The International Journal of Advanced Manufacturing Technology (2021) 114:771–796
https://doi.org/10.1007/s00170-021-06882-1

ORIGINAL ARTICLE

Artificial intelligence in product lifecycle management

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Received: 21 June 2020 / Accepted: 9 March 2021 / Published online: 22 March 2021

Abstract

Recently, artificial intelligence (AI) technology receives extensive attention in the manufacturing field. As the core technology, it generates considerable interest among smart manufacturing and Industry 4.0 strategy. Product lifecycle management (PLM) copes with various kinds of engineering, business, and management activities concerning a product throughout its whole lifecycle—from the inception of an intangible concept through the recycling of a finished product. In the context of smart manufacturing, this paper reviews various theories, algorithms, and technologies of AI to different stages of PLM (i.e., product design, manufacturing, and service). A structured roadmap is presented to navigate the future research and application of AI in PLM. This paper also discusses the opportunities and challenges of applying AI for PLM.

Keywords Artificial intelligence · Product lifecycle management · Smart manufacturing · Big data

1 Introduction

Product lifecycle management (PLM) copes with many kinds of engineering, business, and management activities concerning a product throughout its whole lifecycle—from the inception of an intangible concept through the disposure of a finished product [1]. The rapid advancement of emerging information technologies, such as cloud computing, the Internet of Things (IoT), big data, and artificial intelligence (AI), is transforming the paradigm of advanced manufacturing through impacts on all aspects of PLM [2]. The developed countries actively promoting the next industrial revolution through national manufacturing strategies/initiatives, for example, Industry 4.0 in Germany, Industrial Internet in the USA, Industry 2050 Strategy in the UK, Manufacturing Innovation 3.0 in South Korea, Society 5.0 in Japan, Made in China 2025 Strategy in China, etc. [3]. These strategies share the same vision of intelligent manufacturing, characterized by the in-depth integration of artificial intelligence (AI) and advanced manufacturing [4].

AI comprises various theories, methodologies, technologies, and tools intended to understand, simulate, and extend human intelligence through artificial means [5]. Recently, concurrent with the rapid development of big data, machine learning (ML), and computer chip, AI applications extensively spread in many different fields [6]. The distinguishing values of AI lie in assisting, supporting, and even replacing human operators to perform complicated tasks requiring significantly higher reliability, accuracy, and efficiency. The well-known AI applications examples include face recognition for payment, transportation security systems [7], speech recognition for smart devices [8], and Google's DeepMind AlphaGo in board games [9].

Compared with other fields, AI applications for PLM in the context of advanced manufacturing are relatively limited [10]. On the one hand, due to the high requirements for quality, reliability, accuracy, and cost-effectiveness in manufacturing, manufacturers are naturally hesitant about adopting AI in PLM, which is especially true for small and medium-sized manufacturers (SMM) [11]. On the other hand, the advantages of AI to PLM are beyond listing. Firstly, since AI can replace humans with repetitive and dangerous operations, a complex manufacturing process can be streamlined towards a less labor-intensive state. Secondly, since a validated AI solution can sustain itself a long time, an expensive manufacturing process can be made more cost-effective. Thirdly, many AI

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algorithms are compatible with industrial big data, which drives the manufacturing decision-making towards a more data-driven fashion. The enhanced ability to handle a large volume of data makes manufacturers more adaptable to a changing industrial environment [12, 13]. Lastly, many sophisticated applications of AI can be readily adapted for industrial environments. For example, computer vision has been applied on automatic control in quality inspection, visual localization, dimension measurement, object sorting, bar code recognition, etc.

Against this background, this paper presents a holistic framework to bridge the state of AI's art and PLM's pressing demands, where PLM is divided into three stages, and AI is classified along three technical dimensions. The technical dimensions of AI are mapped to the stages of PLM to make visible the opportunities of leveraging AI to enhance the efficiency, effectiveness, and intelligence of PLM. The proposed framework provides a roadmap to navigate the future research and applications of AI for PLM.

The remainder of this paper is organized as follows. Section 2 discusses the research trends of AI in correspondence to the different stages of PLM. Section 3 describes the concept, characteristics, classification, and applications of AI. Section 4 presents a theoretical framework of potential applications of AI for PLM. Sections 5 and 6 elaborate on the opportunities and challenges of applying AI in PLM, respectively. Section 7 concludes and outlines future research directions.

2 Developing trend of product lifecycle management (PLM)

2.1 The notion of PLM

PLM’s notion was initially proposed to represent a product’s evolution in the open market divided into promotion, maturity, and decline stages [14]. With the introduction of concurrent engineering in the 1980s, PLM was unfolded progressively in manufacturing engineering field. It led to a new division of PLM processes, including market analysis, product design, process development, product manufacturing, product distribution, product use, post-sale service, and recycling. In light of the continuous transformation of the manufacturing paradigm, various researchers interpreted PLM differently [15]. In previous work, the authors divided the PLM into nine stages from the perspective of data collection, e.g., product concept, design, raw material purchase, manufacturing, transportation, sale utilization after-sale service, recycle/disposal [16]. To classify the methods and objectives of AI technology in different stages, AI is clearly divided into three stages in this paper: the product design stage, product manufacturing stage, and product service stage [17]. Each stage is further divided into sub-stages, as shown in Fig. 1. The product design stage includes conceptual design, embodiment design, detail design, and trial production [18]. The product manufacturing stage includes substages such as material supply, production planning, manufacturing, and warehousing/logistics. The service stage includes different value-adding services, such as sales, utilization, after-sale service, and recycling [16]. Table 1 describes the major activities of each sub-stage.

2.2 Current developing trends of PLM

2.2.1 Definition and function of PLM

PLM was initially developed in line with the popularity of auxiliary design and manufacturing tools such as Computer-Aided Design (CAD), Computer-Aided Engineering (CAE), Product Data Management (PDM), Supply Chain Management (SCM), etc. [19]. PLM's development underwent an evolutionary process from the tool era to the integrated application era and the collaborative platform era [20]. New technologies and tools were continuously developed, adapted, and integrated with correspondence to the business, management, and manufacturing modes' dynamic changes, eventually leading to the current form of PLM. PLM is evolving towards a critical information infrastructure. Manufacturers can continuously integrate emerging technologies and applications concerning the acquisition and processing of product information, management of customer preferences and behaviors, and optimization of enterprise workflow and process.

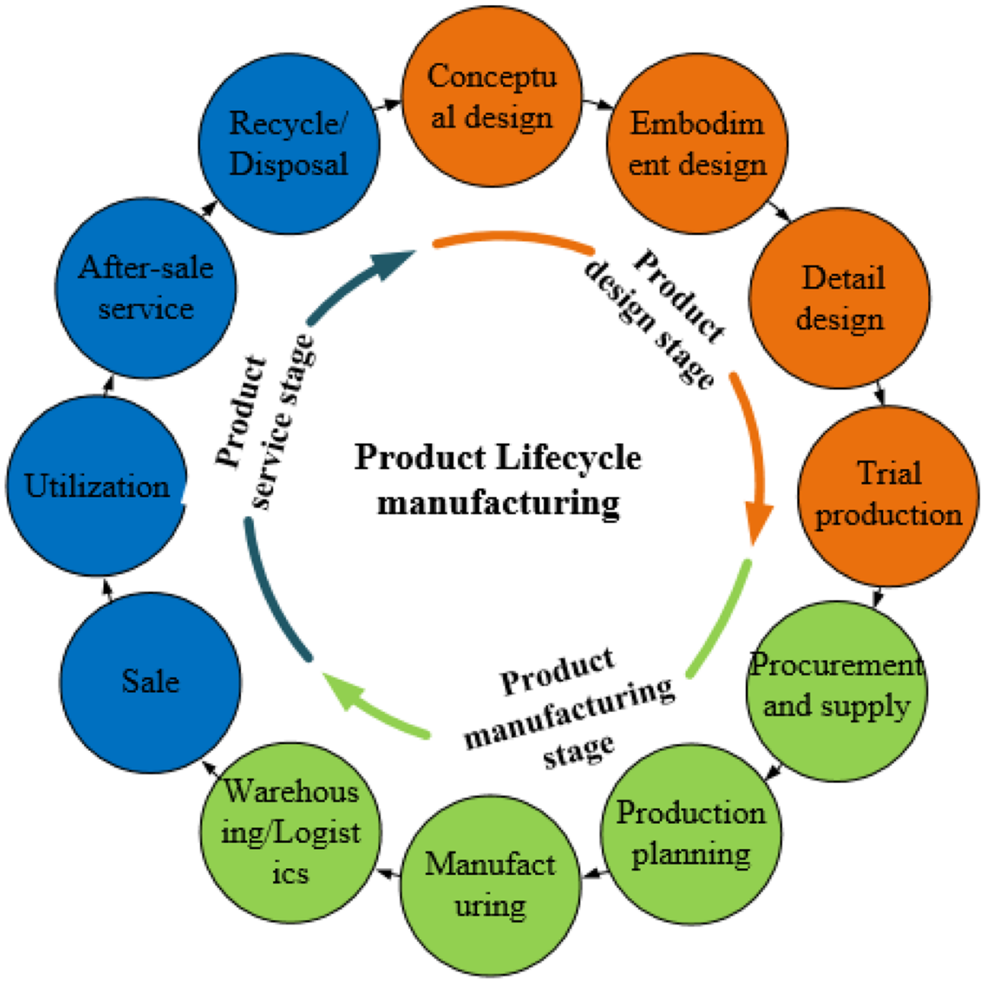
2.2.2 Information integration framework of PLM

PLM implementation in practice depends heavily on a holistic information framework integrating heterogeneous data, information, and systems. The information integration for PLM requires generic theories and methods [21], specific technologies concerning information interaction [22], data mapping [23], knowledge and semantic integration [24], and web service connection [25], etc. The emerging manufacturing modes gradually enhance the requirements and elements of the PLM integration framework. However, as the broad spectrum of PLM, most of the existing frameworks are specifically tailored to a particular application scenario, impeding their universal applications.

2.2.3 Modeling methods and tools in PLM

PLM manages product information obtained throughout a product’s lifecycle concerning product design, manufacturing, and service. Various data models, information models, and

Fig. 1 Continents of PLM



workflow models were proposed to integrate numerous PLM elements [26]. Most of the PLM models are deployed locally to enhance a specific PLM stage's effectiveness instead of the entire PLM process. For example, the design management model is useful for deriving design solutions by synchronizing decisions across various designers using different design tools [27]. BOM-based product modeling is effective for establishing more accurate production plans and tracking execution schedules [28].

2.2.4 Optimization and evaluation in PLM

Many optimization and evaluation methods have been proposed in the context of PLM. For the design stage, common evaluation metrics include appearance, performance, development cycle, and environmental friendliness; typical evaluation methods include Analytic Hierarchy Process (AHP) [29], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [30], Effects Analysis [31], Kano Model [32], etc. For the manufacturing stage, common evaluation metrics include makespan, cost, resource utilization, and energy consumption [33]; typical optimization methods are represented by various meta-heuristic algorithms [34]. For the service stage, the Quality of Service (QoS) is an important metric for evaluating service effectiveness, which indicates to what extent customers receive personalized services [35].

2.2.5 Data management in PLM

Embedded technologies such as RFID tags and advanced sensors have been widely utilized in the manufacturing and service stages, leading to PLM data explosive growth [36]. Many efforts are devoted to developing new methods for PLM data modeling, synchronization, integration, transformation, and mining [37]. With the rise of emerging technologies such as digital twin [38] and Industrial Internet [39], the volume and variety of PLM data will continue to surge. Many AI algorithms have advantages over traditional methods for processing high volume and high dimensional data. The integration between PLM and data science constitutes one of PLM's most promising opportunities throughout its design, manufacturing, and service stages.

Table 1 Three stages in PLM

Product design stage	Conceptual design	Analyze market demand, formulate design problems, establish function structures, search for working principles, determine the basic solution structure.
	Embodiment design	Determine the overall layout design (overall layout and spatial compatibility), the preliminary form design (part shapes and materials), and the production process, and provide a solution for any auxiliary functions.
	Detail design	Determine the shape, material, dimension, processing methods, assembly forms, and other key detail factors.
	Trial production	Verify whether the drawings, process, and other technical documents of the new products are correct and whether they can meet the expected requirements and quality standards. It can be divided into sample trial production and small-batch trial production.
Product manufacturing stage	Procurement and supply	Purchase and prepare the resources required for manufacturing according to the bill of materials, including material resources, technical resources, human resources, equipment resources, *etc.*
	Production planning	Make production plans according to the production task (e.g., delivery time, quality, and cost) and available resources (e.g., materials, personnel, machinery, and equipment).
	Manufacturing	Transform raw materials into finished products, mainly including blank manufacturing, part processing, assembly, and inspection.
	Warehousing/logistics	Integrate warehousing and transportation activities that are relevant to manufacturing.
Product service stage	Sale	Various sales methods, including the combination of online and offline sales, mass production and customization, the combination of virtual products and physical products, etc.
	Utilization	Usage process from purchase to recycling.
	After-sale service	After product sales and delivery, support services provided to customers, such as technical advice on use, maintenance, and repair, to ensure trouble-free use of the equipment during its service life.
	Recycle/disposal	When the product reaches the service life or fails to meet the user's needs, the product can be recycled and decomposed to find the valuable modules.

2.3 New requirements of PLM

The pursuit of higher product quality, innovativeness, and cost-effectiveness is imposing new requirements on PLM.

(1) To quickly respond to market changes, manufacturers must adjust their strategies to shorten a product life cycle, especially the cycling pace of the product design and manufacturing stages.
(2) The increasing market demands for customized and personalized products require manufacturers to develop a more modularized, flexible, and responsive design, manufacturing, and service processes.
(3) To design, manufacture, and service customized products globally, manufacturers, must collaborate with relevant stakeholders, share available resources, and develop viable manufacturing networks towards a more sustainable manufacturing ecosystem.
(4) The intensified competition for lower cost, higher quality, and shorter lead time requires manufacturers to enhance the intelligence of their manufacturing processes and systems, which put forward higher requirements for process automation and equipment intelligence.
(5) High customer expectation on service quality requires manufacturers to improve information monitoring, tracking, and management system and establish a more responsive online service platform to provide remote product repair, maintenance, and upgrade.
(6) The emergence of a massive volume of industrial big data requires manufacturers to process, mine, and integrate a variety of high-dimensional, unlabeled, unstructured, and non-standardized data.

As the above discussion, the authors learn the PLM's focus is gradually shifting from product to service, from offline production to online collaboration, and from informatization to intellectualization. To meet the emerging requirements for PLM, both academia and industry have devoted tremendous efforts to developing new information technologies [40], in which AI plays a vital role.

3 AI and its applications

3.1 Concept of AI

As summarized in Table 2, the notion of AI is defined and interpreted differently by different researchers, mainly depending on their research backgrounds, disciplines, and domains. Differing definitions of AI share the same set of keywords: personification and intelligence.

As shown in Table 3, since the emergence in 1956, there appeared three main schools of thought on AI, namely Symbolicism [50], Connectionism [51], and Actionism [52]. The notion of AI was initially introduced by Symbolicism, who suggested that knowledge representation, cognition, reasoning, and application lie in the center of AI. A major contribution of Symbolism was the development of various expert systems. Connectionism argued that AI is derived from bionics (or biologically inspired engineering), especially concerning the understanding of animal/human brains. An important contribution of Connectionism was the invention of artificial neural networks, which was inspired by the fundamental structure of animal brains—the biological neural networks. As a relatively new school, Actionism focused on studying cybernetic systems concerning self-optimization, self-adaptation, self-stabilization, self-organization, self-regulation, and self-learning.

In light of the existing definitions, the authors regard AI as the theories, methodologies, technologies, and tools that are intended to understand human intelligence, develop artificial systems with intelligence, empower artefacts to perform intellectual tasks, and leverage computational means (both software and hardware) to simulate intelligent behaviors.

3.2 Brief history of AI

As shown in Fig. 2, despite the overall upward trend, AI's development had experienced notable alternations between surging and declining [53]. After the notion was proposed in 1956, the development of AI rapidly entered its first golden age. However, in 1973, a report submitted by James Lighthill to the UK government suggested that most AI goals were too ambitious to be achieved by existing technologies. Since then, AI had been criticized and questioned. Subsequently, the research of AI fell into the first winter in the 1970s. Starting from the late 1970s, the emergence of expert systems, which simulated how human experts solve domain-specific problems using knowledge, represented AI's reorientation from theoretical investigations to practical applications. As a result, the development of AI experienced a second surge. Starting from the late 1980s, the growth of expert systems met the bottleneck. For example, the general knowledge was lacking; the knowledge acquisition was difficult; the reasoning methods were overly simple. As a result, the development of AI experienced a second significant decline. In the 1990s, as part of the Internet's sweeping trend, AI's importance was highlighted once again. Since 2011, with the boost of mobile Internet and cloud computing, the data volume has shown explosive growth. With the rapid development of AI technologies represented by the deep neural network, AI has surpassed human performance in many fields, ushering in a new upsurge.

3.3 Classification of AI

AI can be classified into three categories: artificial narrow intelligence (ANI), artificial general intelligence (AGI), and artificial super intelligence (ASI) [54]. ANI enables artificial systems to perform a single domain-specific task. As shown in Fig. 3, ANI can be further classified into three subcategories: perception, cognition, and learning, as well as behavior. AGI represents a more advanced state of AI, where AI is regarded, more or less, equivalent to human intelligence in terms of its ability to perform generic intellectual tasks. However, the current understandings of AI are far from enough to develop fully

Table 2 Different definitions of AI

Time	Representative	Definition
1956	McCarthy [5]	*AI is the science and engineering of making intelligent machines, especially intelligent computer programs.*
1982	Newell [41]	*Different cultures and knowledge backgrounds have different views on the concept of AI, so there is no need to define and differentiate arbitrarily.*
1987	Marvin [42]	*The question is not whether intelligent machines can have any emotions, but whether machines can be intelligent without any emotions.*
1990	Winston [43]	*AI is the study of how to make computers do intelligent work that only human beings could do in the past.*
1995	Simon [44]	*AI uses computers as a revolutionary tool to simulate, indeed exhibit, intelligence, thereby providing a means for examining it in utmost detail.*
1998	Nilsson [45]	*AI is concerned with intelligent behavior in artifacts.*
2019	Jackson [46]	*AI is the field of computer science that studies how machines can be made to act intelligently.*

Table 3 Three schools of AI

Schools	Concept	Time of emergence	Representative
Symbolicism	AI is derived from mathematical logics	From the end of the 19th century to the 1980s	Newell, Simon, Nilsson.
Connectionism	AI is derived from bionics	1960s and 1970s	McCulloch [47], Hopfield [48]
Actionism	AI is derived from cybernetics	The end of the 20th century	Brooks [49]

functional ASI systems. ASI represents a yet hypothetical AI state, where AI is equipped with more advanced intelligence than human intelligence. Hence, it can cope with highly challenging tasks that cannot be handled by human intelligence. In this work, the authors mainly focus on the applications of ANI in PLM.

3.3.1 Perception

Perception indicates the computers' ability to interact with the external world and process sensory information [55]. The modern smart devices are equipped with cameras, sensors, microphones, and other IoT modules to obtain external data, including structured data (e.g., size, temperature, and pressure) and unstructured data (e.g., sound, video, and pictures). Intelligent perception is evolving from the traditional model-driven approach to the data-driven approach.

Computer vision studies how computers extract information and develop in-depth understandings based on the raw data of images or videos [56]. Computer vision focuses on extracting target features from images/videos such as edge detection, shape detection, corner detection, and color-based segmentation. Deep learning is an effective approach to computer vision [57]. The main areas of computer vision include image classification [58], object detection [59], target tracking [60], image segmentation [61], using different deep convolutional neural networks (CNN) such as region CNN (R-CNN), faster R-CNN, full convolutional network (FCN), etc. [62]

Natural language processing (NLP) enables computers to interpret the meanings of natural language, including natural language understanding (NLU) and natural language generation (NLG) [63]. NLU enables computers to process human voices through speech recognition and semantic understanding. In comparison with NLU, NLG focuses on the conceptual level of abstraction and generates text based on a collection of predefined semantic and grammatical rules. After the introduction of deep learning, NLP has made significant breakthroughs. Sophisticated applications of NLP include machine translation, text summarization, text classification, text proofreading, information extraction, speech synthesis, speech recognition, etc. [64]

3.3.2 Cognition and learning

AI systems should be equipped with the intelligence of cognition [65] and learning [66] to learn, analyze, evaluate, judge, and make decisions based on the perceived information. The relevant technologies include logic, planning, knowledge representation, reasoning, and ML, etc.

Logic had been a mature discipline even before AI emergence. Logic means generic rules of the reasoning behind different cases of problem-solving [67]. It solves intelligent reasoning problems and supports analysis, characterization, and programming, representing and simulating intelligence. The common logic branch includes propositional logic and first-order logic.

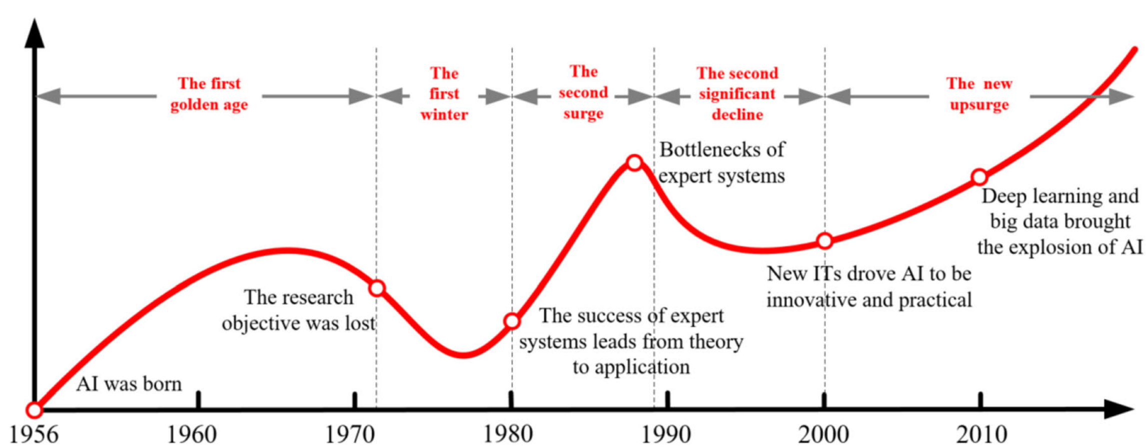


Fig. 2 Reflection of the development history of AI

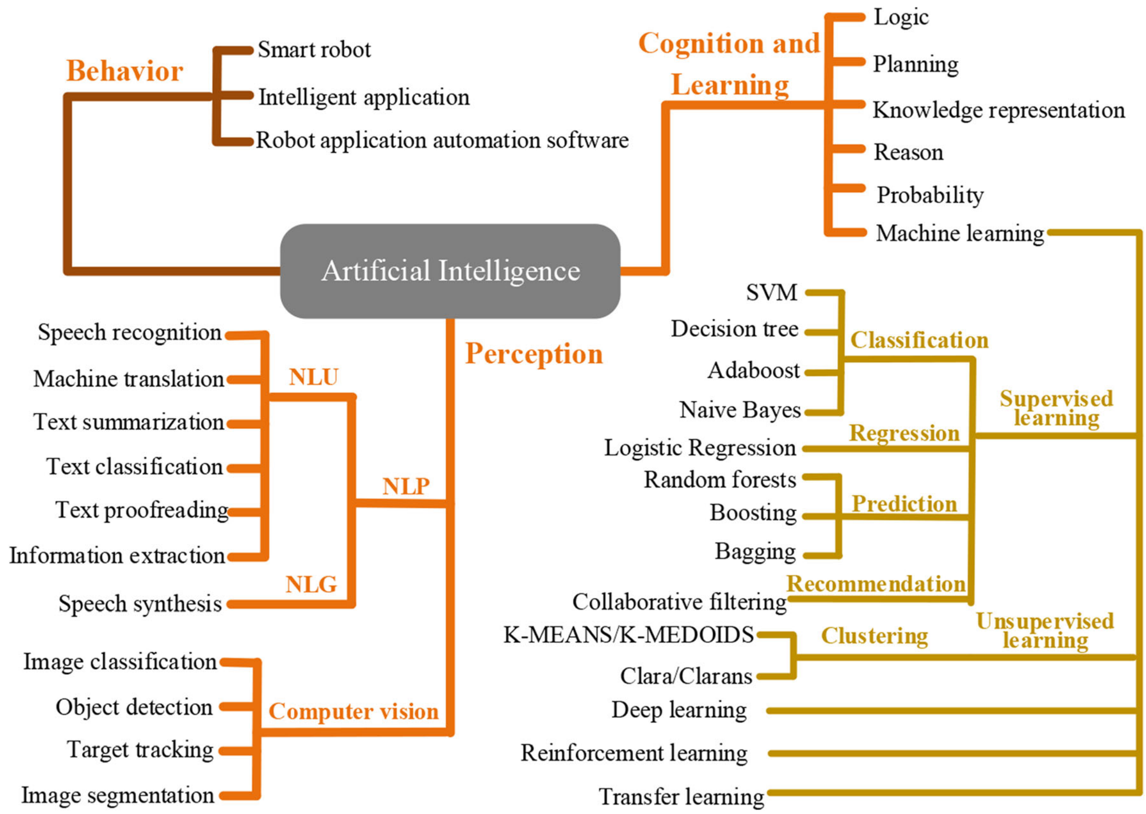


Fig. 3 The brief classification of AI

Planning refers to the intelligent planning and scheduling of tasks [68]. Practical applications of planning in manufacturing include path planning, resource allocation, shop-floor scheduling, etc. The common methods include artificial potential field [69], analytical method [70], enumeration method [71], topology method [72], etc. Besides, heuristic algorithms are useful for planning proved by representing examples like evolutionary algorithms [73] and swarm intelligence algorithms [74].

Knowledge representation studies how to represent facts in the format of reusable knowledge [75]. The studies are based on the assumption that human brains can formulate, reason, and solve different problems because they follow certain reusable and transferable rules. Knowledge representation combines a series of rules to simulate how a human brain functions through artificial means. It can make inferences and judgments based on knowledge provided by one or more experts and simulate human experts' decision-making process. The primary application of knowledge representation is the expert system, also known as knowledge-based inference engines.

The probability model indicates the probabilistic relationships between variables based on mathematical models [76]. Since many AI algorithms can only obtain the probability distribution of a solution set, especially in prediction and classification, they should be mixed with probability models to obtain the exact solution. In decision intelligence, probabilistic models provide computers with rational decisions by analyzing the probability of transactions. Various statistical methods in probability models can support AI algorithms to identify overfitting probability models (i.e., expectation-maximization, Kalman filter, Bayesian model, Markov model, etc.)

ML studies how computers learn progressively by discovering implicit patterns and performing an intellectual task without explicit instructions in advance [77]. ML is adopted in areas such as natural language processing, non-monotone logic, computer vision, etc. According to the learning methods, ML can be divided into supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, and transfer learning. In terms of the learning objectives, ML is divided into regression, classification, clustering, prediction, etc. ML has the advantage of processing high-dimensional, unlabeled, and non-standardized data.

3.3.3 Behavior

Behavior studies the integration of computer systems, sensing systems, feedback systems, and communication systems (e.g., intelligent robots and robot process automation software) to regulate the behaviors of artificial systems [78]. Intelligent robots can perform complex tasks through manual-directed training or self-supervised learning. They can interact with human operators based on common language and even collaborate with human operators based on advanced sensory capabilities. Intelligent robots can replace human operators with higher reliability, lower cost, and higher productivity. Potential applications include medical material handling, prescription dispensing, patient care, direct material handling, inventory replenishment, finished product handling, product picking and packaging, e-commerce order fulfillment, package delivery, shopping assistance, customer care, security, etc. Robot process automation software combines interface recognition technologies and workflow execution technologies. It simulates human operations in using screens and keyboards to drive applications and execute system operations automatically. Robot application automation software is a "glue" type of technology that synthesizes various systems to perform more complex activities than automation.

3.4 AI applications summary

Figure 4 classifies the technological fields of AI against their current development trends. The classification was based on Gartner's presentations at the World AI Conference in 2018 and 2019, respectively (https://www.gartner.com/smarterwithgartner/). AI-related algorithms and their applications have been well studied, such as recommendation engines, predictive analytics, and decision intelligence. Some emerging algorithms are considered more powerful than traditional algorithms, such as reinforcement learning and transfer learning. NLP and computer vision have made great progress recently and have entered the stage of commercial application.

Independent AI, AI-driven development, immersive technologies, augmented intelligence, and AI chips represent AI's development trend in the future. Although these technologies are relatively premature, they have shown great potentials. Independent AI can interact with an unknown environment and perform complex tasks more naturally. AI-driven development is committed to building AI-based solutions and frameworks such as AI cloud services, AI PaaS, edge AI, etc. The applications of immersive technologies (i.e., VR, AR, and MR) can change how people interact with the physical world. Augmented intelligence can enhance the ability of data analysis and realize the automation of data-driven tasks. At present, the further advancement of many AI technologies is seriously restricted by computation capability. Hence, the research on various accelerating chips (e.g., GPU accelerator, TPU accelerator, FPGA accelerator, etc.) is of paramount importance for AI's long-term prosperity.

After the technology-driven and data-driven phases, the application of AI has entered the scene-driven phase. As shown in Fig. 5, AI find extensively application in many industries such as the retail industry [79], security industry [80], healthcare industry [81], e-commerce industry [82], manufacturing industry [4], financial industry [83], transportation and logistics industry [84], and home furnishing industry. These applications rely on relatively mature AI technologies such as computer vision, NLP, and ML.

4 AI in PLM

4.1 AI Framework in PLM

The authors investigate the existing and potential AI technologies application as shown in Fig. 6, sorted by differing stages (i.e., design, manufacturing, and service stages) and PLM substage. Their related AI tools are listed in Table 4.

4.2 AI in product design

The popularity of AI technology is spawned by supporting the product design from two mainly aspects: analyze market trends by using AI algorithms PLM data mining; provide decision-making aid for designers to achieve a fast and personalized product design. Figure 7 shows an AI-enhanced product design framework, which consists of a design database, case library, knowledge library, algorithm library, application library, etc. The design database provides data support by accommodating the PLM data, collecting from various channels (e.g., internet, sensor, service robot, and manufacturing/management systems). The case library accumulates successful design cases for reference and review. Knowledge library manages reusable design rules and knowledge involved in design processes. AI algorithms, dynamically invoked according to applications, are designed and stored in the algorithm library. The AI chip in charge of data reading/storage optimization and AI algorithms' running speed enhancement in parallel. As AI chips' computation speed increases, the above components operate interactively and support the various product design processes.

4.2.1 AI for conceptual design

Aiming to develop popular and novel products, the conceptual design phase is increasingly and extensively considered critical during the product design process. An efficient conceptual design cannot be separated from the adequate market investigation [134], intimately influencing the market prospect, customer acceptance, and product lifecycle [135].

Market analysis based on data mining The market analysis goal is to identify target customers, recognize their requirements, and transform their requirements into product features. Compared with analyzing the market manually, market research based on data mining can discover market data's implicit association by integrating ML and statistics [136]. Specifically, based on the feature analysis and fitting of

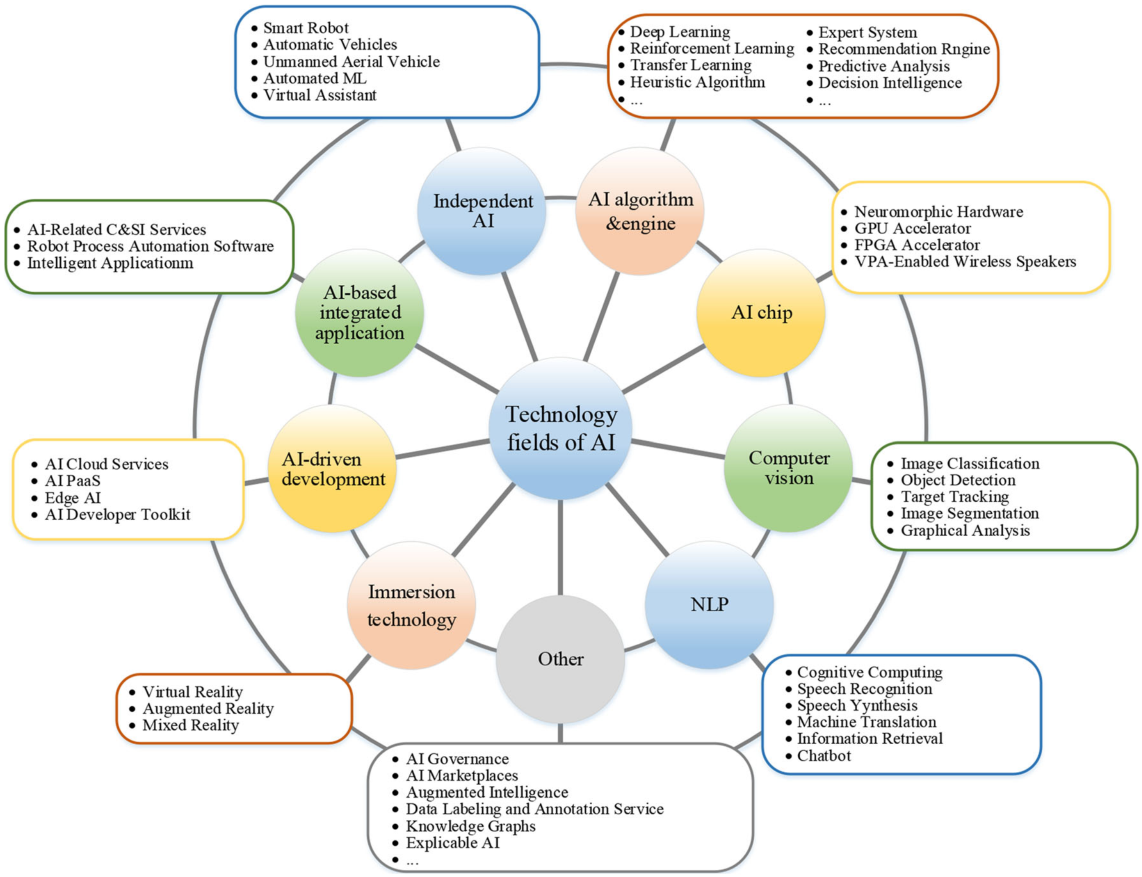


Fig. 4 Technological fields of artificial intelligence

historical market volatility data, ML tools have shown the capability to build market risk assessment models sorting and predicting abnormal customer activities (e.g., a sudden drop in sales or concentrated customer feedback). Statistics, serving as a data mining mathematical tool (e.g., cluster analysis, classification, prediction, and deviation analysis), responsible for analyzing the potential market laws based on customer consumption data. Relevant statistical methods of data mining show excellent capability in discovering unmet product requirements and predicting market opportunities. Apparently, market analysis combing data mining is highly effective in exploring market supply and demand changes and guides manufacturers to adjust product design schemes.

Rapid conceptual design based on case library In the traditional conceptual design process, the design cases are memorized in designers' minds, which shows highly ineffective in sharing and delivering information to other designers. To change this, the case library is established for learning and sharing design cases and helps to develop rapid computer design. In particular, the fragmented cases are easier to classify, store, and learn, and deep convolutional networks are utilized to identify and fragment design cases. New design cases are continuously generated to expand the case base by improving and combining design fragments. The case library automatically collecting new cases with differing variations provide more selections to customers with differing variations. From this point, the case library yields a higher level of design efficiency and the reusability of previous design cases.

Personalized collaborative design based on AR Augmented reality technology is popular for displaying personalized products in an immersive and interactive way at an early stage. Benefiting from the augmented reality (AR), the design concepts are generated by computer modeling and achieves virtual and real interaction in a real environment. The users will directly participate in the design process through the simulation and visualization of product specifications, and the design information is transferred bidirectionally. For a complex design task, globally distributed designers can seamlessly collaborate in an AR scenario, visually communicate their design concepts, and instantly deliver feedback to each other. Designers can also collaborate with customers in an AR scenario, where customers are enabled to raise, modify, and clarify their requirements more adaptively, thereby improving the personalized design.

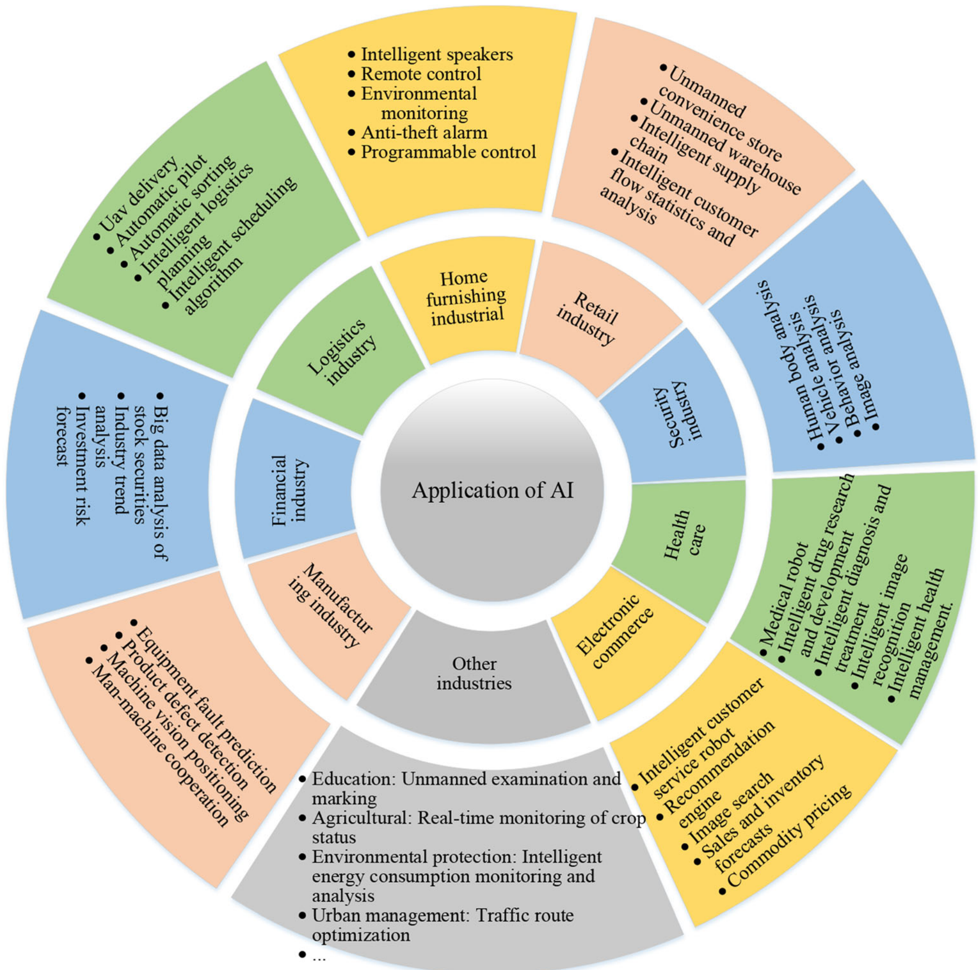


Fig. 5 Application fields of artificial intelligence

4.2.2 AI for embodiment design

Originating from the design concept, embodiment design aims to develop a tangible product's overall layout and structural dimensions based on technical, economic, and aesthetic aspects. Designers develop layout schemes in terms of product function, appearance, and ergonomics to consider factors such as market demands, materials, structure, and manufacturing [137]. The layout design is highly ineffective for a human designer to perform well as many uncertainties existing in implementing the activity.

Product layout design based on decision intelligence

The product layout design links the embodiment design and detail design. Firstly, the combination of product layout elements requires comprehensive evaluation criteria and advanced decision methods. Secondly, a product structure is continuously revised and optimized by comparing different layout schemes. The increasing level of product complexity leads to the manual decision-making method suffering from a laborious and time-consuming process. However, the integration of the decision intelligence (e.g., Rough Set Theory and Fuzzy Theory) and heuristic algorithms are demonstrated to optimize the target attributes of design layouts [138] for achieving the layout design with the desired quality and functionality.

4.2.3 AI for detail design

The products' performance, quality, ergonomics, and cost significantly are highly susceptible to detail design. The conventional detail design has a strong dependence on the designers' subjective design knowledge and experience. However, modern product design involves numerous design parameters, implicit design couplings, complicated design structure, increasing possibilities of material selection and combination, and higher requirements for efficiency and flexibility [22]. Hence, the new design method provides important guidance to solve the above problems.

Design parameter recommendation The detailed design quality is highly sensitive to the parameter selection of a specific structure product. The intelligent CAD system provides design parameter recommendations for designers by integrating expert systems (e.g., knowledge base and inference engine)

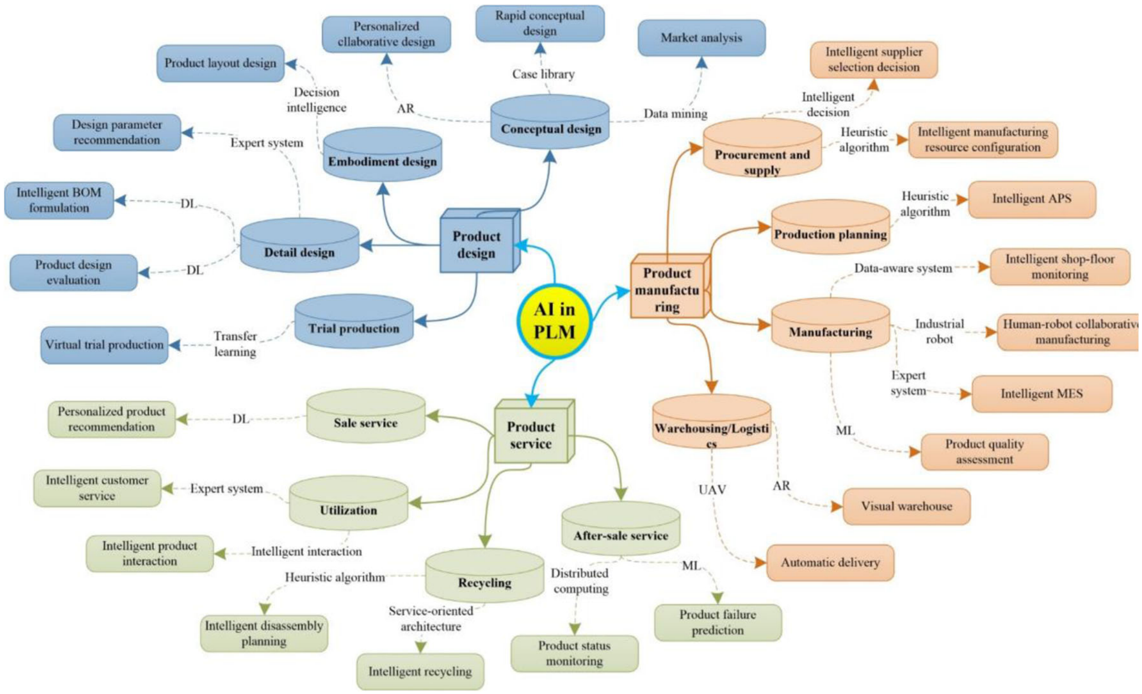


Fig. 6 AI framework in PLM

and traditional CAD systems (e.g., engineering calculation, 2D drawing, 3D modeling, and finite element analysis) [139]. Specifically, the expert system has the function of extracting common design rules from previous design cases, generating parameter-relevant design propositions, and recommending modification design parameters to designers. By collaborating with the expert systems with human designers, the intelligent CAD systems can improve the automation level of a detail design process and assist designers in making rational decisions, easing the difficulty level in the detailed design.

Intelligent BOM formulation Bill of materials (BOM) refers to a comprehensive list of a product's components, sub-components, raw materials, and assemblies. The quality of BOM heavily affects product quality and performance. Material selection activity has long focused on BOM formulation. The conventional material selection depends on the designer's knowledge and experience on material properties. However, modern products featuring more functionalities, design parameters, and complicated structures suggest increasing difficulty in materials selection activity. Evolving toward a multi-objective, multi-disciplinary, and multi-variable direction, material selection activity integrated with advanced AI technology is indispensable, rather than just relying on human designers.

Deep learning is employed for material selection activity [140]. Based on deep learning algorithms (e.g., CNN and Multi-layer perceptron), intelligent selection methods are constructed to transform the inputs of functional requirements, design constraints, and material properties into the output of material combination. The deep learning algorithms provide designers new insights to explore the solution space effectively and automatically. The self-reinforcing feature in deep learning algorithms also facilitates the progressive accumulation of design knowledge (e.g., material characteristics and expert experience in material selection) and actively adapts to the dynamic design environment.

Data-driven product design evaluation The design evaluation aims to optimize design details by exploring the differences between product requirements and design schemes. The product development and the incorrect selection of design parameters not only increases product development cost but also causes extra modifications. Traditional methods depend on expert experience to determine the evaluation criteria and utilize fixed rules for evaluation by utilizing AHP, Taguchi, Failure Mode, Effects Analysis, etc. causing the evaluation process lack of objectivity and dynamics.

The exponential growth of PLM data provides a data-driven support for design evaluation. Data features can be extracted and input into various deep neural networks for training. Different convolutional layers can be deployed to evaluate different design aspects, such as performance, cost, and quality. Through the combination of multiple convolution layers, a comprehensive design evaluation outcome can be obtained. Meanwhile, the model can be incorporated into the virtual design platform towards virtual design evaluation before trial production. With the continuous accumulation of

Table 4 Application of AI tools in PLM

PLM stage	AI application in PLM	Related AI tools
Product design stage	Market analysis	Support vector machine [85], Apriori [86], ARIMA [87] et al.
	Rapid conceptual design	Semantic clustering [88], Swarm intelligent algorithm [89] et al.
	Personalized collaborative design	Reality tracking [90], Gesture control [91], MRTK [92] et al.
	Product layout design	Rough set [93], Fuzzy multivariate decision [94] et al.
	Design parameter recommendation	Expert system [95].
	Intelligent BOM formulation	CNN [96], Multi-layer perceptron [97] et al.
	Product design evaluation	CNN [98], Deep residual network [99] et al.
	Virtual trial production	Transfer learning [100], Virtual assembly modeling [101] et al.
Product manufacturing stage	Intelligent supplier selection decision	Fuzzy TOPSIS [102], Fuzzy ART [103], Grey VIKOR[104] et al.
	Intelligent manufacturing resource configuration	Teaching-learning-based optimization algorithm [105], Swarm intelligent algorithm [106] et al.
	Intelligent APS	Evolutionary algorithm [107], Swarm intelligent algorithm [108] et al.
	Intelligent shop-floor monitoring	Wireless sensor network [109].
	Human-robot collaborative manufacturing	Human-robot synchronization control [110], Gesture control & Visual feedback [111] et al.
	Intelligent MES	Expert system [112], Generalized partial global workshop planning [113], Agent-based intelligent control [114] et al.
	Product quality assessment	CNN [115], Machine vision [116] et al.
	Visual warehouse	Head-up display [117], Pick-by-vision system [118] et al.
	Automatic delivery	Route planning [119], Automatic navigation [120] et al.
Product service stage	Personalized product recommendation	Collaborative filtering [121], CNN [122] et al.
	Intelligent product interaction	Wireless heterogeneous sensing [123], Distant speech recognition [124] et al.
	Intelligent customer service	Natural language processing [125], Expert system [126] et al.
	Product status monitoring	Distributed intelligent computing [127].
	Product failure prediction	Support vector machine [128], Random forest [129], Linear discriminant analysis [130] et al.
	Intelligent disassembly planning	Evolutionary algorithm [131], Hyper heuristic algorithm [132], et al.
	Intelligent recycling	Cloud recycling system [133].

data, the evaluation model will change dynamically. Hence, the evaluation outcome will become more accurate over time.

4.2.4 AI in trial production

The cost of traditional trial production is high and usually takes a long period. Characterize a design prototype's performance basing on trial production data can yield incorrect conclusion. Also, the verification of test products suffers from defects such as large fault limits, uncontrollable processes, and insufficient testing information. Manufacturers have difficulty to adjust various supporting facilities just based on the trial production condition. Virtual simulation and AI are introduced to solve these issues. First, virtual technologies (e.g., virtual reality, augmented reality, and virtual prototype) have the function of modifying the product design continuously in a virtual environment and obtain the simulation data of a large sample size [141]. Then, through transfer learning (TL), the virtual simulation data is mapped to the actual production environment for design verification. This method perfectly amends the data insufficient problems in trial production, improves product design quality, and decreases trial production costs.

4.3 AI in product manufacturing

Figure 8 shows an AI-enhanced product manufacturing framework, including material procurement, resource configuration, production planning, machining, assembly, quality control, storage, logistics, etc. AI contributes to the product manufacturing stage enhancement in two mainly ways: optimizing AI algorithms' manufacturing execution and management process, replacing human labor with AI devices. Additionally, the integration of AI and manufacturing systems

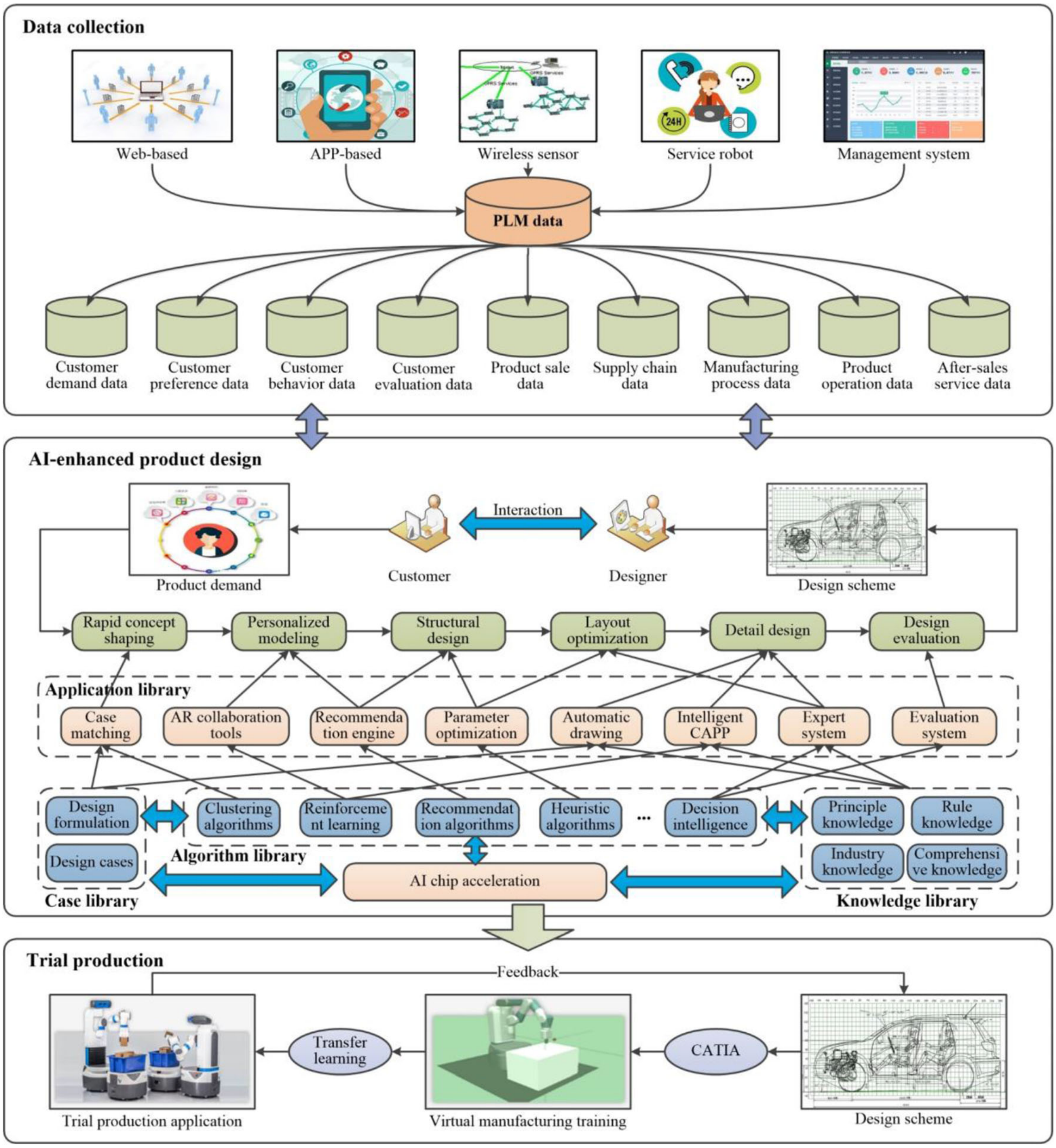


Fig. 7 AI-enhanced product design

yields significant progress in human-machine collaboration, fault prediction, intelligent decision, and other aspects.

4.3.1 AI for procurement and supply (P&S)

P&S refers to the identification, acquisition, and management of resources and suppliers. P&S is responsible for choosing the most suitable supplier based on the BOM and allocate resources to different manufacturing units accordingly [142]. The process of supplier evaluation, comparison, and selection is inherently a multi-criteria decision-making problem [143]. It determines the value of a supplier based on subjective and objective data. However, the key information reflecting the evaluation criteria is multi-sourced and fuzzy [144]. For manufacturers, the optimal resource configuration needs to consider a series of complex factors, such as product characteristics, corporate objectives, customer needs, and different resource combinations [145]. Apparently, the above decision-making problems existing in P&S are difficult to be solved by human designers under a complex manufacturing circumstance.

Intelligent supplier selection decision Supplier selection is an important part of supply chain management. The results affect product cost, quality, and manufacturing processes substantially. Faced with complex and changeable procurement

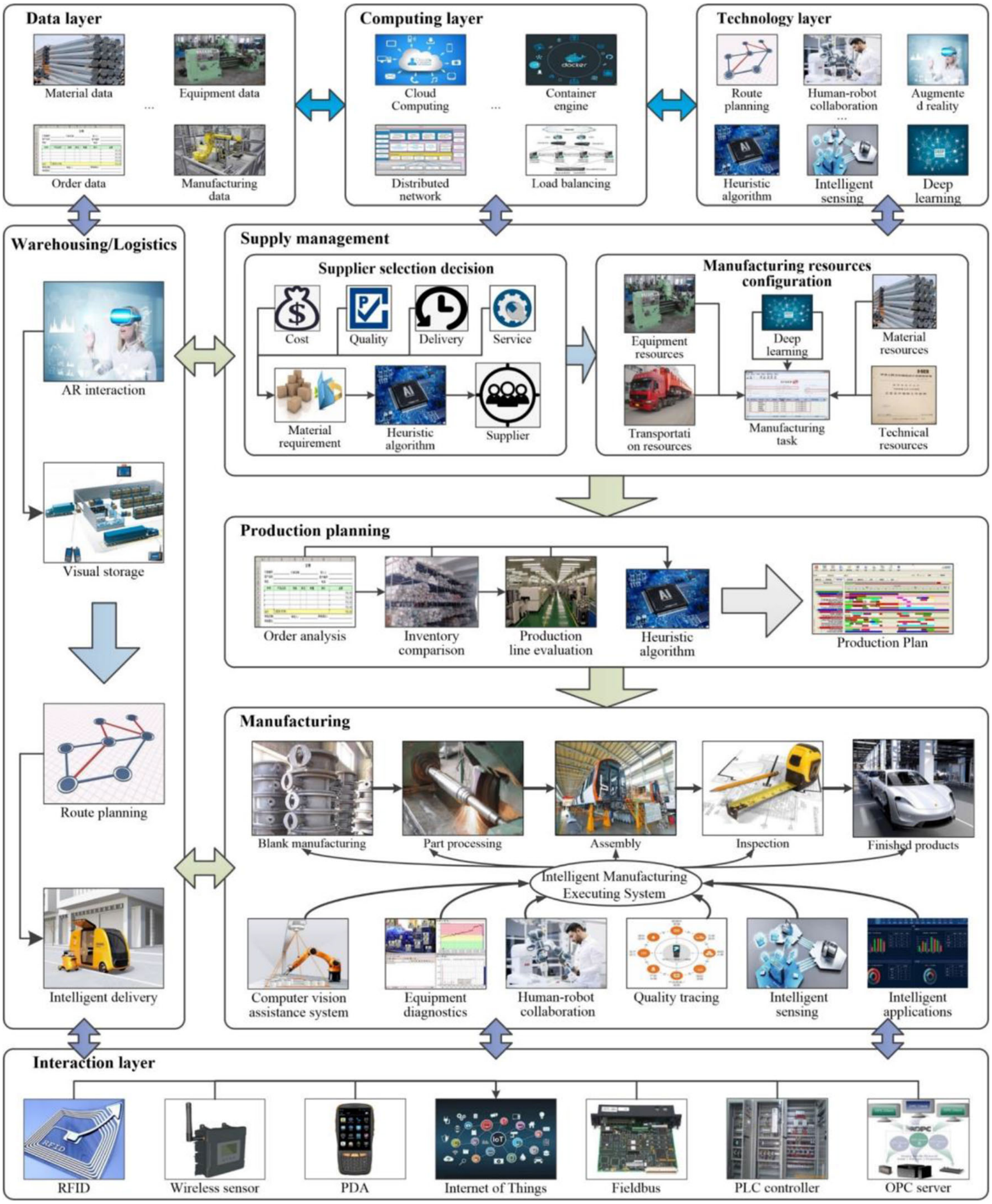


Fig. 8 AI-enhanced product manufacturing

requirements, the multi-attribute decision-making methods (e.g., fuzzy theory and grey theory) is recommended to build the supplier selection models, and heuristic algorithms are suitable for solving these combinatorial optimization model [146]. Besides, for the circumstance of abundant supply chain samples, deep learning can establish a network of mapping relationships between suppliers and manufacturing targets. The trained mapping network provides a valuable conclusion for manufacturers to determine the optimal supplier.

Intelligent manufacturing resources configuration Manufacturing resources include hardware resources (e.g., production equipment, testing equipment, and production lines) and software resources (e.g., engineering analysis software, simulation software, and data management software) [147]. The configuration result of manufacturing resources directly affects the quality, reliability, and efficiency of the manufacturing process and the follow-up services. Faced with complex manufacturing tasks, AI technology provides solutions for resource configuration decisions that are difficult to handle manually. Specifically, intelligent planning (e.g., state-space search and planning-graph) [148] is suitable for model optimization of heterogeneous resource combinations to simulate specific manufacturing constraints. Artificial neural networks [149] can optimize the configuration function by constructing feature mappings between manufacturing resources and manufacturing tasks. Moreover, complemented by evolutionary algorithms [150] and group optimization algorithms [151], the optimization models of resource combination can obtain the optimal solution using fewer computing resources.

4.3.2 AI for production planning

Production planning is essential for arranging the production process, consumables, and manufacturing resources in the shop-floor (e.g., processing machines, transportation equipment, and operators). It influences the production cost, resource utilization efficiency, and order delivery time. However, the production plan with rigid rules causes low production flexibility, slow response to market dynamics, order delay, and waste resources [152]. For a more complex and dynamic situation, Intelligent planning algorithms is strongly recommended solution to the pre-mentioned issues.

Advanced planning and scheduling (APS) + AI Due to the increasing complexity of the product manufacturing process, manufacturers seek a higher adaptable and flexible production schedule. Collaborating with ERP, MES, PLM systems, Intelligent advanced planning and scheduling (IAPS) system is key to realizing the flexible production operation and management. Unlike conventional APS systems, the core decision agent integrated by heuristic scheduling algorithms [153] and operation planning rules can effectively address the lack of experience in manual production scheduling problems. IAPS system is of immense benefit to planning quality and resolves production conflicts.

4.3.3 AI in manufacturing

The manufacturing management system is order-driven, distributed, responsive, and flexible [154]. Traditionally, shop-floor operations are largely separated from manufacturing resources. It is difficult for the manufacturing process to integrate management and manufacturing decision making based on the shop-floor monitoring data, manufacturing execution data, and process quality data [155]. AI supports manufacturing system modeling, manufacturing process decision-making, and manufacturing data integration. The integration of AI and manufacturing systems promises an imperative future direction of intelligent manufacturing.

Intelligent shop-floor monitoring based on data-aware system The Data-aware system is popular with its responsibility for improving physical objects' perception in a shop-floor environment [156]. The system contains the integrated technologies of precise tracking and positioning of resources and data transmission optimization based on the wireless sensor network. By utilizing the data-aware system assists, the manufacturers realize real-time monitor in the workshop. Besides, the data-aware system can achieve automatic management and data quality control by using the core algorithm (e.g., weighted centroid algorithm), refine the data collection efficiency and information accuracy in shop-floors [157].

Human-robot collaborative manufacturing Industrial robots collaborated with human operators to be a new requirement for advanced manufacturing systems, especially for complex working environments. Human-robot collaboration performs tasks with high automation, flexibility, and productivity in many different advanced manufacturing fields [158]. For instance, in the automotive industry, Nissan employed human-robot collaboration to address the failed scheduling timeouts issue [159]. In the medical device industry, the collinear production by industrial robots and experienced operators replaced the traditional Cartesian coordinate robots to produce complicated medical connectors [160]. This collaboration can yield a significantly higher level of diversity and flexibility enhancement for the manufacturing system.

AI applications in manufacturing execution system (MES) MES emphasizes process integration, control at the workshop level, and reasonable resource allocation functions in manufacturing process. It functions to increase the transparency of shop-floor operation and improve the efficiency of production management. In the face of complex and dynamic manufacturing processes, AI exhibits stronger decision-making capability than humans, which enables the traditional MES to achieve active management [161]. For different manufacturing constraints, expert system can build knowledge base and an inference engine to support manufacturing execution in terms of production order allocation, production material flow, and production equipment collaboration. In unexpected conditions, MES can automatically cope with certain production conflicts (e.g., insufficient raw materials, emergency insertion orders, and equipment conflicts) through the integration of heuristic algorithms and processing rules. Besides, by interacting with sensors and controllers through intelligent interfaces, MES can monitor the equipment operating status in real time and automatically adjust the equipment operating mechanism. Such a mode provides the automatic control of MES systems with enhanced error prevention mechanism and lower labor costs.

Product quality assessment based on DL Traditional quality assessment approaches demonstrated a strong dependence on manual identifications, resulting in inaccuracy, low-efficiency issues, and inapplicable to complex manufacturing environments. DL algorithms are suitable for product quality analysis in an environment with sufficient data. Specifically, clustering algorithms are used to extract features from large-scale product quality data. Then a DL evaluation model is established based on the evaluation rules concerning product quality [162]. Besides, machine vision systems embedded with DL can perform image-based inspection and analysis. Through CNN, machine vision systems can replace human operators for various occasions of quality inspection, object identification, and size measurement, especially for the high-speed, high-volume, and automated production [163]. Compared with traditional manual detection, machine vision inspection has the prevailing advantages of high performance and high reliability, especially in dangerous inspection circumstances.

4.3.4 AI in warehousing/logistics

Non-digital warehouses are prone to chaotic warehouse information. It is challenging to carry out enterprise inventory management effectively [164]. Besides, insufficient workforce and low logistics efficiency have an important impact on the manufacturer's product delivery.

Visual warehouse based on AR With AR and advanced sensors' support, a visual warehouse enables manufacturers to manage distributed warehouses more collaboratively [165]. In a visual warehouse, physical materials are mapped to virtual materials in the database through data sensing and AR information modeling. Human operators can query information, update materials status, and regulate material operations on-site through mobile devices and smart wearable devices. Compared with traditional warehouse management, the visual warehouse can reduce the information inconsistency between online and offline inventories, optimize the storage cost of materials, and locate target goods, which refines warehouse management's transparency and efficiency.

Automatic delivery The realization of an automatic delivery service depends on AI-based delivery management. Specifically, deep learning has the ability to manage the complexity of logistics transportation networks [166], and routing planning algorithms can improve the processing capacity and efficiency of complex road conditions [167]. An unmanned aerial vehicle (UAV) is used for delivery, whose behaviors are controlled by an automatic pilot [168]. In a complex distribution environment, automatic delivery services streamline the transportation process, reduce the loss of goods, transportation costs, and eventually enhance logistics services' quality.

4.4 AI in product service

Figure 9 shows an AI-enhanced product service platform. AI supports the product service stage from two mainly aspects: humanized customer service system and intelligent remote equipment monitoring and maintenance.

4.4.1 AI in product sales service

Conventional sales services featured rule-based product evaluation and recommendation have difficulty adapting to personalized scenarios [169]. How to generate informed product recommendations in integrated considerations of dynamic customer needs and specific product features becomes a key challenge for current sales service [170]. Based on the sales big data, the combined application of deep learning and recommendation algorithms (e.g., DNN + collaborative filtering) can enhance the personalized decision level of recommendation by analyzing the demand associated information of user set and product set [171]. Besides, the time-series network can extract preference features based on the user's historical purchase behaviors and make recommendations by modeling the content of the product sales network and user group [172].

4.4.2 AI in product utilization service

At the product utilization phase, AI smooths the complex user-product interactions. The complexity of interactions originates from the increasing diversity of customer needs, product functionalities, usage scenarios, and value-adding services [173]. It finds difficulty in satisfying customer requirements and guarantee product experience without scenario-based service design [174].

Intelligent product interaction Intelligent product interaction provides a more abundant user-product interaction in the context of specific application scenarios; a notable example is a smart home [175]. It enables users to know home information and control home appliances anytime and anywhere. The realization of intelligent product interaction is an outcome of multiple technologies cooperative operation. Through human-computer interaction technologies (e.g., wireless sensing, computer vision, and speech recognition), intelligent product interaction makes the application scenario humanized and transfers the information between users and products from unidirectional to bi-direction. With the IoT development, intelligent product interaction provides intelligent dialogue, electromechanical control, sound and light control, remote control, and environmental monitoring by connecting various devices (e.g., audio and video equipment, lighting system, air-conditioning system, and robotic equipment) [176]. Moreover, diversified interaction modes (e.g., mobile phones, pads, voice control panels, and intelligent robots) break the

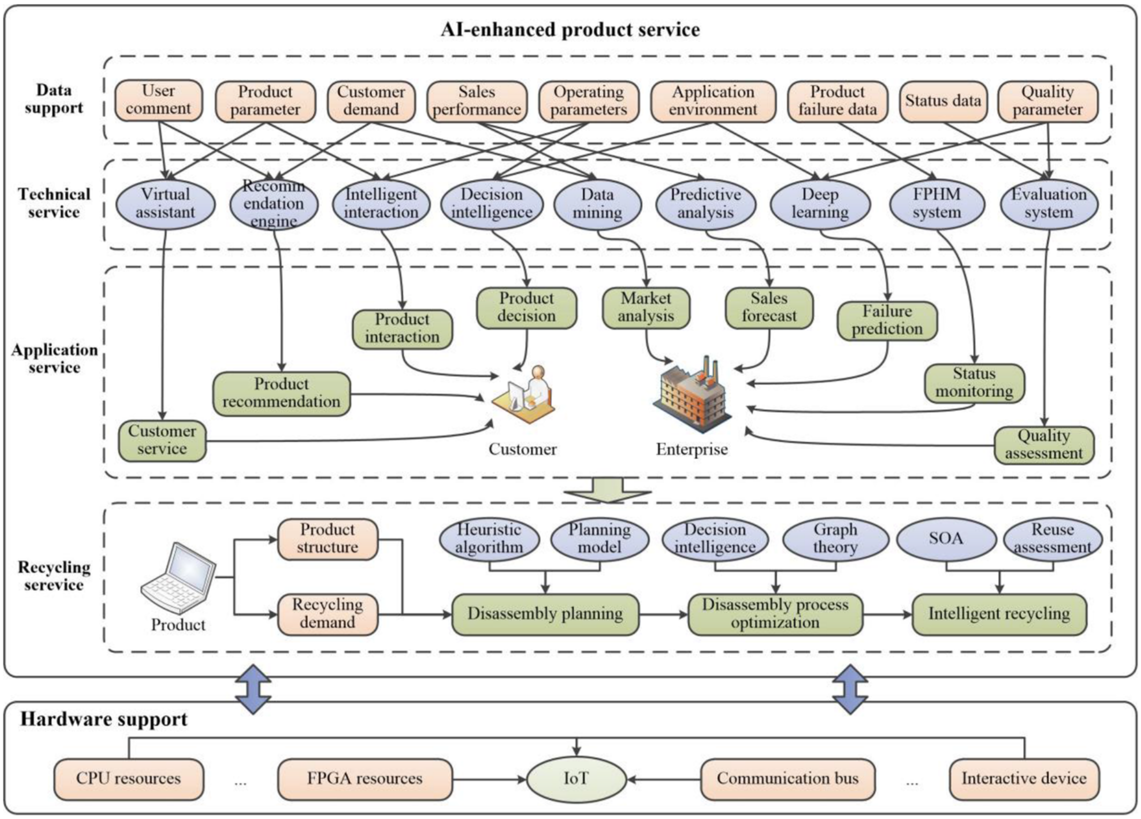


Fig. 9 AI-enhanced product service

limitations of product function interconnection and provide users with a multi-dimensional intelligent interaction experience. Intelligent interaction technologies equip the product with network communication and automation functions and comprehensively improve its safety, convenience, and user-friendliness.

Intelligent customer service The intelligent customer service system, a large-scale knowledge processing system, includes semantic retrieval technology based on natural language processing [177] and knowledge service technology based on expert systems [178]. Firstly, semantic retrieval automatically builds the knowledge base through feature extraction and knowledge classification from customer dialogue data. Then, the expert systems formulate answers fitting the characteristics of customer questions by rapid knowledge matching. Additionally, the intelligent customer service system provides timely services through various channels (e.g., websites, call centers, and smartphone APPs) and refines the cost-effectiveness and service efficiency.

4.4.3 AI in product after-sale service

After-sales service needs technical guidance for product maintenance according to consumer requirements. Traditionally, it is difficult for customers to perceive gradual product changes in state, quality, and performance [179]. Therefore, unaware product degradation affected the user experience and reduced after-sales service quality [180].

Product status monitoring Product status data, part of product lifecycle information, is used to evaluate equipment performance and prevent product failures. Monitoring real-time product status can be challenging due to the geographical distribution of products and the restricted network transmission capacity. The integration of distributed computing and intelligent algorithms, proposed as an ideal approach for the real-time monitor, effectively reduces the pressure of network transmission and improves the efficiency of massively parallel computing [181]. Besides, combining with cluster servers, intelligent algorithms can prescribe an optimal allocation of computing resources to achieve data interaction reduction and improve decentralized information processing.

Product failure prediction Since the traditional maintenance strategy often fails to detect product failures in time, the product maintenance activity develops towards intelligent failure prediction and health management (FPHM). Collecting data from various sensors, FPHM applies autonomous decision-making models (e.g., decision tree, data fusion, and fuzzy logic) to monitor, predict, and manage products' health status [182]. FPHM, integrated with AI technology, further improves the knowledge-based failure diagnosis and data-driven failure prediction. Follow the rule-based expert system, knowledge-based failure diagnosis has the advantage of solving the accuracy problem of static time series prediction [183]. Besides, the data-driven failure prediction can establish self-learning models (e.g., autoregressive moving average models, artificial neural network models, and Kalman filter models) to analyze potential correlations of product failures [184]. This method is useful for integrating equipment fault diagnosis information, reducing equipment maintenance costs, and improving maintenance operators' efficiency through the organization and reuse of historical product failure data.

4.4.4 AI in product recycling service

Clearly, the disassembly and recycling of products have very important to sustainable development. Traditionally, disassembly planning is conducted by the subjective experience [185]. However, the deviations between manual disassembly planning and actual product structure tend to output recycling sequences theoretically sound but practically infeasible [186]. Due to the increasing product complexity, the above limitations are becoming more obvious. After disassembling the finished product, manual identification, classification, and recycling of disassembled parts have the defects of inefficiency and insufficient decision ability [187].

Intelligent disassembly planning Since the disassembly planning of complex products has evolved into an NP-hard problem, traditional manual experience planning is difficult to play a role. Instead, the integrated application of the planning and heuristic algorithms is the main method for the above problem [188]. Compared with manual decision, the combined optimization modeling of the disassembly sequence has shown more comprehensively in considering the influencing factors during the complex disassembly process. Meanwhile, the application of heuristic algorithms enhances the efficiency of solving NP-hard problems, which obtains the approximate optimal solution of the complex disassembly problem using fewer computing resources [189].

Service-oriented intelligent recycling With the growing tendency of intelligent manufacturing, recycling activity transforms from product-oriented to service-oriented architecture (SOA). Intelligent recycling technologies encapsulate recycled product resources as a service, including the optimization of recycling resources by heuristic algorithms and the evaluation of re-manufacturability/reusability towards the highest recycling rate [190]. The goal is to optimize the execution of recycling tasks through the recommendation and matching of recycling services. These service-oriented technologies are expected to enhance the integration ability of scattered recycled resources and improve product reuse efficiency.

5 Advantages of applying AI in PLM

5.1 Promoting manufacturer business mode transformation

The conventional manufacturing mode features with responsiveness and adaptability relying on manufacturer's resource, capability, and priority. Such a model has low against market changes. AI empowers manufacturers to transform towards mass customization and personalization. Customers can directly put forward personalized orders based on intelligent recommendations, whereas manufacturers can fulfill the customized/personalized orders with ultra-flexible production lines in smart factories. Smart customization is most applicable to the design and manufacturing of consumer products, where there are high demands for differentiated, customized, and personalized products and services. The successful applications of smart customization can be found in products such as automobiles, computers, clothing, furniture, and home appliances. For example, the RED COLLAR group in China has been running an industrial Internet platform and intelligent shop-floors for a decade, which enabled customers to customize suit designs through the Internet and smartphone app, hence achieving the paradigm shift from "Business to Customer" to "Customer to Business" [191].

5.2 Enhancing the quality and efficiency of product design

AI, integrated with existing methods and tools, improves product design quality. For example, the product design platforms, Fusion 360 and Netfabb 3D, developed by Autodesk, have incorporated AI and ML modules. These intelligent design modules propose design solutions according to their interpretations of the requirements and constraints. Besides, the Internet of Things enables manufacturers to obtain a large amount of manufacturing data, reinforcing digital design systems' simulation capability. Digital twin systems enable designers to monitor, control, and optimize physical product activities through their digital counterparts.

5.3 Improving the automation and intelligentization of product manufacturing

Many mature AI applications can be implemented to improve the automation and intelligentization of the product manufacturing processes, such as computer vision, smart robots, and autonomous vehicles. Also, AI algorithms are integrated into manufacturing systems to enhance the system's planning and decision-making capabilities. Smart manufacturing systems can logically plan, coordinate, and adjust a complex production process with minimum human intervention, improving the collaborative configuration of manufacturing resources on a shop-floor. When a production process is interrupted by uncertainties (e.g., equipment failure, order change, and temporary insertion), manufacturing systems can respond to the change in real-time and fulfill differentiated production tasks.

5.4 Improving reliability of product manufacturing

The product manufacturing system is substantially complex since the reliability is affected by numerous factors such as materials, process, environment, personnel, equipment, etc. AI can improve the system reliability from many aspects. Firstly, AI can simulate the task execution process detect unusual conditions during the manufacturing process and simulate the task execution process to identify potential problems in advance. Secondly, AI enables the equipment maintenance activity proactive. Based on the sensors data, AI algorithms can detect anomalies during equipment operations and request suppliers to reserve fraying parts and prepare for unexpected failures in advance. Thirdly, AI agents can replace operators for tasks such as workpiece positioning based on computer vision and product quality inspection based on ML.

5.5 Ensuring personal safety in the shop-floor

Employing intelligent robots to replace human operators contributes to an enhancement in the safety level on the shop-floor. Additionally, using image segmentation, feature extraction, and target recognition, personnel, equipment, and vehicles' behavioral information is extracted from the surveillance video in work environments. This behavioral information is used to constitute the data basis for developing intelligent security systems, which has the ability to identify the operator behaviors and is highly promising for ensuring human safety.

5.6 Developing intelligent supply chains

The traditional supply chain model is mostly linear, focusing on the physical goods movement. Combined with big data analytics, AI helps manufacturers capture uncertainties in supply chain networks and take proactive measures. Big data analytics is extensively used for predicting inventory risk, supplier performance, product sales, market demands, production planning, and weak transportation links. Meanwhile, ML featuring predicting unusual demand changes in the market helps manufacturers make informed decisions regarding inventory adjustment, time-to-market, and cost control.

6 Challenges

The deep integration of artificial intelligence and advanced manufacturing in PLM faces many theoretical, methodological, technological, and operational challenges.

6.1 Data collection, transfer, and integration

The performance of AI applications depends heavily on large training data, especially in terms of perception, cognition, and learning. As the unstructured data size increases in PLM, it is increasingly difficult to verify data consistency, and the complexity of AI algorithms increases proportionately. Therefore, a key challenge is the effective collection, transfer, and integration of high-quality data.

The first challenge is to achieve ubiquitous connectivity (i.e., connecting intelligent systems and transferring data in real-time) in various PLM stages. For example, the customer requirements collected by the enterprise through different platforms are often unstructured and fragmented. Most of the existing network technologies and systems in the current shop-floor intranet are often incompatible. To solve the above problems, cross-network, cross-platform, and cross-device data exchange is very necessary. Besides, it is challenging to clean the massive heterogeneous data from different platforms and devices and convert them into a unified format for distributed storage.

Another challenge is to integrate data from all PLM. For the existing paradigm, most of the data in each stage of the PLM is mainly for its own service, and there are still great difficulties in realizing the data integration of the whole process. For example, designers rely more on market analysis data and their own experience when designing products and less on the manufacturing and service stage data. The data is not integrated and translated into the form required for the product design stage. Data collected from various information systems have different standards and formats, making it different to communicate and share, significantly increasing the complexity of integrating numerous subsystems.

6.2 Reliability, interpretability, and adaptability of AI algorithm

An intelligent algorithm lies in the center of AI in perception, cognition, learning, and decision-making. Complex PLM requires more advanced AI algorithms to improve the reliability, accuracy, and timeliness in industrial scenarios. Although many scenarios accept the current accuracy of object recognition (e.g., 90% accuracy rate), it is insufficient for most industrial applications. For example, in a factory producing hundreds of thousands of products daily, product reliability can be questionable when accuracy is lower than 99%.

Many AI algorithms theory is not published in the open literature, confusing the outsiders to understand their working mechanisms. However, industrial applications would require understandable, manageable, and reconfigurable PLM solutions. For example, the design parameter recommendation based on expert systems requires the support of a large amount of data in PLM. The design results are highly unconvinced without proving the process parameters and selection logic. There is a need to improve AI algorithms' transparency with protecting data security and business intelligence.

Furthermore, different kinds of AI algorithms can achieve the same function. For example, deep learning, SVM, random forest, and Naive Bayesian are all applicable to classification. However, the effectiveness of these algorithms is highly sensitive to the scenarios and data quality. It needs efforts to target algorithms for implementing in different industrial applications and achieving the desired performance.

6.3 Influence of external factors

Unlike a laboratory environment where most AI algorithms are developed and validated, PLM's actual environment is full of uncertainties, affecting data quality and algorithm reliability. In the manufacturing stage, the variations of light and dust in the shop-floor can affect visual recognition algorithms' accuracy. Machine noises damage the accuracy of speech recognition algorithms. The product, applied to complex outdoor scenarios in the service stage, requires extensive testing and validation to ensure reliability. Many AI algorithms are designed to learn new rules based on big data, while they cannot cope with accidental low probability emergencies. It is more advantageous to solve these low-probability emergencies by human interventions. Therefore, how to establish a mechanism combining human intervention with AI is also a major challenge.

6.4 Universality of AI cloud service application

AI service application based on the industrial cloud platform (AI&ICP) is an important PLM development direction. It functions to conveniently access AI algorithms, provide visual choreographic tools for managing services and resources, and reduce costs through standardized interfaces. Enterprises can quickly invoke appropriate AI services for the requirements in PLM. A significant challenge for AI&CSP is the mapping between application requirements and AI algorithms. On the one hand, advanced AI algorithms are being developed daily, making it difficult for a single enterprise to update and maintain. On the other hand, the requirement, context, and constraint of AI applications vary significantly from case to case. As a result, it is often difficult for enterprises to choose the most suitable algorithm for a given task and scenario. Against this background, the notion of "artificial general intelligence" is drawing growing attention.

6.5 Security of information, equipment, and trust

Security is an underlying prerequisite of intelligent design, manufacturing, and services. The security of PLM concerns information security, equipment security, trust authentication, etc. To ensure that numerous customers, manufacturers, and suppliers can access different facets of a whole product lifecycle, a massive volume of data and information will flow over the network. Hence, it calls for secure, reliable, user-friendly, and reconfigurable enterprise information security systems equipped with advanced encryption authentication, firewall, and intrusion detection technologies.

Terminal equipment is the end carrier of AI. However, it is still difficult to combine the software and hardware security technologies, resulting in the lack of protective means for terminal equipment. Under the premise of insufficient reliability of AI algorithms, intelligent equipment driven by AI algorithms tends to be exposed to the risk of unknown attacks.

The end-to-end flow of industrial data raises high requirements for the manageability, controllability, and trustworthiness of PLM. Any breach in any link naturally jeopardizes the whole network as well as all the PLM nodes. The trusted authentication demands new methods and technologies for data encryption, data transmission, distributed storage, data synchronization, and the coordination and cooperation of organization, management, and personnel.

7 Conclusions and future works

As the growing breakthroughs of platforms, algorithms, and interaction modes, AI research and application have shown explosive growth in modern industries. This paper thoroughly investigates the sophisticated and promising applications of AI in the context of PLM. In the product design stage, AI can enhance design decision-making in conceptual design, embodiment design, and detail design by mapping, in a highly customized fashion, customer needs and preferences to product attributes, functions, and performance. In the product manufacturing stage, AI can support perception, analysis, and decision-making in material selection, supplier selection, production planning, shop-floor organization, and warehouse logistics. In the product service stage, the main task of AI is to enhance human-computer interaction, behavioral control, and intelligent decision-making in terms of customer service, product maintenance, disassembly, and recycling, as a way, to improve the informationization, intelligence, and sustainable development of product-service ecosystems.

Recommendations for the future are summarized as follows:

(1) Specific application of AI technologies in different industrial scenes. This paper discusses the existing and potential applications of AI technologies in each stage of PLM. However, most of the propositions are not fully implemented in practice. Both mature and new AI technologies, when they are applied to industrial scenarios, still need to be further studied to ensure adaptability and reliability.
(2) Integration of AI technologies with other new IT technologies. The successful implementation of AI technologies depends on data, communication technology, and hardware resources. Therefore, it is imperative to investigate the integration between AI technologies and other new IT technologies, such as big data, 5G network, cloud computing, edge computing, etc.
(3) Standard establishment and system integration. Different is another challenge for the researcher. Industries, systems, devices, and algorithms have different standards concerning data formats and communication protocols, making it difficult for AI technologies to integrate with other technologies. Therefore, building a unified standard system or studying communication among different standards will help integrate and develop AI systems.

Author's contribution Lei Wang: literature review, data collection, manuscript writing and funding.

Zhengchao Liu: literature review, data collection, and manuscript writing.

Ang Liu: critical advice, manuscript proofread and valuable comments.

Fei Tao: paper original idea, supervision and guidance, critical advice, manuscript proofread, valuable comments, and funding.

All authors read and approved the final manuscript.

Funding This research is financially supported by the National Key Research and Development Program of China (2016YFB1101703), the National Natural Science Foundation of China under Grant (No. 51905396) and the Beijing Science Fund for Distinguished Young Scholars (no. JQ19011).

Data availability All data generated or analyzed during this study are included in this published article.

Declarations

Ethics approval Not applicable.

Consent to participate All the authors involved have agreed to participate in this submitted article.

Consent for publication All the authors involved in this manuscript give full consent for publication of this submitted article.

Competing interests The authors declare that they have no competing interests.

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