipment transformation, network deployment, system interconnection, data governance and business reorganization. The pace of promotion is too fast, which is easy to cause prolonged on-site downtime, repeated interface transformation and insufficient personnel adaptation. Advance the pace too slowly, will make early investment difficult to form continuous income. Combined with the common transformation scenarios of manufacturing enterprises, this paper divides the implementation process into four stages: basic access, integration, collaborative linkage and intelligent deepening, and adopts the promotion method of "pilot first, step by step expansion, edge construction and test, and rolling optimization". In the basic access stage, data access and coding unification were carried out around key equipment, backbone production lines and core processes, and the field data link was established first. In the integration phase, system interfaces such as MES, ERP, QMS and WMS were opened, so that order, process, quality and inventory information could flow continuously in cross-layer business. In the collaborative interaction stage, production scheduling, quality control, energy consumption monitoring and equipment operation and maintenance were integrated into the unified response link. In the intelligent deepening stage, digital twin, predictive analysis and optimization decision modules are deployed, and the construction focus is promoted from "system availability" to "better operation".

In order to ensure the clear sequence of phase advancement, this paper introduces a task dependency-driven implementation scheduling model. Let the set of antecedent tasks of task j be Pre_j, then its start time is as follows.

$$t_j^s = \max_{i \in Pre_j}(t_i^e) + \Delta_j \qquad (11)$$

Here, t_i^e is the completion time of prepend task i and Δ_j is the preparation interval time of task j. This formula is used to constrain the unfolding sequence of tasks in each stage, to avoid launching high-level collaborative modules in advance when the underlying access is not stable, and to avoid directly entering intelligent analysis deployment when the data standard is not unified. Relying on this method, enterprises can first select the production line with moderate influence scope and good data foundation for pilot, and then extend the effective practice to the workshop level and factory level to reduce the implementation disturbance caused by one-time overall switching.

The task arrangement for the phased implementation of the digital factory is shown in Table 2.

Table 2: The task arrangement of the digital factory is implemented in stages

Implementation Stage	Core Tasks	Development Focus	Advancement Approach
Basic Access Stage	Equipment networking, protocol conversion, unified coding, and basic dashboards	Open up on-site data entry points	Pilot implementation on key equipment first
Integration Stage	Interface transformation for MES, ERP, QMS, and WMS	Realize cross-system data flow	Gradually expand from production lines to workshops
Collaborative Linkage Stage	Coordination of scheduling, quality, energy consumption, and operation & maintenance	Form a closed-loop business linkage	Roll out in phases along the business chain
Intelligent Deepening Stage	Digital twins, predictive analysis, and optimized control	Improve decision-making and optimization capability	Continuous iterative deployment

4 Experimental Evaluation

4.1 Experimental Design

In order to verify the effectiveness of the built digital factory implementation path in system integration, real-time perception, business interaction and operation optimization, a discrete manufacturing workshop is selected as the application scenario, covering 3 production lines, 68 key equipment, 214 sensor acquisition points and four core business systems such as MES, ERP, QMS and WMS. The experiment period was set as 60 days, the original decentralized operation mode was used in the first 30 days, and the high-efficiency industrial automation system integration scheme was deployed in the last 30 days, and the comparison test was carried out under the same order load and shift conditions. The collection content includes equipment status, process parameters, work order flow, quality test results, energy consumption records and operation and maintenance logs, so as to ensure that the evaluation results can reflect the technical performance and production effect at the same time. The experimental platform configuration and evaluation index Settings are shown in Table 3.

Table 3: Experimental platform configuration and evaluation index Settings

Item	Configuration or Content	Description
Application Scenario	Digital workshop for discrete manufacturing	Includes 3 production lines
Number of Key Equipment Units	68	CNC machines, robots, inspection equipment, and conveyor units
Sensor Acquisition Points	214	Temperature, vibration, current, vision, and energy consumption
Connected Systems	MES, ERP, QMS, WMS	Enable cross-system linkage
Edge Nodes	4 industrial edge servers	Responsible for protocol conversion and near-end computing
Platform Servers	2 application servers and 1 database server	Support platform operation and data storage
Experimental Period	60 d	30 d before transformation and 30 d after transformation
Comparison Method	Same-load comparison before and after transformation	Keep orders and shifts consistent
Evaluation Metrics	Average response latency, data completeness rate, task closed-loop completion rate, and interface connectivity rate	Reflect performance and collaboration effectiveness respectively

In terms of evaluation methods, this paper divides the experimental indicators into two categories: core evaluation indicators and supplementary validation indicators. The core evaluation indicators include average response time delay, data integrity rate, task closed-loop completion rate and interface connectivity rate, which are used to measure the real-time response ability of the system, the level of data penetration, the effect of business collaboration and the stability of cross-system connection, respectively. At the same time, combined with the requirements of integration testing and operation verification of digital factory, this paper further introduces supplementary indicators such as device access success rate, data synchronization accuracy, function trigger success rate, cross-system business linkage completion rate and comprehensive equipment efficiency, which are used to extend the analysis of the implementation effect from the perspectives of system landing, module collaboration and field operation quality. In the specific calculation, the system response performance is expressed as the average response delay:

$$T_{avg} = \frac{1}{n}\sum_{i=1}^{n}(t_i^{out} - t_i^{in}) \tag{12}$$

Here, t_i^{in} is the ith event entry time and t_i^{out} is the system completion response time. The level of data penetration is measured by the data integrity rate:

$$C_d = \frac{N_v}{N_t} \times 100\% \tag{13}$$

where N_v is the number of valid data and N_t is the total number of data that should be collected. The business collaboration effect is expressed by the task closed-loop completion rate:

$$R_c = \frac{N_c}{N_a} \times 100\% \tag{14}$$

Here, N_c is the number of closed-loop tasks completed on time, and N_a is the number of all triggered tasks. The above indicators correspond to real-time performance, stability and collaboration, which facilitates the subsequent analysis of the system construction effect in sections.

4.2 System integration effect and function realization test

After the completion of platform deployment, interface configuration and module joint adjustment, this paper tests the integration effect of digital factory system, focusing on five aspects: equipment access, interface connectivity, data synchronization, function trigger and cross-system business linkage. The test objects cover the main modules of the equipment layer, control layer, execution layer and management layer, including PLC data access, MES work order issuance, QMS test results return, WMS inventory status synchronization, and operation and maintenance alarm push and other key links. In order to show the test results more intuitively, the test results of system integration effect and function realization are shown in Table 4.

Table 4: Test results of system integration effect and function realization

No.	Test Metric	Test Result / %
1	Equipment Access Success Rate	98.6
2	Interface Connectivity Rate	97.9
3	Data Synchronization Accuracy	96.8
4	Function Trigger Success Rate	95.7
5	Cross-system Business Linkage Completion Rate	94.9

As can be seen from Table 4, the overall integration state of the system is relatively stable, and all core test indicators remain at a high level. Among them, the success rate of device access is 98.6%, and the interface connection rate is 97.9%, indicating that a relatively complete data channel has been established between the bottom device and the upper platform. The accuracy of data synchronization is 96.8%, and the success rate of function trigger is 95.7%, which shows that the system has good reliability in module cooperation and instruction execution. The completion rate of cross-system business linkage reached 94.9%, indicating that there is a strong linkage ability between production, quality, warehousing and operation and maintenance. Comprehensive calculation shows that the average value of the five indicators is 96.78%, indicating that the constructed system can better support the subsequent applications of real-time perception, collaborative control and production optimization in digital factories.

4.3 Production process real-time perception and scheduling response performance evaluation

The real-time perception ability in the production process determines the recognition speed of the system for equipment fluctuations, process anomalies and task congestion, and the scheduling response performance directly affects the production line linkage efficiency. In order to test the performance of the system under complex operating conditions, the concurrent task volume change scene is selected for testing, and compared with the conventional industrial monitoring system A and the integrated scheduling system B. The test indicators include average response time and scheduling success rate, and the two data are collected under the same number of devices, the same task load and the same network environment. The real-time sensing and scheduling response results of different systems under concurrent task growth are shown in Figure 3.

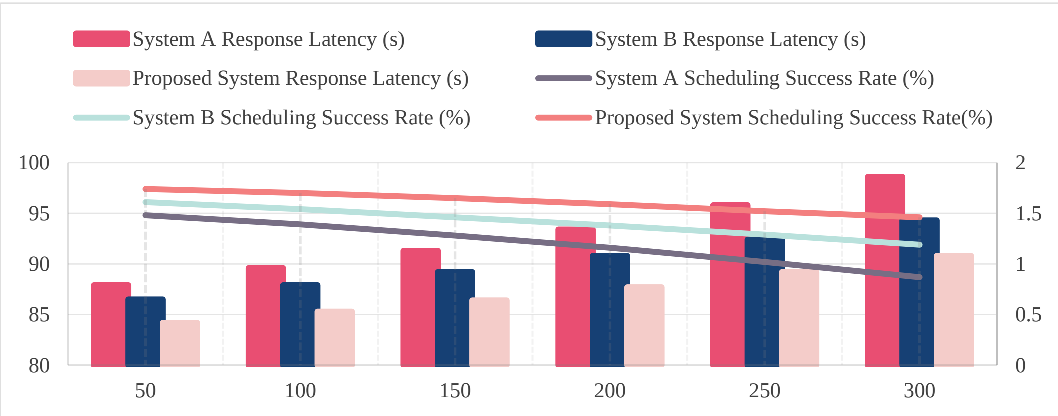

Figure 3: Comparison of real-time sensing and scheduling response performance of each system under different amount of concurrent tasks

It can be seen that as the number of concurrent tasks increases from 50 to 300, the response time delay of each system shows an upward trend, but the growth slope of the proposed system is the smallest, and the running process is more stable. Under the condition of 300 concurrent tasks, the average response delay of system A reaches 1.86 s, system B is 1.43 s, and the proposed system is controlled at 1.08 s. In terms of the scheduling success rate, system A decreased from 94.8% to 88.7%, system B decreased from 96.1% to 91.9%, and the proposed system remained from 97.4% to 94.6%. It shows that under the joint effect of edge-side preprocessing, event-driven transmission and platform collaborative decision, the proposed system can maintain faster state perception speed and higher task scheduling stability under high load conditions. Considering all test points, the average response delay of the proposed system is 0.75 s, which is 39.5% and 24.2% shorter than that of system A and system B respectively. The average scheduling success rate is 96.0%, which is 4.3 percentage points and 2.1 percentage points higher, respectively, indicating that the proposed method has good application advantages in real-time production collaboration scenarios.

4.4 Application verification of quality control, energy consumption management and equipment operation and maintenance

In order to further test the application effect of digital factory construction path in actual production, this paper carries out verification from three aspects of quality control, energy consumption management and equipment operation and maintenance. During the test, the system continuously collects the quality inspection results, energy consumption per unit output value, fault early warning records and maintenance response information, and compares and analyzes them with the existing operation data. The verification results of related applications are shown in Table 5.

Table 5: Application verification results of quality control, energy consumption management and equipment operation and maintenance

Metric	Before Transformation	After Transformation	Change
First-pass Product Qualification Rate / %	93.4	97.1	+3.7
Energy Consumption per Unit Output Value / (kWh/10,000 CNY)	18.6	15.2	-18.3%
Fault Early Warning Accuracy / %	85.7	93.8	+8.1
Average Maintenance Response Time / min	42.5	28.4	-33.2%
Average Monthly Equipment Downtime / h	16.8	11.3	-32.7%

As can be seen from Table 5, after the system is put into operation, the first pass rate of the product increases from 93.4% to 97.1%, indicating that the linkage between quality monitoring and process control is closer. The energy consumption per unit output value decreased by 18.3%, indicating that the energy consumption collection, analysis and adjustment mechanism began to play a role. The fault warning accuracy was improved to 93.8%, the average maintenance response time was shortened by 14.1 min, and the average monthly equipment downtime was reduced by 5.5 h. Overall, the system has achieved obvious application effects in terms of quality stability, energy consumption optimization and operation and maintenance efficiency improvement.

4.5 Comparative analysis of construction results under different implementation stages

In order to investigate the actual construction effect of the digital factory in the process of phased promotion, this paper conducts a vertical comparison of the system operation effect according to the four stages of basic access, integration through, collaborative linkage and intelligent deepening. Three indicators are selected: data penetration rate, business closed-loop completion rate and comprehensive equipment efficiency, which reflect the level of system connectivity, business collaboration ability and field operation quality respectively. Figure 4 shows the changes of construction effectiveness under different implementation stages.

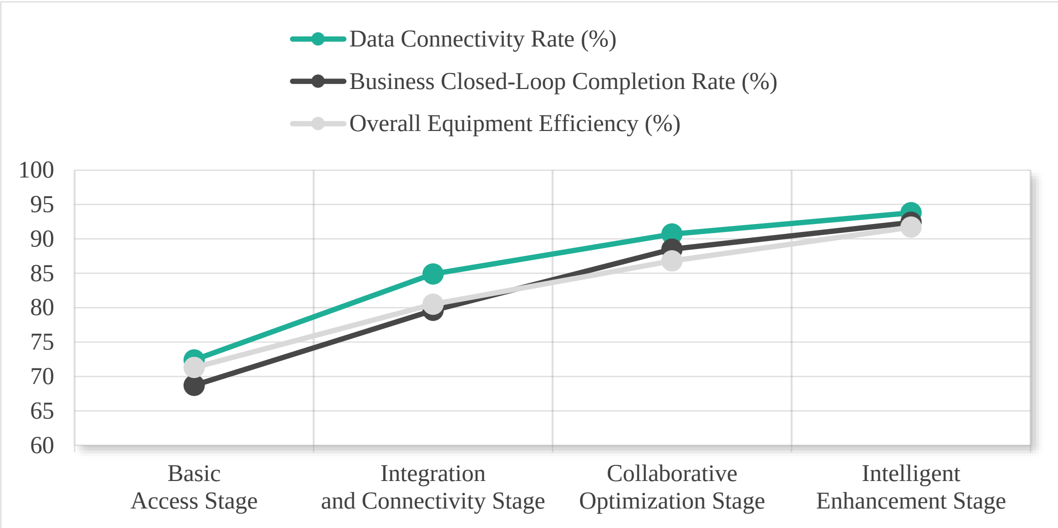

Figure 4: Line chart of digital factory construction effectiveness change under different implementation stages

According to the trend of broken line change, with the continuous progress of the construction stage, all indicators show a continuous upward trend, but the improvement range is not completely consistent. The basic access phase mainly solves the problems of equipment networking and data acquisition, and the data penetration rate reaches 72.4%, but the business closed-loop completion rate and the comprehensive equipment efficiency are only 68.7% and 71.3%, which indicates that the system construction is still in the initial state of visible data but insufficient linkage. After entering the integration through-link stage, the cross-system interface is gradually opened, the data through-link rate is increased to 84.9%, the business closed-loop completion rate is increased to 79.6%, and the comprehensive equipment efficiency is also increased to 80.5%, indicating that the information island problem has been significantly alleviated. The improvement of the collaborative linkage stage is more obvious, the data penetration rate is further increased to 90.7%, the business closed-loop completion rate is increased to 88.5%, and the comprehensive equipment efficiency is 86.8%, indicating that a stable response link has been formed between production scheduling, quality control, energy consumption monitoring and equipment operation and maintenance. In the intelligent deepening stage, the data penetration rate, the service closed-loop completion rate and the comprehensive equipment efficiency reached 93.8%, 92.4% and 91.7%, respectively, which were 21.4, 23.7 and 20.4 percentage points higher than those in the basic access stage. On the whole, the phased promotion method can gradually release the effect of digital factory construction, consolidate the data foundation in the early stage, strengthen the system connectivity in the middle stage, and concentrate on the comprehensive value of business collaboration and intelligent improvement in the later stage.

5 Discussion

From the above experimental results, the actual effectiveness of digital factory construction does not simply depend on whether a certain technology deployment is advanced or not, but the more critical influencing factors lie in the depth of system integration, the efficiency of data flow and the degree of collaboration between business chains. The reason why the implementation path constructed in this paper can achieve stable results in system integration, real-time response, quality control, energy consumption management and equipment operation and maintenance is related to the continuous linkage relationship formed between industrial Internet, edge computing, digital twin and intelligent analysis module. After the device layer status data is preprocessed by the edge nodes, it is no longer just passively uploaded, but can quickly enter the scheduling, early warning and optimization links, which makes the system maintain a low response delay and a high scheduling success rate under the condition of concurrent task promotion, which also shows that the combination of proximal computing and platform collaboration is more suitable for complex manufacturing scenarios.

From the perspective of the construction process, the way to promote by stages is more in line with the transformation law of manufacturing enterprises. The basic access stage solves "whether the data can come in", the integration stage deals with "whether the system can be connected", the collaborative interaction stage deals with "whether the business can form a closed loop", and the intelligent deepening stage further pursues "whether the operation can continue to improve". This advance sequence helps to reduce the implementation pressure brought by the one-time overall transformation, and also enables the construction results of different stages to gradually precipitate the foundation for subsequent upgrading.

Of course, this paper still has some limitations. The experimental scenario focuses on a single discrete manufacturing workshop, and the industry differences, the degree of equipment heterogeneity and the complexity of the network environment have not been fully developed. Some intelligent analysis models are still based on the current production line data, and the cross-factory migration ability needs to be further verified. The follow-up research can continue to expand the sample scope in multi-type manufacturing scenarios, and strengthen the research on adaptive modeling, cross-platform interface reuse, and multi-workshop collaborative optimization, so as to improve the generalization ability and engineering adaptability of the implementation path.

6 Conclusions

Aiming at the problems of system fragmentation, data dispersion and unclear implementation path in the construction of digital factory, this paper proposes a construction and implementation method based on high efficiency industrial automation system integration. And a relatively complete technology chain is formed from six aspects: target scene decomposition, whole process architecture design, cross-layer data integration, real-time perception and collaborative control, digital twin optimization, and phased promotion. The experimental results show that the system integration related indicators reach 96.78% on average, the response delay is controlled at 1.08 s under the condition of 300 concurrent tasks, the first pass rate of the product is increased by 3.7 percentage points, the monthly average downtime of the equipment is reduced by 32.7%, and the data penetration rate is finally increased to 93.8%. These results show that the combination of phased promotion and multi-technology collaboration can better support the construction of digital factory, from local automation to full process collaboration, and provide a feasible basis for the subsequent multi-scene promotion and deep intelligent evolution.

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