Knowledge-Driven Industrial Intelligent System: Concept, Reference Model, and Application Direction

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***Abstract*— The application of automation technology and artificial intelligence technology has promoted the improvement of the business capabilities of enterprises in industrial scenarios. Compared with the improvement or innovation of the business process, in recent years, part of academic research and practical applications has also shifted their attention from a single point of business intelligence perspective to a comprehensive intelligent upgrade of the industrial system. To the best of our knowledge, however, there is little research on the concept and model of the industrial intelligent system (IIS). To make up for the lack, this article presents the concept and reference model of IIS by analyzing the intelligentization requirement of the industrial systems. Different from academic research on general intelligent system capabilities, the reference model given emphasizes factors that need to be considered when implementing IIS in the industry. By analyzing the reference model, knowledge as the core driving force of IIS is recognized. Then, the four main forms of knowledge in IIS, as well as the role and key technologies of knowledge in different stages of IIS, are discussed in detail. In addition, several important potential applications of IIS are pointed out in this article.**

***Index Terms*— Industrial intelligent system (IIS), industry intelligentization, knowledge flow, reference model.**

I. Introduction

SINCE the 21st century, a new generation of information and communication technology (ICT) has shown explosive growth. Plenty of new ICTs, such as the Internet of Things (IoT) technology [1], [2], data analysis technology [3], artificial intelligence technology [4], 5G communication technology, blockchain technology [5], and cloud computing technology, have developed rapidly [6]. The integration of the above-advanced ICTs with Industry 4.0 [7] and intelligent manufacturing [8]–[10] is driving the transformation of industrial enterprises from digital enterprises toward intelligent enterprises. The new intelligent industrial paradigm is enhancing the ability of the enterprise to create industrial value [11], which will promote the high-quality development of the entire industrial economy [12].

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To realize the vision of intelligence, academic research and practical applications have carried out a lot of exploration of integrating intelligent technology into the original business process to improve or innovate the business process. For example, through the deployment of built-in data processing and analysis modules to automatically manage the outbound and inbound materials [13]. To improve product quality, cameras with built-in vision algorithms are deployed to recognize product defects [14]. More and more intelligent dispatching methods are developed by researchers for efficient manufacturing or service systems [15]–[18]. In addition, compared with experience analysis-based enterprise operations, data-driven information fusion, decision-making, and forecasting technology become hotspot technologies, which are expected to help enterprises better understand the front-end customer market [19], [20] or efficiently predict and configure the supply chain [21], [22].

Compared with the improvement or innovation of the business process, part of academic research and practical applications has shifted their attention from a single point of business intelligence perspective to a comprehensive intelligent upgrade of the entire industrial system [23], [24]. Different from the decentralized intelligence of single point business, the intelligentization of industrial systems pays more attention to using the advanced intelligent technology to expand the original industrial information system to the industrial intelligent system (IIS) to make the new system more in line with various and personalized business needs [25], [26].

In the last round of industrial informatization, industrial information systems provided enterprises with industrial data discovery, integration, and application functions in the form of a platform and became one of the most important carriers of the data value chain [27], [28]. With the further development of digitization and networkization [29], the abilities of the enterprise to capture data in various business stages, business processes, and objects in the industry have been continuously enhanced. Traditional industrial information systems cannot convert these new complex data with new features into industrial value. The data utilization of traditional information systems remains at data storage, data query, data matching, and simple data analysis. It also cannot convert data into industrial knowledge. The core of intelligent systems is intelligence. How to integrate intelligence into industrial systems is also an important issue that needs to be considered in the construction of IIS. Besides, the intelligent transformation process will introduce plenty of IoT equipment such as smart sensors, and mobile terminals. The management of this IoT

TABLE I

TARGETS OF INTELLIGENT TRANSFORMATION OF THE INDUSTRIAL SYSTEM

Target	A detailed description of the target	The gap
1. Accumulate industrial knowledge	Enterprises look forward to mini the knowledge contained in business data through the intelligent upgrade of industrial systems, then gradually accumulate industrial knowledge to obtain higher-value digital knowledge assets.	Traditional industrial information system mainly focuses on the interconnection with IoT equipment and other systems through interfaces to realize the acquisition and storage of industrial data. It rarely considers the discovery of industrial knowledge in the process of data capture.
2. Release the value of data and knowledge	Enterprises look forward to achieving insight into data and knowledge-based patterns, proactive reasoning & decision-making, then releasing the value of knowledge.	With the in-depth development of Industry 4.0, more and more enterprises have invested a lot of money to carry out digital transformation, thus the degree of digitalization and networking has been increasing. Although the scope of data involved in enterprise information systems is expanding, a large amount of data is only collected and stored, and it does not really enhance the ability of industrial enterprises to create value.
3. Improve the level of business capability	Enterprises look forward to embedding data and industrial knowledge, into the business processes to achieve the matching of business and resources by active push and decision-making, and to enhance business by automatic execution to the greatest extent of effectiveness.	The main functions of the industrial information system currently used in the industry are mainly information query, statistics, and data analysis. Some advanced industrial information systems are also mainly used for inefficient and passive query reasoning and decision-making assistance. Besides, some industrial information systems are also trying to access various types of ubiquitous IoT equipment and resources to enhance the ability of business process automation. However, these systems often lack an overall management and control plan for equipment and resources, which either causes a lot of waste of resources or requires a lot of manpower in resource allocation.
4. Meet the changing service scenarios	Enterprises look forward to achieving more flexible and open business processes by adjusting the structure and parameters of the system in changing service scenarios to realize the adaptation of the system to service scenarios.	Typical industrial information systems (such as Enterprise Resource Planning and Manufacturing Execution System) usually choose to solidify the business processes built into the system to improve work efficiency. Although business processes could be gradually optimized through long-term accumulation, a solidified system is difficult to meet changing service requirements.

equipment is beyond the scope of the industrial information system.

According to the above analysis, it can be seen that the construction of IIS is multidisciplinary in system science, data and knowledge engineering, intelligent technology, industrial engineering, and management. To the best of our knowledge, there is little research on the concept and model of IIS.

Considering that the academic research and industrial practice of IIS are currently in the early stages, this article studies IIS in an attempt to answer the following questions.

Q1: What is the difference between IIS and the traditional industrial information system?

Q2: What are the basic elements of IIS?

Q3: What is the reference model of IIS?

Q4: What is the knowledge in IIS and how IIS is driven by the knowledge?

The rest of this article is organized as follows. Section II gives the difference between IIS and the traditional industrial information system and derives the basic elements of IIS. The definition of IIS is summarized in Section III. Section IV presents the basic model of IIS. The discussion of knowledge in IIS is presented in Section V. Potential applications of IIS are illustrated in Section VI. Section VII summarizes this article.

II. BASIC ELEMENTS IN IIS

This section focuses on the answers to Q1 (what is the difference between IIS and the traditional industrial information system?) and Q2 (what are the basic elements of IIS?). The following compares IIS and the traditional industrial information system and combines "the cycle of intelligence"[1] to derive the basic elements in IIS.

[1]How artificial intelligence is closing the loop with better predictions, https://hackernoon.com/how-artificial-intelligence-is-closing-the-loop-with-better-predictions-1e8b50df3655/

The research idea of this article is to derive the definition of IIS from the industrial practice requirements and academic research. Following this idea, Section II analyzes the required elements and basis of the conceptual design of IIS, and then, Section III-A gives the typical intelligent capabilities of intelligent systems in academics. Based on both, the definition of IIS can be further obtained, which will be described in Section III-B.

A. Element Derivation

The main research of IIS in academics is its capabilities and functions, while the exploration of IIS in the industry focuses on its applications in actual business. The following analyzes the general targets expected to be achieved through the implementation of IIS from the industry. Based on the targets, the gap that realizes these targets by the general industrial information system is further analyzed. Table I summarizes these targets and the corresponding gaps.

Fig. 1 shows the relationship between the targets of intelligent transformation of the industrial system. Overall, these four targets present a progressive relationship from the perspective of enterprise intelligence implementation paths. Knowledge is the foundation of intelligence, and intelligent business and applications are inseparable from the modeling, processing, and application of knowledge. Therefore, the implementation of IIS needs to consider the modeling and labeling of knowledge first, i.e., Target 1. On the basis of efficient acquisition of knowledge, it is necessary to further consider how to apply knowledge to business processes from a technical perspective, i.e., Target 2. The realization of Targets 1 and 2 will make it possible to implement intelligent services. For enterprises, however, intelligence is not an end but a means. The ultimate target of upgrading existing information systems or directly establishing IIS is to reduce costs, increase efficiency, and improve service satisfaction.

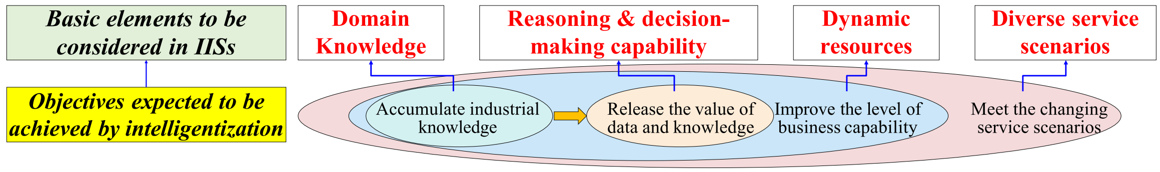

Fig. 1. Relationship between the targets of intelligent transformation of the industrial system.

Therefore, from the operational level of enterprises, the knowledge-based systems implemented by Targets 1 and 2 need to be further balanced with resources to reduce costs and increase efficiency (i.e., Target 3) and keep pace with service scenarios to meet changing business requirements (i.e., Target 4).

Target 1 (accumulate industrial knowledge) emphasizes the importance of domain knowledge accumulation to the industrial system. Target 2 (release the value of data and knowledge) emphasizes the importance of data and knowledge to the improvement of business processes. On the one hand, by embedding intelligent data analysis technology into business processes, the value of data could play an important role in promoting the level of business. For example, in the process of equipment operation, a large number of sensors are used for health monitoring. For the massive sensor data, various data mining algorithms, such as outlier detection and relational analysis, are used to analyze the health status of the equipment. On the other hand, the value of knowledge accumulated in the system also plays an important role in the operation of the business. Still taking the health monitoring of equipment as an example, as the operating time of the equipment increases, failure is inevitable. However, a similar kind of failure usually does not occur only once in the life cycle of the equipment. Therefore, by modeling the failure mechanism and establishing the failure mode by the accumulated failure data, the failure-related data could be retained and accumulated in the form of knowledge. If data are understood as a form of knowledge, then Target 1 could be understood as the accumulation process of explicit knowledge. Furthermore, Target 2 emphasizes the combination of explicit knowledge stored in the system and implicit (data) knowledge in the operation of business processes. In the process of knowledge utilization, the invocation of explicit knowledge, the extraction of implicit knowledge, the combination of knowledge, and the embedding of knowledge into business processes are inseparable from the construction of reasoning and decision-making capabilities of the system.

Target 3 (improve the level of business capability) emphasizes the comprehensive improvement of system capability. For the system, it is generally necessary to coordinate multiple businesses in parallel. Therefore, the restrictive relationship and conflicts between system resources and multiple businesses need to be considered. For example, to establish a feasible intelligent system for predictive maintenance of equipment groups, the maintenance of different equipment can be regarded as a business of the system. For the system, the maintenance process needs to comprehensively consider resources such as the use schedule of different equipment, the personnel input for maintenance, and the spare parts required for maintenance. Therefore, for the actual industrial system, the resource allocation capability of the system is an important manifestation of system capability. Target 4 (meet the changing service scenarios) emphasizes the compatibility and adaptation of the system in complex industrial scenarios since the business needs of industrial scenarios are often not static. For predictive maintenance, the different equipment in different work conditions has different degradation mechanisms, maintenance methods, maintenance cycles, and so on. Therefore, it is necessary to break the built-in and solidified business process of the traditional equipment maintenance system and then establish a flexible, open, oriented to multiple scenarios equipment maintenance service system.

Considering the above targets of intelligent transformation of the industrial system and corresponding analysis, the basic elements in IIS could be derivation, including domain knowledge, reasoning and decision-making capability, dynamic resources, and diverse service scenarios. These elements are further elaborated on in the rest of the section.

B. Domain Knowledge

From the perspective of Target 1, accumulating industrial knowledge emphasizes the importance of systematic domain knowledge for the implementation of business intelligence. A complete domain knowledge system for business within the scope of the system is expected to be established [30], [31]. Therefore, if IIS is required to be constructed, it is indispensable to take the knowledge base of business domain knowledge into account.

Considering that domain knowledge is the basis for the realization of intelligent transformation of the industrial system, the acquisition of knowledge becomes extremely important [32]. Currently, plenty of research has been conducted in the academic community on the acquisition of general knowledge [33]–[35]. Among the research, there are three main approaches to knowledge acquisition, including the knowledge acquisition method with human activities as the main body, the knowledge acquisition method assisted by human activities, and the machine autonomous knowledge acquisition method [36]. Although there are differences in knowledge acquisition approaches, the knowledge acquisition process can be roughly divided into three steps [37], [38], including knowledge extraction, knowledge labeling, and knowledge modeling. Academic research mainly focuses on the exploration of intelligent algorithms in different approaches to knowledge acquisition around these three steps. Few works discuss the knowledge acquisition process from the perspective of the construction of a complete knowledge system. Therefore, academic research on knowledge acquisition is rarely applied on a large scale in the industry.

Discussion: Although the academic community has conducted a lot of research on knowledge acquisition, there is a clear gap between academic research and application in industrial scenarios. Therefore, in the design stage of IIS, the requirement for knowledge in the business process should be first sorted from the application perspective [39], and then, the corresponding domain knowledge system and knowledge base should be established. Based on the establishment of the knowledge system, the steps of knowledge acquisition should be appropriately embedded in the system. Only when IIS has a clear domain knowledge requirement and a complete knowledge acquisition process, knowledge acquisition technology could be applied in actual business scenarios.

C. Reasoning and Decision-Making Capability

From the perspective of Target 2, the value release of knowledge is an important direction of the intellectualization of the industrial system. For this purpose, reasoning and decision-making should be the core capability to deploy in IIS. It emphasizes the analysis of events and tasks based on the knowledge at the business level and then outputs the reasonable inference result.

From a technical point of view, reasoning and decision-making correspond to two intelligent technology systems. Reasoning technology is mainly represented by artificial intelligence, such as machine learning and deep learning. Reasoning technology is widely used in semantic search [40], [41], recommendation systems [42], [43], and knowledge Q&A [44], which emphasizes the realization of the matching function based on the knowledge base or discovering new knowledge and rule in the existing data. Therefore, the reasoning could be the use of explicit knowledge or the discovery of implicit knowledge. Decision-making technology is mainly represented by computational intelligence, such as evolutionary computation and fuzzy computation. The decision-making technology is widely used to solve the optimization problem, the uncertain information fusion problem, and the evaluation problem. Generally speaking, decision-making involves a higher level of business than reasoning. Generally speaking, for a complex business process, two parts of reasoning and decision-making may need to cooperate. For example, for the maintenance business of the equipment group, it is first necessary to reason about the potential failure modes and the expected failure time point of the equipment through real-time sensor data and historical fault knowledge. Then, the potential failure information of the equipment group will be comprehensively considered in the decision-making process to determine the appropriate maintenance time point and maintenance strategy. From the perspective of academic research, although a large number of scholars have studied the modeling of reasoning and decision-making separately in a specific business, few works have focused on the integration of reasoning and decision-making ability into one system. The above status quo has led to many business processes that are expected to achieve automation that still need humans as connectors to bridge the gap between reasoning and decision-making.

Discussion: Although a large number of methods of reasoning and decision-making have been proposed by the academic community, the automatic integration of reasoning and decision-making in complex businesses is still a tough problem that IIS needs to consider. Besides, considering that the decision result expected by the business should be an actionable decision, therefore, it is also necessary to integrate system resources and system constraints in the construction of the decision-making module in IIS.

D. Dynamic Resources

Target 3 emphasizes the comprehensive optimization of the system. Different from the traditional industrial information system, to realize the automated execution of business processes in the physical space or cyberspace, IIS must master the dynamic resources available for configuration and use. For this purpose, resources must be decoupled from business, allowing resources to be independent of business and dynamically participate in the business processes.

IIS should not only manage the dynamic allocation of resources for the business but also the dynamic input and configuration of overall resources for the system. For resource allocation of the system for the business, the literature focuses on the research of event-driven resource allocation [45], [46], that is, a subtask of the business is regarded as an event, and the system allocates resources for the business when the event is triggered. The usual approach to resource allocation is to establish an adaptive model of the system [47], [48]; then, once the event is triggered, the internal parameter of the system is updated to realize automatic resource allocation. The above self-adaption model of the system generally follows first-come-first-served or a series of rules, which causes the allocation of resources to be often not optimal. Different from resource allocation, resource configuration is to determine the total amount of resources open for business use at different times. Taking equipment maintenance as an example, assigning different personnel (resources) to overhaul the equipment belongs to resource allocation. For the entire operation and maintenance system, determining the total amount of personnel (resources) that are invested in the maintenance task under the current situation is a problem of resource configuration of the system. In the process of constructing IIS, the optimization of both business level and system to resources should be considered.

Discussion: The effective management of dynamic resources plays an important role in system performance. IIS should coordinate the resources (people, machines, materials, and so on) contained in the system and establish a reasonable configuration and allocation optimization mechanism for resources. The integration of data-driven resource demand modeling and predictive analysis is a potential optimization approach for dynamic resource management. It requires that IIS could support the dynamic acquisition of data, the perception of data, and learning from data.

E. Diverse Service Scenarios

Target 4 not only requires the system to be optimized for business processes and resources but also requires the system to be able to change the system structure and parameters to adapt to diverse business scenarios. The ultimate goal of developing IISs is to provide efficient services for business processes. The traditional system development idea is to standardize business processes and then solidify the components and resources needed for each process into the modules. Extreme standardization helps improve business efficiency. However, in actual industrial applications, different scenarios may have differentiated business requirements under the same business. Therefore, the system should provide differentiated business processes and services as business scenarios change in the business process. In general, when facing different service scenarios, the system must have the ability for system evolution and system optimization [49], [50]. System evolution refers to the adjustment of service content and form of the system through scene awareness to meet the differentiated business requirements in a specific scenario. System optimization refers to improving business efficiency, reducing resource consumption, and improving service satisfaction based on meeting business requirements in a specific scenario.

For the diverse service scenarios, it can be abstracted as a two-stage optimization problem for the system. In the first stage, the system evolves its structure and parameters according to the current business scenario. There are many forms of system evolution, such as adjustment of resource input, change of resource distribution, change of business processes and business rules, or adoption of different domain knowledge for different scenarios. In the second stage, the system is optimized according to the system and business indicators. There are many types of indicators, such as cost, resource utilization, business satisfaction, and business performance. Taking [18] as an example, different from most production scheduling research, this article developed a machine layout strategy oriented to the dynamic changes of production demand. In the case study of this article, the machine layout has a significant impact on the efficiency of the production process, so changing the layout to adapt to different production needs could better serve the manufacturing process. The abovementioned research satisfies the two-stage optimization process. The first stage is the machine layout change (evolution), and the second stage is the evaluation of production time (optimization). This type of two-stage problem that simultaneously considers changing scenarios and business indicators will be a key issue that needs to be resolved in the operation process of IIS.

Discussion: The diverse service scenarios require that IIS is not only able to adapt to the business in a specific scenario but also has more configurable structures and parameters for the dynamic changing scenarios. From the business level, it is also required that IIS is no longer modularized the entire business but should decompose the entire business into smaller components or elements. Once the business scenario changes, the system could quickly reconfigure the business according to the characteristics of different business scenarios [51], [52].

III. Definition of IIS

IIS is required to integrate the industrial application requirement and the intelligent system. Therefore, in addition to derivate the basic elements of IIS from the industrial application requirement, it should also learn from the academic research on the intelligent system. The basic elements of IIS from the industrial application requirement are derived in Section II. To achieve an advanced, forward-looking, and technically scalable definition of IIS, Section III-A summarizes the definition of intelligent capabilities in intelligent system research. The definition of IIS is given in Section III-B based on the integration of the basic elements of IIS from the industrial application requirement and the definition of intelligent capabilities from academic research.

TABLE II
Summary of Intelligent Capabilities in the Literature on Intelligent Systems

Intelligent capabilities	Refences
Perception	[53]–[55]
Cognition	[56]–[58]
Discovery	[59]–[62]
Interactivity	[55], [63]–[65]
Learnability	[66]–[68]
Adaption	[68]–[71]
Reasoning	[72], [73]
Control	[69], [70], [74]
Self-organization	[70], [75], [76]

A. Intelligent Capabilities

The definitions of intelligent capabilities in intelligent system research are summarized in Table II.

B. Definition

IIS is a kind of self-adaptive and self-organizing system with learning ability, which has multiple capabilities to service multibusiness under multiscenarios, including environment perception; data acquisition; pattern insight; human–computer interaction; knowledge embedding; reasoning; decision-making; and mastery of independent resources, automated execution, and feedback.

IV. Reference Model of IIS

This section focuses on the answer to Q3 (what is the reference model of IIS?). By studying the cycle of intelligence, a reference model of IISs is proposed, and the concept of each module in the proposed model is further studied.

A. Cycle of Intelligence

Fig. 2(a) shows the model of the cycle of intelligence. The model defines the four phases of intelligence, including perception, discovery, decision-making, and action. From a partial point of view, the improvement of the intelligence of each phase could increase the intelligence of the overall cycle. From a whole point of view, the four phases are interrelated and form a closed loop. The closed loop is embodied in that each phase not only could obtain better performance through the improvement of its own intelligence level but also could improve the intelligence level of other phases through the feedback mechanism.

The core idea of the model of the cycle of intelligence is to link the multiple phases of intelligence together through a closed loop. Based on the cycle, the ability of a single phase could be expanded to other phases along the cycle. By mapping the circle and the targets of the IIS, it can be found that the four phases of intelligence could cover the construction requirements of IIS in dynamic data acquisition, domain knowledge discovery, reasoning and decision-making, and dynamic resource utilization. Besides, the closed-loop structure of the circle also meets the requirements of the system under changing scenarios. Once the scenario changes, the perception engine learns the change and the discovery engine perceives the new scenario and helps the system evolve its configuration; then, the decision-making engine makes new optimal actionable decisions to guide the system

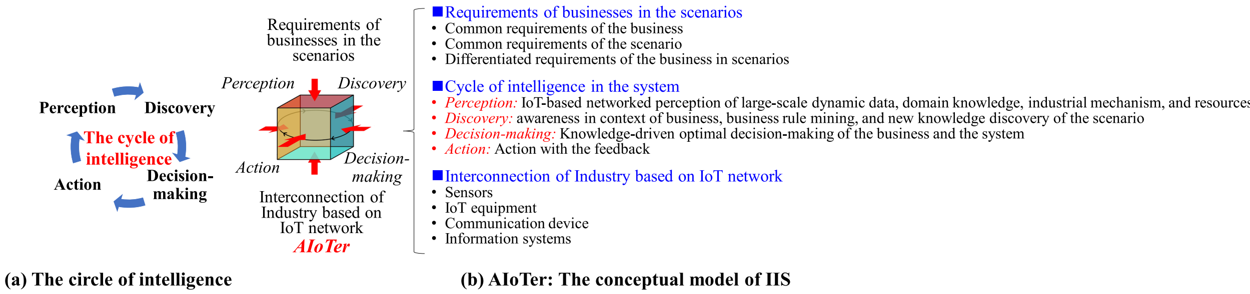

Fig. 2. Cycle of intelligence and the conceptual model of IIS. (a) Circle of intelligence. (b) AIoTer: conceptual model of IIS.

to execute new actions. Therefore, the model of the cycle of intelligence is a meaningful reference to the modeling of IIS.

By extending the model of the cycle of intelligence, the conceptual model of IIS, AIoTer, is given in Fig. 2(b). In the given conceptual model, IIS is understood as an intelligent entity with the entire cycle of intelligence.

The bottom of the AIoTer integrates sensors, the IoT equipment, communication devices, and information systems through the IoT network to provide hardware support and data/knowledge sources. AIoTer, on the one hand, accumulates knowledge by the acquired data from the IoT and, on the other hand, coordinates data, knowledge, and resources through the deployment of intelligent capabilities in the circle of intelligence to provide an efficient and effective service for the upper level business. Compared to the circle of intelligence considered from the theoretical level, AIoTer emphasizes the role of the IoT in practice. Therefore, the term of AIoTer also implies an IoT-based, intelligent entity. Besides, it can be seen from the description on the right of Fig. 2(b) that the term knowledge runs through the entire AIoTer. From the perspective of system dynamics, the flow of knowledge constitutes the main driving force for IIS. To conduct an in-depth analysis, system components of IIS and the knowledge forms in IIS should be further explored. By expanding the model of AIoTer, Section IV-B gives the detailed model of IIS from the perspective of the ontology and the main system modules in the ontology are identified. In addition to the introduction of different system modules, the key elements in each module that need to be considered in the construction process are also illustrated. Then, the main (potential) knowledge forms in IIS are discussed in Section V.

B. Detailed Model of IIS

The detailed model of IIS is shown in Fig. 3. The part in the dashed box is the core of the IIS model, including the data and knowledge acquisition module, knowledge base module, reasoning, and decision-making module. The data and knowledge acquisition module corresponds to the perceptron engine of the IIS, which is responsible for sensing and acquiring data and knowledge from the environment, business, and system. The combination of the data and knowledge acquisition module and reasoning and decision-making module is to form the knowledge discovery engine of the system. The knowledge base module is the container for the knowledge, which is used to store the different forms of knowledge.

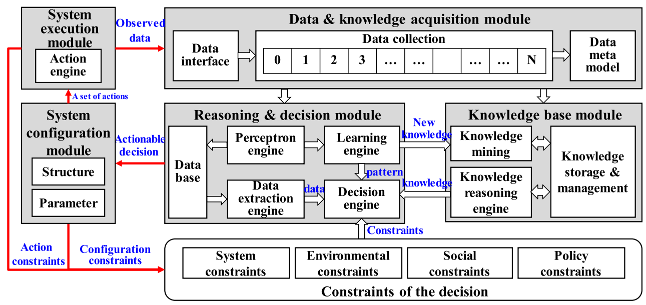

Fig. 3. Detailed model of IIS.

For the use of knowledge, the knowledge base also includes the knowledge reasoning engine. The business-related data, information, knowledge, and system constraints are combined in the reasoning and decision-making to obtain the optimized actionable decisions.

Then, actionable decision-making generates an action set of IIS and checks whether the current system state needs to be reconfigured to meet the needs of the actions. Then, after completing the necessary configuration, the output actions are executed by the action engine. After a round of actions, the state of the environment, business, and system changes. The system obtains feedback through the perceptron engine and then conducts the rediscovery of knowledge, makes new decisions, and outputs new actions again.

The following is divided the model into five modules to further illustrate.

1) Data and Knowledge Acquisition Module: Obtaining business-related information is the first step for IIS to achieve intelligent operation. The acquisition of data and knowledge in the industry has the characteristics of ubiquitousness [76], [77], dynamics changing [78], and multiheterogeneity [79]–[81]. Ubiquitousness requires that the information acquisition involve not only business-related information systems but also business-related IoT equipment and personnel. The dynamic characteristic of acquisition requires IIS could capture updated information dynamically as the business process. The multiheterogeneity emphasizes the heterogeneity of information and requires that IIS could be compatible with various types of data and knowledge.

Considering the complexity of the data and knowledge involved in IIS, the knowledge engineering on the data and knowledge requirements of all businesses in the system is the prerequisite for the effective use of the module. Then, a single meta-model of the data [82]–[84], the standardized data interface, and acquisition protocol [85] are required to be established to ensure the consistency of data and knowledge in the system.

2) Knowledge Base Module: Domain knowledge [30], [86] is the core asset for IIS to achieve business intelligence. To achieve business intelligence, the knowledge module base should contain three core functional submodules: knowledge storage and management, knowledge mining, and knowledge reasoning. Knowledge storage and management focuses on the acquisition, classification, storage, and update of knowledge [87]. Knowledge mining includes rule extraction from the knowledge and mining of deep-level knowledge based on the knowledge base [88]. Knowledge reasoning is the engine and interface of the knowledge base module for use [89], [90]. It emphasizes the use of accumulated knowledge to solve problems of the business process in the system. The knowledge base module integrates knowledge storage, knowledge creation, and knowledge application. Through the establishment of tools and interfaces for the external one, knowledge services are output by the knowledge base module for the business process of IIS in the form of the inference engine.

From the perspective of knowledge type, the domain knowledge in the knowledge storage and management submodule should include but not be limited to engineering mechanisms, engineering documents, reference manuals, history cases, data, expert experience, and so on. It is necessary to sort out different knowledge structures of the above and establish a unified knowledge system. Considering the complex associations between knowledge, compared with the traditional relation-based storage database, the graph database that supports ontology association expression exists as a wide application prospect in knowledge storage and management. The knowledge mining submodule is regarded as a knowledge learnable system. It further mines knowledge features, extracts knowledge rules, and mines deeper hidden knowledge based on the existing knowledge. Therefore, the construction of this submodule should fully consider how to use data mining, machine learning, deep learning, and other technologies to further the exploration of implicit knowledge from explicit knowledge. The ultimate goal of the knowledge module is to use the accumulated domain knowledge in the business process. To better match domain knowledge and specific business, in addition to the traditional logic rule-based and neural network-based knowledge reasoning, new knowledge reasoning methods based on ontology and representation learning [91]–[94] are expected to be implemented in the knowledge reasoning submodule. Besides, from the perspective of the construction of the knowledge base module, the thinking of traditional database construction should be shifted. It should be clear that the purpose of constructing the knowledge base module is to use it. Therefore, the domain knowledge system and the relationship between knowledge are required to be clear before the module is built.

3) Reasoning and Decision Module: The reasoning and decision module are the key to supporting IIS to realize the automation and intelligentization of business processes. The reasoning and decision module have four main engines: the perceptron engine, the learning engine, the data extraction engine, and the decision engine. The perceptron engine is responsible for data and knowledge perception of business information in the business process [81], [95]. The learning engine learns the pattern behind the data, such as knowledge, rules, and laws. The data extraction engine is automatically extracted the historical data of the database required for business decision-making [96]. Then, the decision engine calls the required data, patterns, and knowledge for the problems in the business and generates actionable solutions within the constraints of the system [97].

The learning engine in the reasoning and decision module is not the only service for the decision engine but also the knowledge base module. For the data pushed by the perceptron engine, the learning engine needs to determine whether the content behind the data is a pattern or knowledge. A pattern could be considered as the knowledge that emerges under a certain business, which is only valid under the current business. Therefore, the pattern is temporary. The term knowledge represents the common rule and mechanisms in a domain. Therefore, the knowledge is long-term existing. For the pattern, the learning engine will push it to the decision engine. For the knowledge, the learning engine will push it to the knowledge base module for storage or further processing.

The construction of the reasoning and decision module will involve two types of key technologies. One type is the technology related to data fusion, data analysis, and data utilization [98]. Only the effective implementation of the above technologies could ensure the operation of these engines. Especially for the generation of the actionable solution, the integration of data, pattern, knowledge, and system constraint in the decision engine, the fusion of multiple heterogeneous information is a tough task. The other is the technology related to engine and module interaction. As a system that is expected to be executed automatically and achieve interoperability [99], [100] between its modules, it is required to get through the data flow and business flow between engine and engine, between engine and module. For example, when data are transferred between modules, it is necessary to ensure consistency of data to ensure the reliability of decision results.

4) System Configuration Module: The function that the system configuration module is to provide an executable system state for the actionable set issued by the reasoning and decision-making module. The configurability of the system generally includes the ability of the system to manage and allocate resources, and the ability to change the attributes of each component of the system [52], [101], [102]. IIS is a system that needs to output flexible actions according to different businesses or scenarios. The configurability of the system determines the capability of IIS to a large extent. The more configurable items are included in the system configuration module, the more actionable solutions the decision engine can generate. It provides more potential optimization space for the decision engine. Therefore, the configurable items of the system have an important influence on system evolution and business optimization.

5) System Execution Module: The actionable set is executed by the system execution module. System execution can be software-defined or hardware-driven. The execution processes of IIS are accompanied by a large amount of meaningful data feedback. To ensure the effectiveness of the execution at the business level and the cognition of the scenario, the feedback mechanism of the system should be integrated into the system execution module. The feedback mechanism of data could help the system evaluate the status of business completion. Plenty of business processes in the industry are complex, and the actions planned by the system may not be able to achieve ideal execution results. Especially for the business that requires awareness in context [75], feedback on business status plays an important role. Data generated in the business process are expected to make up for the inadequate or insufficient decision-making of the system. Besides, the mechanism feedback of data could help the system enhance the cognition of industrial scenarios. For the complex engineering problem, the traditional approach to obtain the solution is to manually explore the underlying models and mechanisms behind the business and characterize them with human experience. Human experience, however, is usually implicit knowledge that is difficult to formalize. With the continuous perception and feedback of data, plenty of underlying models and mechanisms behind the business could be modeled by the data-driven method [103]. The data-driven business modeling method ensures that the system could learn the changes in different business scenarios. Therefore, the feedback mechanism of the system should be emphasized in the construction of the system execution module.

V. Knowledge in IIS

This section focuses on the answer to Q4 (what is the knowledge in IIS and how IIS is driven by the knowledge?). The main forms of knowledge in IIS are given in this section. Then, the acquisition and utilization of knowledge at different stages of IIS are analyzed. Finally, the key technologies to integrate knowledge into IIS are summarized.

A. Forms of Knowledge in IIS

Different from the intelligent system in a broad sense, the specific scenario in the industry gives concrete forms and meaning to the knowledge. Knowledge in IIS could be divided into the following four forms: business mechanism model, business process model, system-level available resource, and optimization tool.

The definition of each form of knowledge is given as follows.

1) Business Mechanism Model: The business mechanism model refers to the rules that need to be referenced to achieve business within the scope of IIS, as well as the formulas, theorems, laws, human experience, and other domain-related knowledge that could support any business operations [39], [104].

2) Business Process Model: The business process model refers to the predefined subbusiness running sequences, subbusiness triggering rules, and the operating relationship between different subbusinesses in a complete business process [105], [106]. Business processes can be serial, parallel, or mixed. Different businesses may have different business processes. Therefore, the business process model is an important form of knowledge that supports IIS in consistently implementing complex business logic. The difference between the business process model and the business mechanism model is that business process models refer to the process method of business realization, while business mechanism models focus on the specific knowledge that solves specific problems. In practical applications, business mechanism models need to be embedded into the business process model to realize complex business functions.

3) System-Level Resource: The system-level resource refers to the set of available resources, including business-specific resources and shared resources of multiple businesses. The execution of IIS for the business is inseparable from the use of related resources. The resource itself could be regarded as a special kind of machine that processes information and then outputs actions or results. When IIS issues a command on resource usage, a certain machine (i.e., a resource) needs to output corresponding actions or results through its internal operating mechanism, thereby promoting the realization of business logic. Despite the vast progression in resource- and knowledge-based view research [107], the system-level resources of IIS can also be defined as a kind of knowledge machine that encapsulates a special mechanism from the perspective of system usage. Different resources are knowledge machines with different mechanisms. The combination and configuration of these knowledge machines together serve the business. Besides, the system-level resource does not emphasize ownership of the resource, but the right of IIS to obtain, control, and use the resource, that is, if IIS has access to other external resources, then the resource could also be an available resource at the system level of IIS. It means that the available resource could be inside or outside of IIS.

4) Optimization Tool: It refers to the strategy tools and algorithm tools that could provide IIS with continuous improvement and optimization space. The optimization tool could be the optimization at the business level, such as the configuration of business operations and the improvement of business mechanisms [108]. It could also be the optimization at the system level, such as the adjustment of the system configuration and resource allocation and [109]–[111], and the optimization of the energy consumption. In the above optimizations, there are a large number of potential applications of algorithms such as artificial intelligence and computational intelligence. Considering that IIS is a system that needs to perform specific businesses, different business mechanisms, different business processes, different system resources, and different system targets make such optimization tools customized. Customized strategy and algorithm lead to optimization tools related to domain business and system structure. Therefore, it is necessary to treat the optimization tool as a special kind of knowledge.

B. Knowledge in Four Stages of Intelligentization

Section V-A defines the main knowledge forms contained in IIS. Knowledge is closely related to the intelligence level of IIS. According to the degree of knowledge utilization, the intelligence level of IIS could be divided into four stages [11]. The following describes the relationships in knowledge and the four stages.

1) Stage 1: Robotic Process Automation: At the stage of robotic process automation (RPA) [112], [113], IIS is required to master the three main forms of knowledge: business mechanism, business process, and resource. Through the cooperation of business mechanisms, business processes, and resources, IIS automatically processes business information and executes business processes, thereby reducing the labor cost of business operations and improving the efficiency of business operations. From the perspective of knowledge utilization, the intelligence of IIS at the stage of RPA is mainly embodied in the descriptive analysis of the system ontology, business process, and elements required by the operation. The construction of IIS at this stage is required to complete the following two core tasks.

1) Establish the complete business element identification for the business within the scope of IIS and conduct knowledge modeling of the know-how in the business field as much as possible.
2) Encapsulate each subbusiness of the business in the form of structured data and standardized interfaces, and effective business process automatic trigger mechanism for those businesses or subbusinesses that could be automatically executed as much as possible to significantly improve the degree of automation of the system.

2) Stage 2: Intelligent Robotic Process Automation: Compared with Stage 1, the intelligence of IIS under the stage of intelligent robotic process automation (IRPA) emphasizes two aspects [114].

1) *Intelligentization of Data Acquisition:* It means IRPA needs to expand the function of RPA from data utilization to data acquisition. It requires IIS to efficiently uses IoT. Through the dynamic acquisition of data streams, the ability to update and supplement the knowledge of IIS is expected to enhance.
2) *Intelligentization of Business Analysis:* IPRA is required to increase the level of knowledge utilization in the business process based on the automation of PRA. The descriptive analysis is expected to upgrade to predictive analysis. It requires IIS to have the reasoning and decision-making capabilities to predict the state of the future based on the current state and then optimize the business process and system status.

The above two aspects emphasize the need for IIS at the stage of IRPA to upgrade from a system with automated execution capability to a system with optimization capability. It requires that IIS not only needs to master the business mechanism, business process, and resource but also the optimization tool.

It should be pointed out that although the capabilities of IIS at the stage of IRPA are significantly improved compared to that at the stage of RPA, the intelligence embodied at the stage of IPRA is still based on software robots. The available resources of IIS are mainly in cyberspace. Therefore, for business problems in complex physical scenarios, mapping the entities in the physical space to cyberspace through digital twin technology [115] may be an important prerequisite for IIS to exert its application potential at this stage.

3) Stage 3: Augmented Intelligent Process Automation: IRPA emphasizes how to use appropriate optimization tools to optimize business execution at the business level based on business mechanisms, business processes, and system resources [116]. As a complex system, IIS needs to provide services for multiple business processes simultaneously. Therefore, it is necessary to realize the optimization at the system level. Compared to IRPA, augmented intelligent process automation (AIPA) is required to have the system-level optimization capability. The capability includes two aspects.

1) The predictive analysis of a single business should upgrade to the predictive analysis of multiple businesses. The results of reasoning and decision-making for different businesses are subject to system resources and attributes. How to resolve business execution conflicts and competitive relationships between multiple businesses caused by system constraints is a core problem that AIPA needs to solve.
2) The capability of prescriptive analysis [117] should be introduced and used extensively in system optimization. IIS at the stage of AIPA is required to coordinate the relationship between business and system. The optimization scope of IIS at the AIPA rises from the business level to the system level, which means that the system no longer only considers the requirement of the business optimization but also the requirement of the system optimization, such as the overall system resource consumption, system efficiency, and system sustainability.

The above two aspects emphasize that the ability of IIS to master resources and optimization tools at the stage of AIPA needs to be further improved. The resource is no longer being used, and its overall optimization of it needs to be considered at the system level. Also, the optimization tool is no longer being used in the optimization at the business level. The collaborative optimization between the businesses and the overall optimization of the system also needs to be further considered.

4) Stage 4: Autonomous Agent: Autonomous agent (AA) emphasizes the self-learning ability of the system [118]. The essence of learning is to continuously acquire new knowledge and update the existing knowledge system. It requires AA to break the closeness of the system, deeply integrate with business scenarios through the open interface, and then update its knowledge system in the changing business scenarios. In the stage of AA, IIS is treated as a subsystem of a complex ecosystem that revolves around a set of businesses. In this ecosystem, IIS autonomously evolves the structure and parameters of its system based on the knowledge learned from the ecosystem around the business. Traditional system or ecosystem research always independently considers material flow, energy flow, and information flow in one system. Then, an integration model is used to integrate the above flows. Such a system recognition method is effective in closed system research, which has great limitations on the perception of a complex ecosystem. This is why all these elements of business mechanism, business process, resources, and optimization tools should be unified into the concept of knowledge. The concept of knowledge helps to unify the relatively independent concepts of matter, energy, and information in the system. Once these elements are defined as knowledge, the core task of IIS at the stage of AA could be positioned to enhance the flow of knowledge within IIS. IIS is treated completely as a learner who needs to understand the ecosystem. The learners independently learn the knowledge contained in the ecosystem and automatically output and promote actions that are beneficial to the ecosystem. The driving force for the two-way interaction could be considered as the flow of knowledge between IIS

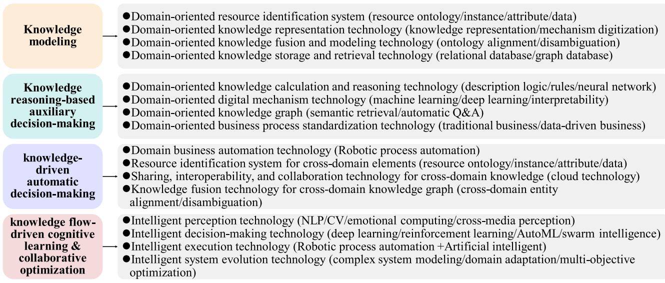

Fig. 4. Key technologies of knowledge modeling and knowledge utilization.

and the ecosystem. The flow of knowledge could promote IIS to autonomously adjust the structure and parameters of its system to optimize business execution in the changing business scenarios. Besides, if human participates in the business ecosystem as agents, human cognition [119], emotion, and personalized experience [120]–[122] also be important type of knowledge that IIS needs to learn [123]. Therefore, in addition to descriptive analysis, predictive analysis, and prescriptive analysis, the cognitive analysis should be further integrated into IIS [56]. It can be seen that IIS at the stage of AA should be integrated into the multiagent ecosystem generated by complex business scenarios in a more open form. It requires IIS to strengthen knowledge exchange and knowledge flow with other agents in this multiagent ecosystem and coordinate the development of the entire business ecosystem.

C. Key Technologies

In the process of integrating knowledge into IIS, knowledge modeling is an indispensable topic in the construction of IIS. The key technologies of knowledge modeling [33], [34], [124]–[126] are summarized in the first part of Fig. 4. Knowledge utilization includes auxiliary decision-making based on knowledge reasoning [94], [125], [127], knowledge-driven automatic decision-making [128], [129], and cognitive learning and collaborative optimization based on knowledge flow [130]–[132]. The key technologies of knowledge utilization are also summarized in the second-to-fourth parts of Fig. 4.

D. Discussion

The knowledge in the industrial field is a large amount of industrial technology, industrial mechanism, operating mechanism, and even the regularized digital expression of man–machine operation methods after abstraction. For the smooth use of knowledge, the knowledge in IIS should be further encapsulated into a software form [133]. Therefore, the softwarization of knowledge will be an important process to realize the reusability of knowledge [134] in IIS. Nowadays, the componentization of knowledge and then encapsulation of knowledge into microservices [135], [136] to form an industrial app is the most typical representative of the softwarization of knowledge.

Moreover, knowledge should be regarded as an industrial asset to be further considered in IIS. Especially when plenty of knowledge is softwarized, the three knowledge forms of business mechanism models, business process models, and optimization tools will have the same asset attribute [107] as the knowledge form of system-level resources, with asset attributes. It requires IIS to recognize its authority to different knowledge. Therefore, the asset management of knowledge in IIS needs to be further discussed as an important topic.

VI. Potential Applications of IIS

A. Complex Product Design

As a knowledge-intensive activity, the success of complex product design depends on the ability to effectively manage, share, and use the knowledge and experience related to design tasks [39]. The dispersive and heterogeneous characteristics of design knowledge itself and the design process that is mainly driven by experience have led to the low design efficiency and the long development cycle of the complex product. The establishment of IIS for design knowledge service is expected to solve this dilemma. By modeling the product mechanism of the design field and process knowledge of the design task and then establishing the knowledge graph of design knowledge [137], [138], IIS could push design knowledge for designers by embedding technologies in the reasoning and decision-making module [139], [140]. It will effectively transform the traditional passive search of decentralized design knowledge into the active push of task-oriented design knowledge, thereby greatly reducing the dependence on the design experience of the expert and helping designers improve their design efficiency.

B. Manufacturing and Industrial Engineering

Plenty of product manufacturing processes need to adjust the production configuration according to the customer requirement for the product [75]. Integrating manufacturing knowledge into the manufacturing system is expected to solve the problem of inefficiency in the manufacturing process of personalized customization. By packaging the manufacturing information and production system configuration information as the knowledge in the modular form and then integrating the knowledge into the manufacturing system, the manufacturing process could be automatically configured. Once personalized production orders appear, RPA-driven automatic configuration will help the manufacturing process to achieve customization. In addition, through the integration of historical orders, real-time data, supplier information, order demand, and supply chain conditions, then the introduction of the algorithm for predictive analysis [141], the cost optimization of the manufacturing system in the entire production cycle could be achieved.

C. Prognostics and Health Management

Prognostics and health management is a kind of typical predictive analysis task of equipment [142], [143]. Plenty of industrial enterprises are establishing their prognostics and health management systems. In real industrial scenarios, equipment maintenance often needs to consider equipment operation on the production line [144], [145]. Therefore, a feasible equipment operation and maintenance plan must comprehensively consider equipment health status, the work plan of the production line, maintenance methods, historical maintenance information, and maintenance personnel. The establishment of IIS for prognostics and health management is expected to achieve comprehensive optimization of equipment operation and maintenance. Through integrating equipment operations mechanism, maintenance knowledge, and maintenance resources into IIS, knowledge-driven equipment operation monitoring, equipment failure prediction, the active push of historical maintenance plans, and configuration optimization of maintenance resources could be realized by the capabilities of predictive analysis and prescriptive analysis [117].

D. Product–Service System

Product–service system refers to a business model that provides consistent delivery of products and services. With the rise of intelligent interconnected devices, smart product–service systems (SPSSs) are trying to capture user activity behavior and product–service demand data through the ubiquitous perception and connection of smart interconnected products to achieve value co-creation [11], [146], [147]. IIS is expected to help the realization of SPSS. By integrating an intelligent interconnected device with the data knowledge acquisition module of IIS, SPSS could dynamically perceive user portraits and activities in real time. Besides, the reasoning and decision module of IIS could also integrate data- and model-driven methods in the SPSS design to derive customer needs, so as to realize the value co-creation of customers in the product configuration design [148].

E. Intelligent Transportation System

It focuses on the collaboration of people, vehicles, environment, and society [149]. Plenty of intelligent transportation systems could be regarded as complex ecosystems. For example, the urban logistics system needs to comprehensively consider multiple factors, such as delivery personnel, truck drivers, road conditions, and service time, to realize multitask collaborative optimization [150]. For another example, the air transportation network needs to consider air routes, traffic flow, flight (delay) information, and crew configuration, to enhance customer experience and reduce the workload of the staff [151], [152]. Therefore, intelligent transportation systems usually cover all aspects of descriptive analysis, predictive analysis, prescriptive analysis, and cognitive analysis. Integrating the knowledge of the transportation field into the intelligent transportation system could be beneficial to the improvement of the overall service quality of the transportation industry.

VII. Conclusion

For the trend of the overall intelligent upgrade of the industrial system, this article presents the concept and reference model of IIS. By analyzing the reference model, knowledge as the core driving force of IIS is recognized. Then, the form, the role, and the key technologies of knowledge are discussed in detail. Also, several potential applications of IIS are pointed out.

The technical contributions of this article could be summarized in the following two points. First, the proposed concept and reference framework of IIS establishes links between industry and academia and then provides opportunities for academic research to serve industrial practice. Our framework is helpful for enterprise managers to propose targeted and more specific intelligent improvement goals and paths from the perspective of modules. Besides, the modular framework also helps researchers focus on specific module functions, which will facilitate the development of specific technical research. Second, the sorting out of the common knowledge system required in at different stages of IIS could contribute enterprise managers being easier to identify the implementation path of IIS based on their own conditions.

It can be seen from the perspective of implementation that there are still plenty of practical problems to be solved in the application of IIS, such as how to set a unified interface compatible with different data types for the system, how to establish a single data meta-model for the business, and how to establish a knowledge system for the domain. Besides, from the perspective of the application, the coordination and optimization of IIS for multiple services and the adaptation of IIS for different scenarios are also a topic worthy of further exploration.

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