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Implications of data-driven product design: From information age towards intelligence age

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ABSTRACT

Data-driven design (D^3), a new design paradigm benefited from advanced data analytics and computational intelligence, has gradually promoted the research of data-driven product design (DDPD) ever since 2000 s. In today's Intelligence Age, some theoretical and practical studies have tried to achieve the advanced intelligence capabilities in DDPD. However, to the authors' best knowledge, there is still a lack of a holistic summary of DDPD with chronological concern in the intelligence age. To bridge the gap, this research undertakes a literature review of DDPD publications from 2000 to date (19/09/2022), of which 172 relevant papers are discussed via bibliometric analysis and state-of-the-art analysis. The results shown that DDPD has vitality in the Intelligence Age by combining the cutting-edge digital technologies, such as AI, additive manufacturing, digital twin, and so on. Moreover, current DDPD studies could outperform the classical design methods on the well-defined tasks, but it still cannot master the creative/innovative design tasks which require the cognitive capability. This survey further highlights several future research potentials including cognitive intelligence-enabled design, end-to-end design integration, advanced design knowledge support, design for additive manufacturing, and sustainable smart product-service systems. It is hoped that this work can be regarded as a reference to understand the roadmap of DDPD and offer insights for the design practitioners to complete relevant tasks in today's intelligence age.

1. Introduction

Digitalization, which opens the Information Age and the third industrial revolution [1], has radically changed the world for decades, including how people communicate and collaborate [2], how manufacturers produce [1,3], and how companies create business values [4,5]. In this context, data-driven design (D^3), a new design paradigm owing to big data and computational intelligence approaches, has gradually promoted the research of data-driven product design (DDPD). DDPD mainly refers to the process of design analysis and computational design synthesis activities by leveraging massive product through-lifecycle data [6]. Compared with conventional product design paradigms dominated by engineers, DDPD shifted many design activities as semi-automated or automated activities, such as decision-makings in product design and computational design synthesis [7,8] with the application of the advanced digital technologies (e.g., IoT, CAD, PLM) and intelligence approaches (e.g., AI algorithms), thus boosting the efficiency on product design.

Nowadays, DDPD research themes have become more profound and much broader. From the technological aspect, lots of well-defined design tasks can be excellently conducted. However, different techniques and algorithms were adapted into various well-defined design tasks, causing delicate DDPD niches [9]. From the business aspect, the academics and practitioners in DDPD have concerned with an increasing number of issues, such as the time to market, quick response to the dynamic requirements, human cognition workloads in human–machine interaction, and user interface layout, thus making the product design broader as an ecosystem [10].

All those dramatic transformations facilitated the product development field but also made the design concerns miscellaneous and without a mainstream. In other words, with plenty of disparate design concerns, the students, researchers, and practitioners can hardly understand the existing achievements in DDPD and further explore the next research

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Nomenclature

AI	Artificial intelligence
AD	Affective design
AM	Additive manufacturing
AR	Augmented reality
BEM	Boundary-element method
CAD	Computer-aided design
CBR	Case-based reasoning
CFD	Computational fluid dynamics
CI	Computational intelligence
CNN	Convolutional neural networks
D^3	Data-driven design
DDPD	Data-driven product design
DEMATEL	Decision making trial and evaluation laboratory
DL	Deep learning
FBS-ontology	Function-behavior-structure ontology
FEA	Finite element analysis
FEM	Finite element method
GAN	Generative adversarial networks
GD	Generative design
GD&T	Geometric dimensioning and tolerancing
IoT	Internet of Things
KBS	Knowledge-based system
KE	Kansei engineering
KG	Knowledge graph
MCDM	Multi-criteria decision-making
ML	Machine learning
MR	Mixed reality
NLP	Natural language processing
PLM	Product lifecycle management
QFD	Quality function deployment
SCPs	Smart and connected products
SVM	Support vector machine
TRIZ	Theory of inventive problem solving
UCD	User-centered design
UGC	User-generated contents
UX	User experience
VAE	Variational autoencoder
VR	Virtual reality

directions of DDPD. To the authors' best knowledge, although some studies have summarized the data-driven methodologies in the engineering field [6,8,11–13], there is still a lack of a survey to illustrate the evolution process of DDPD with chronological concern from the information age to the intelligence age. To bridge this gap, this paper relooks at the status of DDPD and further addresses the challenges and future perspectives of the existing DDPD approaches. Through the systematic survey, it is hoped to clarify the following research questions:

(1) What is the essence of DDPD? How to distinguish it from other similar design terms?
(2) What are the driving forces that trigger the development of DDPD? Will they continuously influence DDPD?
(3) What can the current DDPD methodologies achieve?
(4) What are the challenges and future perspectives of DDPD?

The rest of this paper is organized as follows. Section 2 compares the essential meanings of DDPD with other similar terms. Section 3 shows the literature selection process and demonstrates an overall statistical analysis of DDPD. A comprehensive review was conducted based on the selected literature from the perspective of driving forces behind the DDPD (Section 4) and the evolution of DDPD (Section 5). The state-of-the-art DDPD methods is summarized in Section 6. Main challenges and future perspectives were also addressed in Section 7 and Section 8, respectively. Finally, research contributions and main findings are summarized in Section 9.

2. Clarification of data-driven product design

Before discussing the state-of-the-art of DDPD, the first step is to clarify the meaning of DDPD. Since DDPD can be regarded as a discrete field of data-driven design in product design and development, this section aims to distinguish DDPD from other similar design terms to avoid misunderstandings or confusions.

2.1. DDPD vs Computer-aided product design

Computer-aided product design and *data-driven product design* are the two design paradigms that are easily mixed. Since the large-scale datasets must be manipulated on computers, Computer-aided product design is a broader paradigm that emphasizes the computational power of digital computers. It refers to the design paradigm that applies computer-assisted design tools, such as solid modelling, numerical analysis, and computational design synthesis (CDS). In contrast, data-driven product design intends to apply large-scale data for design.

2.2. DDPD vs Data-enabled, data-informed, and data-centric product design

Focusing on product design based on data, there are still several similar design terms: *data-enabled product design*, *data-informed product design*, *data-driven product design*, and *data-centric product design*. They can be clarified according to the extent of the data involved in design processes [14].

- *Data-enabled product design* indicates that the design activities can be aware of the data but are not required to leverage it.
- *Data-informed product design* means that the design activities can analyze the data for decision-making.
- *DDPD* refers to the activities that use data as the primary enabler for generating values, including design modelling and design reasoning.
- *Data-centric product design* is the paradigm in which the steps/processes of design activities, including design modelling and design reasoning, are predominated by the data; human's contributions become subtle.

3. Literature search methodology

The systematic literature selection about DDPD in this survey follows the bibliometric process [15], as depicted in Fig. 1. Firstly, Web of Science is selected as the database due to its broad scope of high-quality articles and reviews. The literature collection is conducted with a set of expert-predefined keywords that covers the scope of "data-driven" and "product design". The search string is:

Topics =
(data-driven design OR artificial intelligence OR machine learning OR deep learning OR neural network OR data science OR data analysis OR data mining OR big data OR text mining) AND
(product design OR product development OR product planning OR conceptual design OR embodiment design OR detail design OR engineering design OR industrial design OR computer-aided design OR CAD OR requirement analysis OR user experience)
AND Language = English

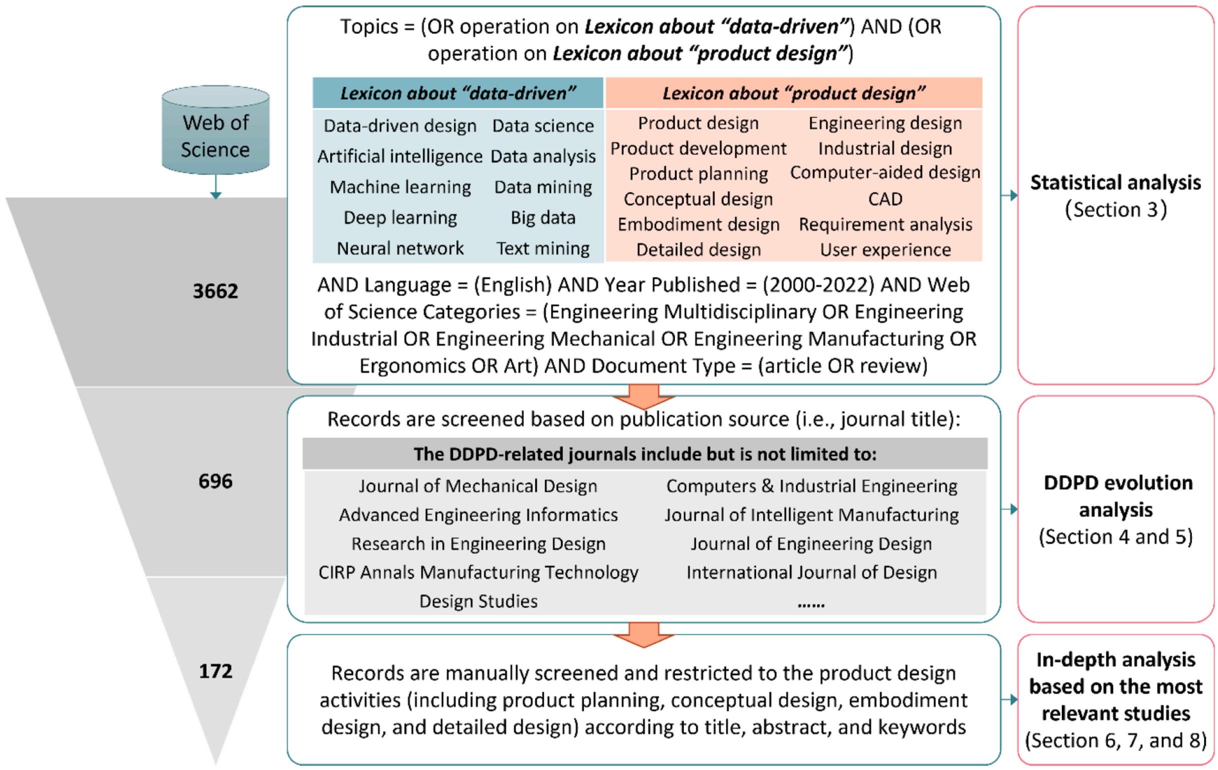

Fig. 1. Literature selection procedure.

AND Year Published = (2000–2022)
AND Document Type = (article OR review).

The search results are restricted by *Web of Science Categories = (Engineering Multidisciplinary OR Engineering Industrial OR Engineering Mechanical OR Engineering Manufacturing OR Ergonomics OR Art)*' The irrelevant literature in other fields such as chemistry, education, etc. are excluded. A total of 3662 research articles are gathered. Secondly, the publications from the irrelevant journals are removed, resulting in 696 research items. The DDPD-related journals include but is not limited to *Journal of Mechanical Design*, *Computers & Industrial Engineering*, *Advanced Engineering Informatics*, *Journal of Intelligent Manufacturing*, *Research in Engineering Design*, *CIRP Annals Manufacturing Technology*, *Journal of Engineering Design*, *Design Studies*, and *International Journal of Design*. At last, the literature records are manually screened and restricted to the product design activities, such as product planning, conceptual design, embodiment design, and detail design according to the title, abstract and keywords. As a result, 172 research journal articles are refined for in-depth analysis to represent the extant DDPD and explore future research directions.

A general statistical analysis was conducted based on the 1st-round literature search result. As shown in Fig. 2(a), research interests on DDPD proliferate since 2015. From 2000 to 2015, the related document counts stably increased from around 50 to 120. Thereafter, a significant increase occurred from 2015 to 2020, with 467 research studies published in 2021.

Fig. 2(b) shows the universities or research institutes that account for the top 20 % of publications in DDPD. Shanghai Jiao Tong University ranks the top with 60 publications in the past two decades, followed by Georgia Institute of Technology (55), Hong Kong Polytechnic University (46), Massachusetts Institute of Technology (43), Pennsylvania State University-University Park (42), and Beihang University (37), to name a few. China and North America are the primary districts devoting to the research of DDPD.

In Fig. 2(c), the Q1 or Q2 academic journals based on Journal Citation Reports (JCR) that contribute 80 % DDPD-related publications are listed. *Industrial Management & Data Systems (IMDS)*, *Journal of Mechanical Design (JMD), Computers & industrial Engineering, Advanced Engineering Informatics* and *Journal of Intelligent Manufacturing* outnumber the other journals. Most of the articles from *IMDS* underline the cross-disciplinary research in the field of operation management and information systems, and a small portion of the *IMDS* articles are related to DDPD. *JMD* addresses nearly all the engineering design activities. Notably, *JMD* probed into the potentials and advances of DDPD by announcing a special issue in 2016 [16].

4. Influential factors towards DDPD

Fig. 3 offers a chronological summary of typical product design methodologies. Product design approaches are generally grouped into four types, namely *descriptive product design paradigm, prescriptive product design paradigm, computer-aided product design, and DDPD*. *Descriptive product design approaches* intends to enhance the designers' creativity, focusing on the creative design process/strategies/methods/tools, such as brainstorming and analogy [17]. *Prescriptive product design* covers numerous systematic design methodologies, such as TRIZ, QFD, FBS-ontology, Axiomatic design, and so on. *Computer-aided product design* greatly enhance the product design process with higher efficiency and effectiveness by utilizing numerous mathematical algorithms and computer software. With the advance of the Internet, social network, and intelligent algorithms, *DDPD* applies multimodal data, including user-generated content, products/services data, and stakeholders' interaction data/records for design activities.

The product design methods are significantly affected by technological progress (i.e., the top part of Fig. 3) and marketing transformations (i.e., the bottom part of Fig. 3). To understand the influential factors that motivated DDPD, this section provides a broad discussion on the impacts of technological innovations (Section 4.1) and business strategies (Section 4.2).

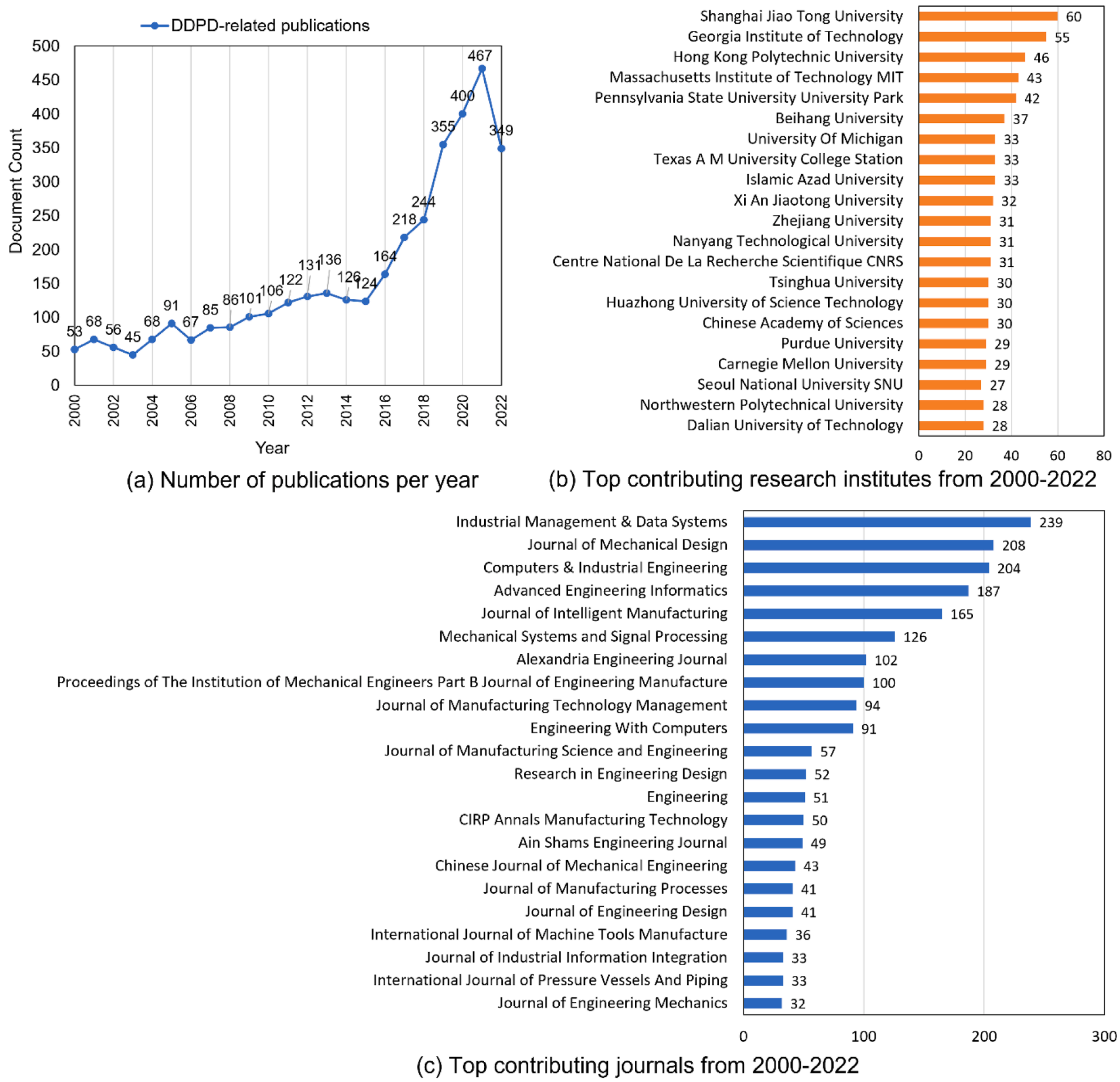

Fig. 2. Statistical analysis results from Web of Science (Accessible Date: 19/09/2022).

4.1. *Technological driving forces*

The technological driving forces usually radically change product design along with the industrial revolutions. As the top part of Fig. 3 shown, the product design has been upgraded through design with versatile craftsman in Handicraft age, design with labor-division cooperation in Mechanical and Electronic age, design with computerization in the Information age, and AI-enabled design in the Intelligence age.

Since the *Information age*, electronic digital computers, as the driving force, have thoroughly changed the product design paradigm, as shown in Table 1. Since the mid-1960 s, *design with computerization* has gradually evolved the paradigm of *CAD* for higher design efficiency and lower human errors in the engineering drawing process [18]. On the one hand, computer graphics technologies enable the geometric modelling of complex curved surfaces, e.g., the Bezier curves and surfaces [19], achieving *digitalized design records* from paper-based design record and realizing fewer human errors. On the other hand, *computational analytics* [20], such as data mining, evolutionary computation, and CBR, enable the simulation, evaluation, and validation of product models with higher efficiency and lower probability of quality failures during manufacturing. Besides, with the emergence of information management systems, the value of data is revealed by *product lifecycle management (PLM) systems with a systematic view*, which became the initial of the latter data-driven design.

With the development of Industry 4.0, the *Intelligence Age* begins with the application and integration of multiple technologies, such as cloud computing, Internet of Things (IoT), big data and analytics, additive manufacturing (AM), autonomous robots, augmented reality (AR), artificial intelligence (AI), and so on [21–23]. Those technological advances have changed the product design mainly from three aspects: (1) new design issues triggered by AM and AR [24]; (2) more decision-makings [25,26] with big data in the design stage; and (3) computational design synthesis (CDS) requiring more design concepts generation with limited resources. For the first one, new design issues such as standard data exchange files (e.g., Standard data exchange files (STL files)) are proposed because of AM. For the second one, computational intelligence, such as big data/analytics and AI, began to assist design engineers to make rational decisions [27]. Massive product-related data are vertically integrated throughout the product lifecycle, and more user-generated content (UGC) becomes accessible owing to the widespread SCPs [28]. Meanwhile, the design decisions are made based on a comprehensive concern about user experience, including customer

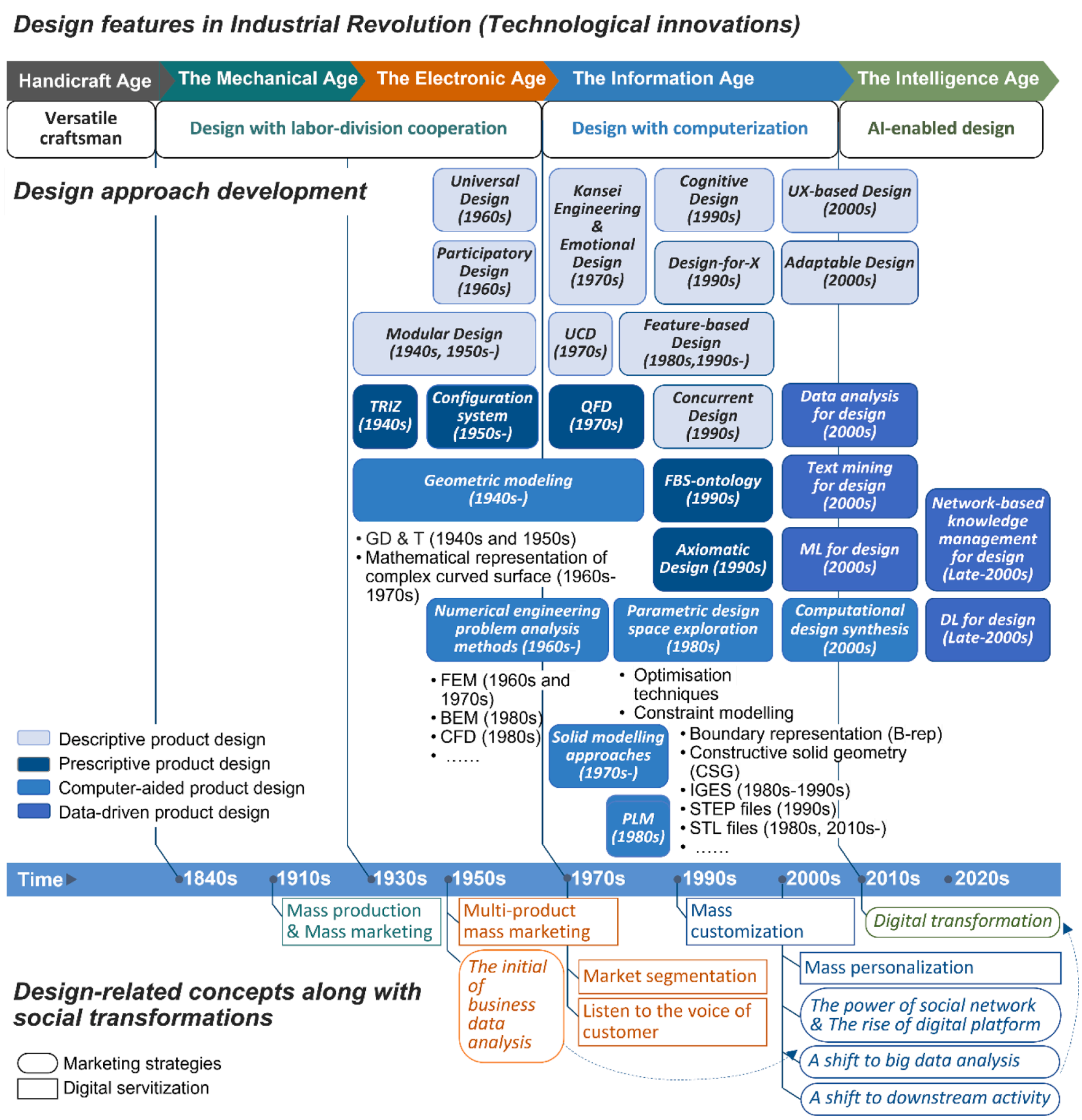

Fig. 3. Design paradigm shifts from the past to the present.

Table 1
Product design spotlights along with the industrial revolutions.

Ages	Driving forces	Product design spotlights in the age
Information Age	• Digital computers, • Internet	• Design with computerization • From paper-based records to digitalized records • Computational analytics in product design • Product design with systematic concerns
Intelligence Age	• ICTs, e.g., IoT, Cloud computing, and CPS • AR • AM • SCPs • Big data • Cognitive computing	• New design issues triggered by new technologies, e.g., AM, AR • More decision-making with big data • Based on SCPs • User-experience-based design • Data-driven design • AI-enabled design • More design concept generation (i.e., computational design synthesis) within the limited time • AI-enabled design

requirement [29,30], affective and cognitive design [31], personalized design [32], and co-design [33], in which those dimensions were emphasized as the value propositions. To achieve it, data analysis techniques and AI techniques have boosted design informatics with their impressive performances via pattern recognition among the multi-sourced data and autonomic and reasonable decision-making. For the third one, generative design (GD) achieved by deep learning techniques has also shown its strength in generating thousands of design alternatives within limited resources [27,34,35]. AI techniques have become one of the primary enablers in the *Intelligence Age*.

4.2. Market transformations

The market transformations towards DDPD also need to be clarified. The progress of product design caused by the market transformation can be discussed from two perspectives, i.e., market strategy transformation and digital servitization (originated from big data), as shown at the bottom of Fig. 4.

Manufacturers have adopted various market strategies in different ages, including mass marketing, multi-product mass marketing/market segmentation/listen to the voice of customer, mass customization, and

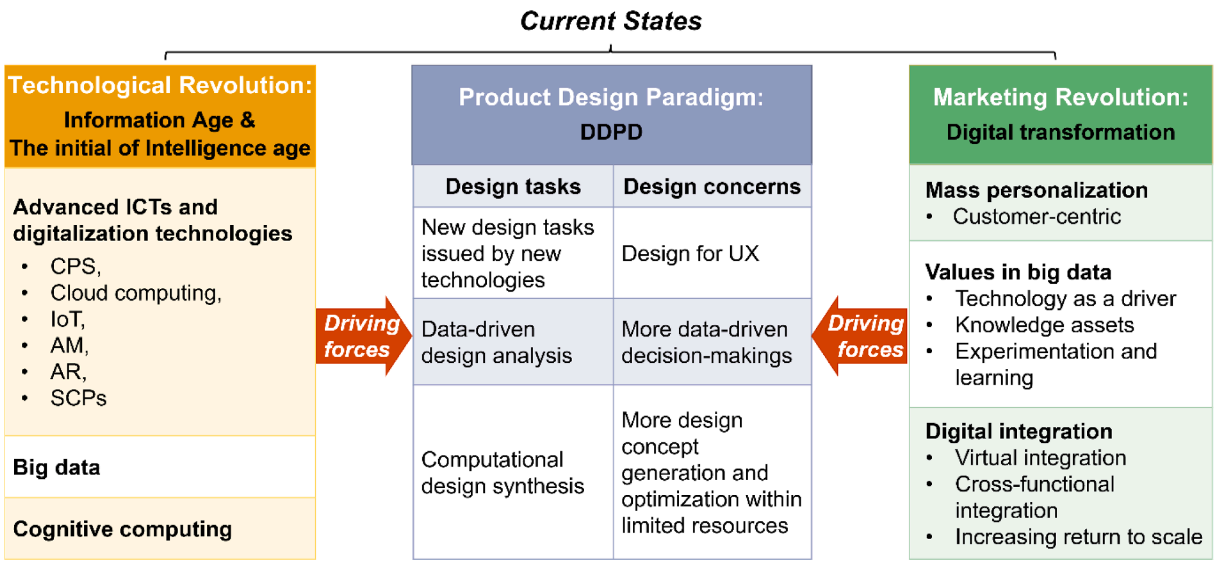

Fig. 4. Influential factors on DDPD.

mass personalization. As summarized in Table 2, mass customization went further from the market-of-few to the market-of-one, namely mass personalization [36]. The realization of mass personalization requires multiple resources and technologies, including personal data, Internet, digital platform, and configurable products [36]. The evolution of product development along with the marketing strategies is a way of pursuing the exact fulfilment of individual requirements with flexibility and quick responses.

Another progress in the market transformation is digital servitization initialized by the use of big data. As the arrows in Fig. 3 shown, since the mid-2000 s, social networks and digital platforms have connected individuals, allowing *big data collection and analysis*. Since then, big data analytics has become a significant role in the current *digital transformation* strategy. Digital transformation is a broad strategy that comprehensively integrates big data analysis and other technologies, and further profoundly alters the business. It is worth mentioning that the digital integration of upstream and downstream, as a digital ecosystem, also significantly affect the organizations of product design engineering from the system level.

4.3. Summary of the influential factors on data-driven design

As shown in Fig. 4, advanced ICTs and digitalization technologies, big data, and cognitive computing support the upgrades of product design and development from the technical perspective. Mass personalization, values in big data, and the shift towards downstream also upgrade the conventional product design to DDPD from the business perspective. Digital transformation, as an umbrella, wrapped up the business strategies under the context of technology advances. As for the DDPD paradigm itself, besides the new design tasks issued by new technologies, the main design tasks can be grouped into design informatics and design synthesis. Both are facing the challenges of more decision-making and more concept generation under limited resources.

Table 2
Product design spotlights along with the marketing strategy transformation.

Marketing strategies	Time	Design spotlights	Examples
Mass customization [37,38]	1990 s-2000 s	• Promoted by Internet • Design for fragmented demands	Ford's assembly line and Budd's all-steel vehicle [18]
Mass personalization [36]	2000 s-present	• Design for individual demands • Requires multiple data and technologies	Amazon's personalized recommendation [31]

5. Evolution of DDPD

This section reviews the total trend of DDPD and the evolution of each stage in DDPD, including product planning, conceptual design, embodiment design, and detail design [9].

5.1. Total trend of DDPD

Fig. 5 shows the keywords about DDPD based on the 667 research items in the 2nd literature search round. It is visualized by a widespread scientific literature visualization tool called *CiteSpace* [39]. The keywords are labelled from the circle centres, and the circle radius refers to the term frequency. The larger the radius is, the higher the frequency of the keyword appears. Meanwhile, the horizontal axis represents the timeline, and the vertical axis indicates no meaning. The circles of the keywords are vertically arranged to avoid the overlapping.

Since technologies usually grow from infancy to mature adoptions, we can explore the evolution of DDPD according to the changes of circle radius and the keyword meanings. Fig. 5 shows that DDPD can be generally grouped into three phases, i.e., *DDPD with IT*, *DDPD with Computational intelligence (CI)*, and *DDPD with digital transformation*.

Phase I mainly focuses on the *optimization* and the *modelling* of *product design*, which generally indicates the design modelling/synthesis tasks such as design optimization exploration. Besides, the *management* of product design tasks based on the *Internet* was also attracted research interests to a certain extent.

The emphasis of **Phase II** is *big data* analytics with *data mining/neural networks/machine learning/text mining* techniques, which is enabled by the computational power and the learning capability of intelligent algorithms. More product design tasks, such as *quality control*, *diagnosis*, *decision making*, appear in this phase. Those design tasks require advanced data analytics and decision makings on the *performance* of product design.

Furthermore, beginning from 2018, it can be observed in Fig. 5 that many new *technologies* and *innovations*, e.g., *additive design* (*3D printing*) and *Cyber-physical systems*, appeared under the environment of digital transformation in **Phase III**. Till the day that created Fig. 5 (19/09/

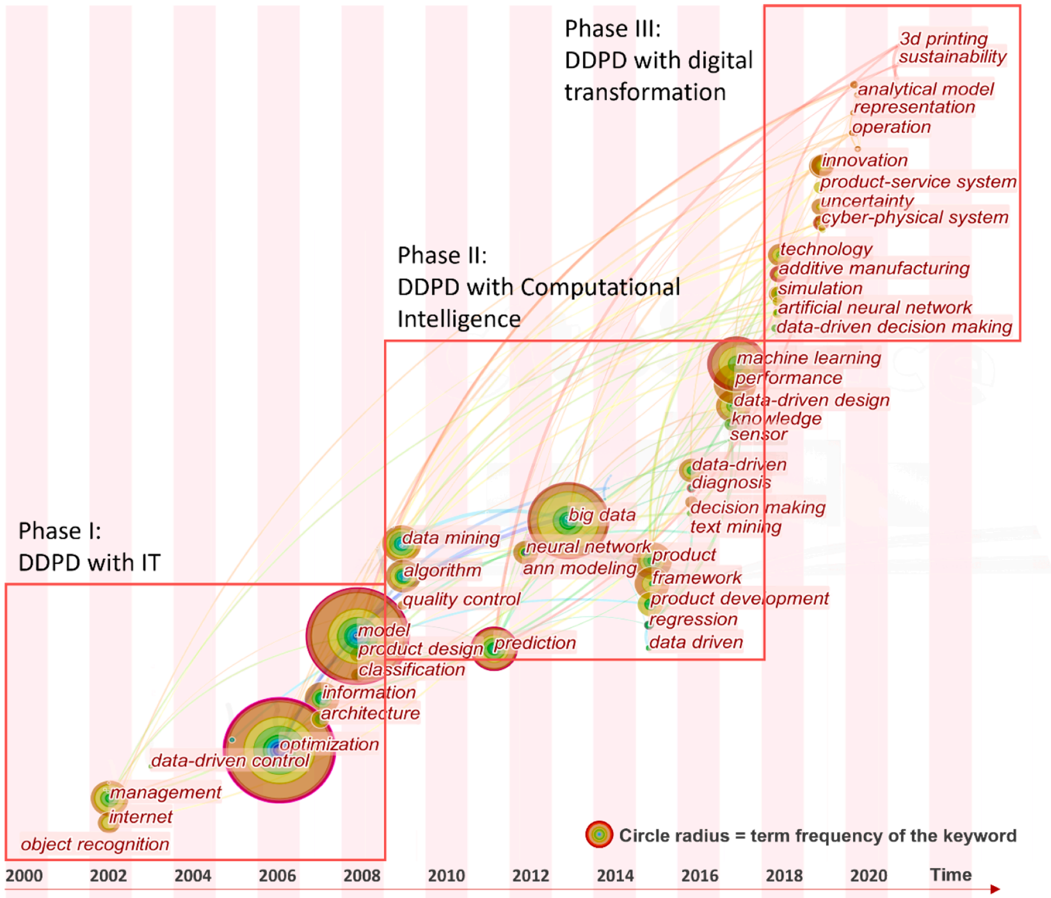

Fig. 5. Research keywords evolution of DDPD.

2022), no outstanding technologies have dominated the product design field. Meanwhile, new concerns also emerged, including *product-service systems*, *uncertainty*, and *sustainability*, besides the continuation of Phase II's *analytical and decision-making tasks*. It is worthwhile noting that although some terms are not newly created in their own fields, we still cannot overlook their potentials of inspiring new possibilities/opportunities by integrating them into the DDPD.

5.2. Evolution of each stage in DDPD

The literature in the 2nd search round is further grouped into the stages of product planning, concept design, embodiment design, and detail design. The evolution of research keywords in each stage of DDPD is illustrated in Fig. 6. Similar to Fig. 5, the research keywords are extracted from the title, abstract, and keywords in the literature in the 2nd literature search round and visualized by *CiteSpace* [39]. The x-axis refers to the timeline of the appearance of the keywords. The y-axis indicates no meaning. For the ease of visualization, the circles are vertically arranged to prevent overlapping texts.

Broadly speaking, detail design has the most active research interests in DDPD, illustrated by the significantly larger radius on the great mass of research keywords.

From a specific point of view, as highlighted in Fig. 6, some common keywords appeared in all stages but with different timestamps, namely, neural network, big data, and deep learning. First, since 2013, the studies of detail design are the first batch to apply neural networks in product design, followed by product planning and concept design (both ascend to 2006). With huge radius on neural networks and product quality, it is clear that Phase I of DDPD pay the most attention to detail design, aligning with the result of Phase I in Fig. 5. Second, since 2015, big data was firstly deployed in concept design, followed by the other stages around 2017 or 2018. This big data trend is consistent with the timestamp of big data of Phase II in Fig. 5. Third, since 2019, the keyword of deep learning has stood out from other keywords in product planning. Meanwhile, it also appeared in concept design and detail design in 2021 and 2020, respectively. Although it appeared together with other keywords such as digital twin and AM, the trend of deep learning to achieve higher intelligence capabilities in DDPD is still apparent. By laterally comparing the three keywords' evolution lines in Fig. 6, we can also find that the gaps between different design stages on prevalence have been gradually decreased that deep learning technique has been deployed in to DDPD at about the same time.

6. Status of DDPD approaches in design stages

This section investigates whether the data-driven methods can efficiently and effectively achieve the design tasks in different stages, including product planning, concept design, embodiment design, and detail design. Fig. 7 provides an overview of the summary of DDPD methods in each stage.

6.1. Product planning

Product planning, covering marketing analysis and preliminary assessments on technical and manufacturing features of the products, should be done initially before constructing the product concepts. This stage could take several months for personnel from marketing, design, manufacturing, finance, etc., to build up a business case, including market segmentation, product positioning, product family construction, etc.

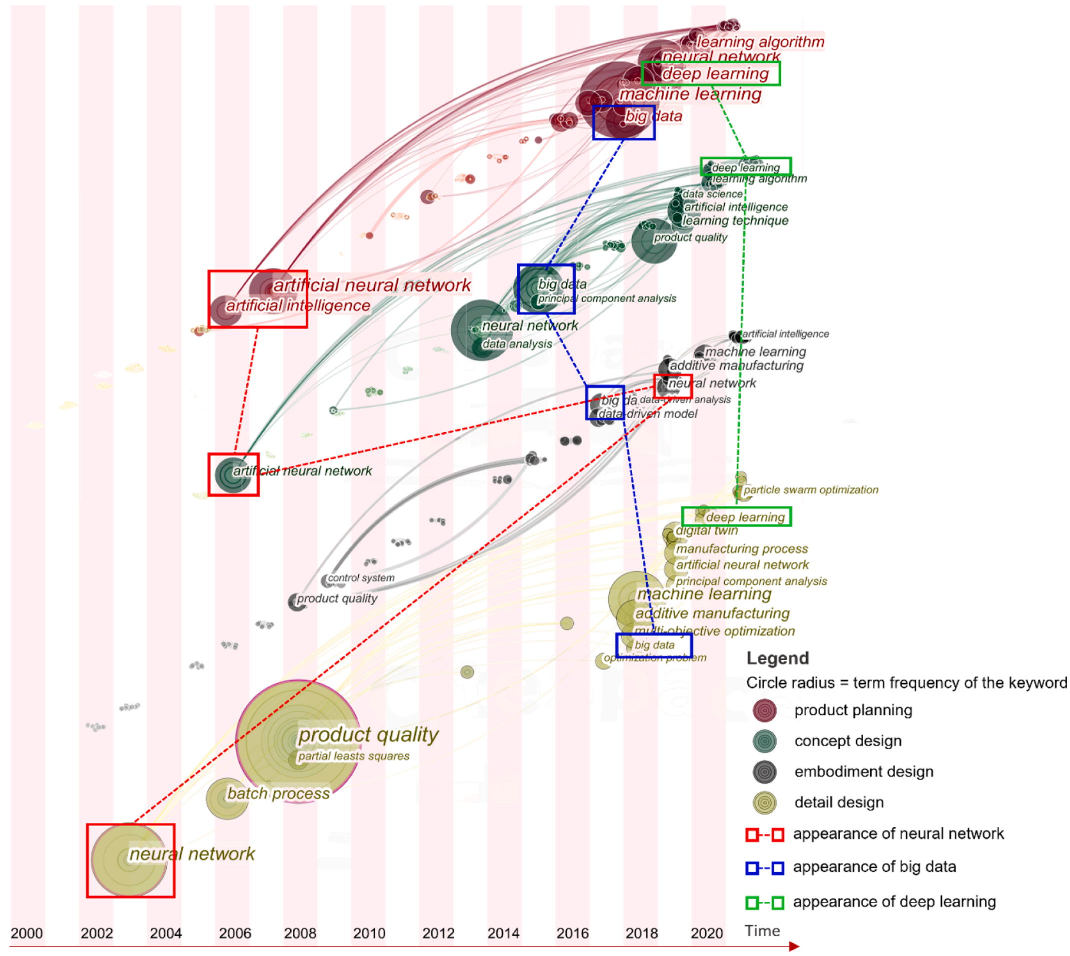

Fig. 6. Research keywords evolution of each stage in product design.

Requirement management is the core step of product planning, containing three subtasks: *requirement elicitation*, *requirement evaluation and prioritization*, and *dynamic requirement management* [40], as shown in Table 3.

Conventional *requirement elicitation* has applied many business analysis approaches can be found in this stage, including questionnaire, focus group, interview, brainstorming, etc. [41]. They highly rely on the intuition of the market analysts and the interactions between end-users and the market teams, which cannot guarantee effectiveness because of the high reliance on professional domain knowledge and the efficiency due to the long time spent. However, the trend of data-driven approaches, such as data mining techniques [47], NLP techniques [43,44], and knowledge mining techniques [45], began to be applied in requirement elicitation.

To *evaluate and prioritize the requirements*, classical decision-making methods (e.g., AHP/ANP [70,71], DEMATEL[71,72]) and mathematical algorithms (e.g., fuzzy theory and rough set theory [73]) still dominate the research. Nevertheless, they are the non-data-driven approaches because the evaluation indicators are manually predefined. Moreover, the rating scores for analysis are relatively small-scale. In the intelligence age, machine learning approaches (e.g., artificial bee colony algorithm [57] and Naïve Bayes [59]) and deep learning models such as hierarchical attention network [60] have already been attempted based on the accessible UGCs. They surpass the classical MCDM methods by their self-learning capabilities to reveal hidden patterns among the UGCs.

The data-driven studies for *dynamic requirement management* have begun since the 2010 s [63]. The intelligent approaches driven by AI, such as artificial immune system [63], neural network system, and NLP [61], have been continuously attempted to complete the design tasks in the uncertain and heterogeneous product design environment. The data majorly applied in this stage is the textual UGC, including customer reviews and comments, whereas user behavioural data, such as eye movements [58] and historical browsing/purchase data [49], were also integrated into the research as well.

6.2. Conceptual design

Conceptual design contains a series of design activities to identify the functions and structures of products. It usually needs to align the functional requirements with the customer requirements (i.e., *function specification*), generate concepts (i.e., *design concept generation*), and evaluate and select proper design concepts (i.e., *design concept evaluation*), as shown in Table 4.

To quickly produce products that meet customers' requirements, *function specification* methods have already been maturely developed with data-driven approaches. To reuse the design knowledge from the previous design cases, case-based reasoning (CBR) has been applied to solve the new problems by associating similar cases and modifying based on them. CBR can overcome the bottlenecks in the knowledge acquisition process [6,126]. However, it will show reduced effectiveness while previous design cases are inaccessible or limited; meanwhile, it cannot outperform in the radical product design. Besides CBR, other data-driven methods, including neural network (NN) [48,80], genetic algorithm (GA) [79], Support vector machine (SVM) [74], text mining techniques [78], deep learning algorithms (e.g., convolutional neural networks (CNN) [127], transfer learning [76], hierarchical attention networks [60]) have also been attempted in the function specification

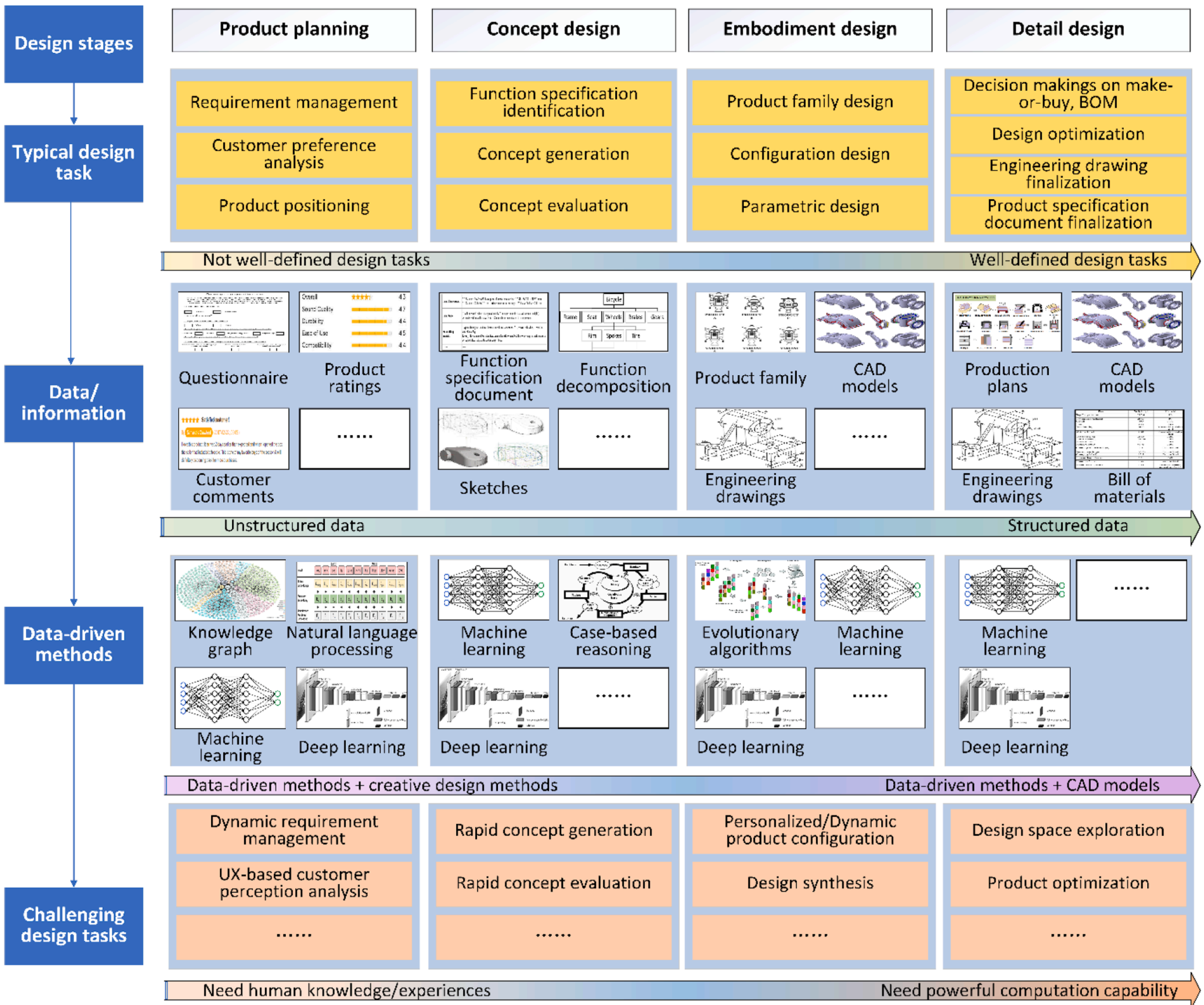

Fig. 7. State-of-the-art of different design stages of DDPD.

Table 3
Data-driven approaches in requirement management.

Design tasks	Pain points of conventional design tasks	Typical data-driven methods	Refs
Requirement elicitation	1. Difficulties in understanding and prioritizing user needs 2. Hard to manage dynamic requirements	• Data mining/ text mining • Knowledge mining approaches • NN • NLP	[30,41,42–56]
Requirement evaluation & prioritization	1. Need experts to manually identify the evaluation indicators 2. Apply algorithms without learning capability	• AI algorithms, e.g., artificial bee colony algorithm	[57–60]
Dynamic requirement management	1. Not timely update dynamic requirements 2. No dynamic requirement forecast	• Data mining/ text mining • Knowledge mining approaches • AI algorithms	[49,55,56,58,61–69]

tasks. Technically, NN can quickly extract patterns from large-scale data; hence, it can handle the ever-evolving and incremental data such as customer comments. SVM can outperform on relatively small datasets. GA has strength in ease of use and extensibility. Furthermore, text mining, computer vision [127], and knowledge graph-based models [75] can analyze end-user's sentiments or semantics in terms of their expected products. Briefly, the essence of function specification is the mapping process between customer requirements and product functions [74,128], numerous data-driven approaches suit this task only if they have the ability of pattern extraction.

Design concept generation intends to create conceptual product models with functions, design structures/features but without the dimensions and tolerances in order to distinguish it with the design synthesis task in detail design [129]. Many design heuristics approaches have been developed for concept generation, such as brainstorming [95], TRIZ [94], general sorting technique [96], morphological chart [97], etc. However, they depend on the domain knowledge/experience of the product designers. To tackle the drawback of intensive labor demand, three kinds of data-driven approaches have been developed: (1) crowdsourcing, (2) case-based/knowledge-based approaches, and (3) generative design. Crowdsourcing [93,99], the process of soliciting large-scale inputs from Internet, has become faddish in the 2010 s. Besides, similar to the function specification, historical design cases integrated with CBR/KBR can also be reused for concept generation. For instance, Chang and Chen [98] proposed a graphics-based concept generation approach that integrates knowledge-based system (KBS) and

Table 4
Data-driven approaches in conceptual design.

Design tasks	Pain points of conventional design tasks	Typical data-driven methods	Refs
Function specification	1. Highly rely on the experience/domain knowledge/inspirations of engineers	• CBR • Neural network (NN) • Support vector machine (SVM) • Genetic algorithm (GA) • Text mining • Knowledge graph models	[48,51,60,68,69,74–92]
Design concept generation	1. Highly rely on the experience/domain knowledge/inspirations of engineers	• Crowdsourcing • Generative design with ML/DL approaches • Knowledge-based/case-based	[92–110]
Design concept evaluation	1. Need experts to predefine the evaluation indicators 2. Restricted by merely textual data 3. Hard to quickly respond due to strict laboratory environment settings, long experiment duration, proper subject recruitment, etc.	• Data mining/text mining in a crowdsourcing environment • Sensory user experiment approaches, e.g., eye movement, sensory data analysis • Deep learning approaches, e.g., LSTM, RNN	[89–92,102,104–106,111–125]

3D printing, verified by generating a large number of graphic golf club concepts. Furthermore, generative design [9,130], a creative design strategy that generates many feasible design alternatives via iterative algorithms, has raised widespread research interests from conceptual design to detail design. Khan and Awan [100] proposed a generative design (GD) technique called space-filling GD technique for innovative design creation, in which the criterion of space-filling is applied for the aim of uniformly explore designs in the design space. Machine learning/deep learning algorithms have recently capacitated the generative design strategy with learning capability and generative capability. However, major relevant studies lay in embodiment design rather than concept generation [34,131].

The goal of *design concept evaluation* is to choose several satisfactory design concepts for further detail design. The evaluation can be conducted from multiple dimensions for companies' benefits, including functional dimensions (e.g., customer satisfaction), physical dimensions (e.g., product quality, reliability, and durability), and economic dimensions (e.g., cost, investment appraisal) [132]. In this context, classical multi-criteria decision-making (MCDM) approaches are qualified [6]. In contrast, if the design team concentrates more on user experiences, such as customers' satisfaction, affection, and cognition, then axiomatic design [116,117], text mining techniques [115], and sensory user experiments [113,114] will play their roles. Nevertheless, all the above approaches are still facing challenges. Both the classical MCDM methods and axiomatic design require predefined evaluation metrics, they do not have the adaptability to adjust the evaluation indicators once the design/market environment has changed. Fortunately, the exploration of introducing intelligent algorithms for either automatic evaluation metric identification or automatic decision-makings have been noticed and attempted [112]. Additionally, the text mining techniques are constraint by the decorated textual data actively generated by users but omitting the other multi-sensory data which reflects users' true behavior or sentiments. The sensory user experiments, however, cannot quickly response with robust results due to the limitation of strict laboratory environment settings, long experiment duration, proper subject recruitment, and so on.

6.3. Embodiment design and detail design

We discuss *embodiment design and detail design* together since their boundary has become blurred. The integration happened by emphasising concurrent design that contributes to moving decisions forward as soon as possible, thus shortening product development life cycle time, which is enabled by computer-aided engineering [9]. The embodiment design and detail design refer to the processes of determining the complete specifications of all the parts (e.g., geometry, materials, tolerances, etc.) and all the other decisions (e.g., make-or-buy decisions, bill of material, manufacturing tools, cost estimation, etc.) [9]. *Product family design* as well as *design exploration and optimization* are a few of the critical tasks in the embodiment design and detail design [9,133].

To achieve the mass customization, researchers and engineers have spurred a concentration on *product family design* and platform-based product development. One endeavour is configurational product family design, which develops a modular product platform to generate product varieties by adding, substituting, and/or removing one or more functional modules [134]. The configurational product family design usually cluster product elements in terms of several predefined metrics, such as modularity, commonality, variety, cost, profit, and so on. For instance, Lin et al. formalized the modularity analysis of a product architecture design as a multi-objective optimization problem and solved it with the consideration of commonality, economic efficiency and performance loss [135]. Baylis et al. proposed a product family platform selection method using a Pareto front of maximum commonality and strategic modularity [136]. Martin & Ishii proposed a "design-for-variety" approach that incorporates standardization and modularization to reduce future design costs and efforts [137]. Alizon et al. integrated Design Structure Matrix, Value Analysis, Commonality versus Diversity Index to improve and existing product family [138]. Peng et al. proposed open-architecture product to achieve the modular product design for mass customization [139]. Emmatty and Sarmah integrated DFMA into the platform-based design to optimize the cost of individual products [140]. Another way to stimulate ideas for alternative configuration generation is the 40 Inventive Principles of TRIZ. Many studies integrated TRIZ with other design methods, including axiom design, grey relational analysis, and system dynamics [94,141]. Although the above methods have been proved effective in many studies and practical cases, they are either empirical principles or mathematical programming methods, rather than data-driven methods. For data-driven product family design, Agard and Kusiak proposed a three-step methodology in which data mining algorithm, association rule mining algorithm, and a product structure were applied for customer segmentation, customer requirement-functional requirement mapping, and product architecture design based on product variability [142]. Moon et al. used association rule mining technique to cluster the functional features and applied fuzzy c-means clustering to determine the initial clusters of the modules [143]. Ma et al. developed a k-means clustering method to group the customer requirements and product architectures [102]. For data-driven product family evolution, Le et al. developed a generative network for product evolution [144].Li et al. used a Bayesian network to analyse the dynamic relationships between the customer requirements and product architectures [145].

The other endeavour is to design product families in a "stretched" or "scaled" way, i.e., parametric product family design. For instance, Simpson et al. proposed a scalable platform called Product Platform Concept Exploration Method (PPCEM) to generate product variants that have same functions with varying capacities [146]. Messac et al. applied physical programming with a product family penalty function to select the common and scaling parameters for product varieties[147].In the scalable product family design, determining optimal values of common and distinctive variables by satisfying performance and economic requirements is a critical problem. The frequently used methods contain the linear and non-linear programming algorithms, such as successive linear programming (SLP), sequential quadratic programming (SQP), and generalized reduced gradient (GRG), as well as the derivative-free methods, such as genetic algorithm [148], ant colony algorithm [149,150], and particle swarm optimization algorithm [151]. For selecting the proper components from available alternative components, Ilhami et al. applied a non-linear programming model mathematical model to trade off among quality, production capacity, and production manufacturing profit [152].

Design exploration and optimization is a critical task in configuration design and parametric design. Several typical mathematical model-based methods have been deployed for decades, including finite element analysis (FEA), boundary-element method (BEM), and computational fluid dynamics (CFD). All FEA, CFD, and BEM are usually conducted within the CAD environment, which requires intensive computational demands due to the iterative FEA [34]. To tackle this drawback, deep learning approaches have been integrated into design optimization and exploration. For example, Oh et al. [34] integrated generative adversarial networks (GAN) with topological optimization, generating a large number of 2D design alternatives with limited historical design data. Yoo et al. extended the 2D generative design method to 3D wheel design using the deep learning approaches [153]. McComb utilized a variational autoencoder (VAE) to accelerate design synthesis and analysis [154]. Similarly, Guo et al. applied convolution neural networks (CNN) for the iterative CFD process [155]. In fact, all those studies follow the generative design paradigm and combined with deep learning algorithms for performance enhancement, especially GAN. Deep learning algorithms are located at the intersections of many disciplines, including the detail design in the engineering field, and serve as the promising enabler for the design automation system.

7. Challenges of DDPD

The crux of DDPD can be found as either the design data/information/knowledge or the algorithmic intelligence. Nevertheless, DDPD still faces several practical challenges.

7.1. Design analysis paradox between effective data analysis and limited cognitive capability

Nowadays, the product design decision-makings need to be accurate and efficient with the least number of resources, including time, money, and effort [156]. A product design concept to be practicable must pass through the tedious, rigid, and iterative product development process, in which a vast number of design decisions are required to be made. By exploiting the explosive product through-life data, the design engineers can harness their design activities with rational analysis by uncovering the hidden patterns, exploring new insights, and reusing design knowledge. However, current prevalent design analysis approaches are facing the paradox between effective data analysis capability and limited cognitive capability.

Specifically, the limited cognitive capability of DDPD analysis approach is reflected in two aspects, i.e., limited generalization and limited explainability. On the one hand, the current DDPD analysis approaches need prescriptive codes and historical design data/information/knowledge for the particular design tasks, which restricts the design outputs within the design variants of the historical designs. On the other hand, extant design analysis approaches, such as machine learning approaches or text mining techniques, can hardly offer convincing explanations for design engineers. Considering that the early product design stage decisions will commit 60 %-80 % of the total product's life cycle cost [157], rational decisions with convincing explanations are promising and necessary. Moreover, the decisions with convincing explanations will increasing credibility from the product designers/engineers' point of view. In brief, it is still a far way to develop DDPD analysis approaches with humanlike cognitive capabilities.

7.2. Large quantity of design concept generation/synthesis within a limited time

The product development process has been accelerated to generate more design concepts within a limited lead time, at lower cost, and higher quality [158]. A new wave of intelligent design synthesis has become realizable based on AI techniques with learning capability and even generative capability, in which engineers dedicate their creative efforts to what they are building rather than how to follow the workflow [159]. In particular, KBS that mines and reuses historical design data/information/knowledge to automatically generate design alternatives has played an essential role in fostering quick-response and user-centric design [160,161]. Besides, generative design strategy combining generative models such as VAE or GAN can significantly improve the generative capability meanwhile with high efficiency via iterative algorithms [34,100,130]. But importantly, the supports on the generative design algorithms/approaches onto the conceptual design is still limited. Most studies explore the potential of GD in embodiment design and detail design. Moreover, the generated alternatives are sometimes restricted by historical cases with low creativity [25]. To extend the GD applications onto conceptual design, the core issue is to enrich and manage various product data/knowledge from multidisciplinary domains, not only the design but also the other open-sourced domains to explore design stimulus [6,160].

7.3. Design based on multimodal data

In the big data era, explosive product-related data, such as customer requirements, historical design features and specifications, design constraints, production process, and other data, have been vertically integrated into systematic product design support tools. However, nearly 80 % of data is unstructured data in the database [162]. Furthermore, they are usually multimodal data with different representation manner, which can be generally divided into five categories, namely (1) *pictorial data* such as sketches and engineering drawings, (2) *symbolic data* such as assembly trees, (3) *linguistic data*, for example, customer requirements, (4) *virtual data*, for instance, CAD models, and (5) *algorithmic data* such as parametrizations [163]. Lack of a unified knowledge representation protocol is the primary concern of the interoperability of the knowledge-based design support tools, especially in the product design stage [163]. Additionally, developments in knowledge discovery techniques to automatically extract valuable information among the massive, unstructured, and multi-sourced data will lead to better integration and digitalization of product-related data [163].

7.4. Design based on tacit knowledge

Considering that SCPs have become even more intricate, thus making product development knowledge-intensive, there is a significant demand for an automatic knowledge-based support tool to reduce product development duration and improve design efficiency. Existing DDPD, to a large extent, relies on explicit design knowledge [164], such as prioritized customer requirements, uncoupled function specifications, well-organized design constraints, etc. Nevertheless, a large proportion of design knowledge is still embraced in the personalized and contextualized tacit knowledge. Tacit knowledge extraction is still a challenge for the next generation of DDPD.

Contrary to the formal knowledge embedded in product-related documents, design repositories, decision support tools, and other resources, tacit knowledge refers to the knowledge tied to personal experiences, intuition, and justification [165]. As argued by Nonaka [165] and verified by plentiful academic experiments [166–168], tacit knowledge is deeply rooted in personal actions and minds under specific contexts. In product development, tacit knowledge can be frequently generated by specialists or skilled technicians or occurred in co-working activities [163]. At present, DDPD based on tacit knowledge is still facing two challenges. Initially, although plentiful tacit knowledge extraction approaches have been developed in engineering design and manufacturing [168], major tacit knowledge extraction methods are still confined to restricted efficiency and effectiveness by face-to-face interactions, long-duration and in-depth interviews, and repeated verification processes occupy a long time for the tacit knowledge acquisition process. Secondly, few research studies investigate the means of extracting experts' hidden intents, whereas the intents, indeed, are an indispensable part of the tacit knowledge [169].

8. Future perspectives of DDPD in intelligence age

This section highlights a couple of potential research directions of DDPD.

8.1. *Cognitive intelligence-enabled product design*

Following the data-information-knowledge-wisdom (DIKW) model [170], the DDPD tasks will be further enhanced by integrating the multimodal data and product lifecycle data, exploiting multidisciplinary domain knowledge, and incorporating the cutting-edge interactive technologies such as AR/VR/MR. As a result, a cognitive intelligence-enabled product design paradigm could be foreseeable [159,171,172]. It intends to achieve humanlike capabilities, such as listening and speaking, natural language understanding, understanding emotions, and image recognition. Fig. 8 shows the layered intelligent capabilities of cognitive intelligence.

The learning capability should be maintained in the intelligence age since it is the basis of the other advanced intelligent capabilities. With learning capability, intelligent algorithms can explore the hidden patterns on their own [13]. Moreover, advanced algorithmic intelligence gradually levels up to an *autonomy design paradigm* to achieve product design tasks, including self-aware capability, adaptive capability, cognitive capability, and generative capability. Self-aware capability refers to the system's ability to know the status of itself and the environment. Adaptive capability indicates the capability to adapt the system's results/performance when inputs or environments change. From the cognitive capability upwards, the algorithm intelligence promotes an essential change. Cognitive capability means that the system can understand the ontological concepts and logic, and able to reason. And generative capability is regarded as the system's capability to create or generate things. With the affective computing and cognitive computing technologies, the cognitive intelligence-enabled product design tasks contain but not are not limited to:

(1) Emotional and cognitive communication system for CIPD. Emotions of human beings gradually become a direct reference index for spiritual world. Emotion cognition will become an important application of the CIPD. The emotion cognition of the current DDPD tasks could achieve the emotion detection or perception evaluation based on the large-scale dataset.
(2) In-depth mining of the implicit customer requirements. By deploying the affective computing technologies and natural language processing technologies, it is feasible to mine the implicit customer requirements from the multimodal user-generated data, such as facial expressions and user comments.
(3) Multimodal design inspiration capture. Design inspirations are usually implicit and fleeting. In the future, it is possible to automatically capture and record a designer's inspiration by monitoring the status of the design system and designer. Specifically, the design system could recognize the pattern changes in the designer's physiological states, such as eye movements and EEG data.
(4) Intelligent design based on domain knowledge. By integrating the domain knowledge base, inference engine, and query mechanism into the CAD system, the intelligent design system is empowered to make decisions based on knowledge and coordinate the databases/graphic libraries/knowledge bases to complete design tasks with the designers. The intelligent design system is expected to support the product scheme selection, product architecture design, design exploration and optimization.
(5) Intelligent design automation: generative design. Generative design systems have transformed from using evolution algorithms or generative grammars [130] to applying deep learning algorithms [131,153]. With the support of deep generative models such as GANs and autoencoders, design synthesis is no longer solely based on the changes in technical parameters but becomes a multi-objective optimization problem that maximizes the similarity to the market reference designs on a large scale. To keep the diversity of the generated models, reinforcement learning models could be operational.

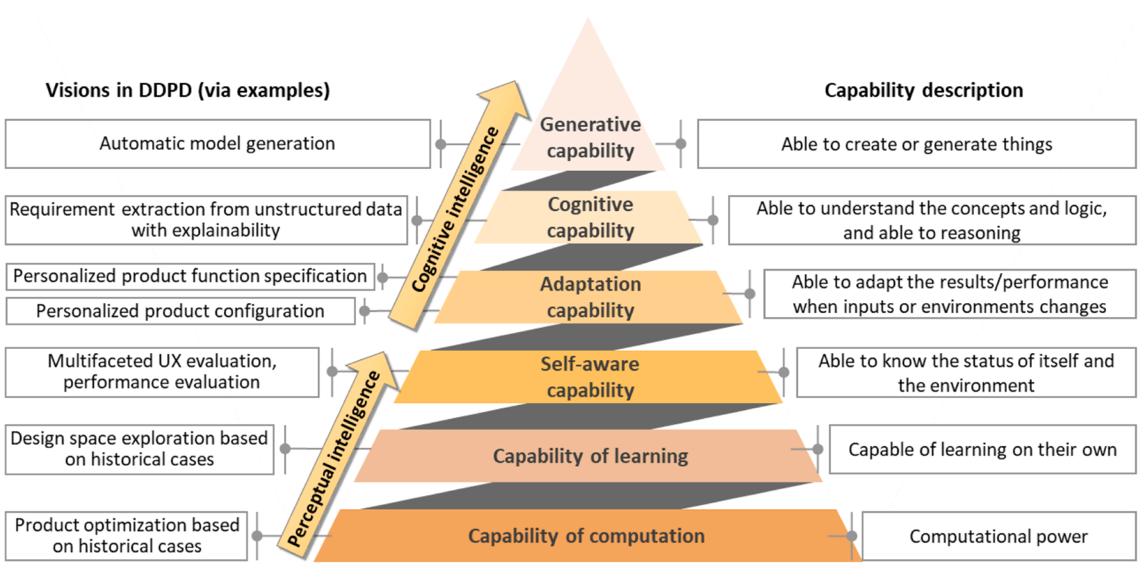

Fig. 8. Cognitive intelligence capabilities.

The key technologies to achieve the cognitive intelligence-enabled product design may focus on human–machine interaction, natural language processing, sentiment analysis, and computer vision. To further achieve the generative capabilities, generative models such as GAN, will be expected for automatic design generation.

8.2. End-to-end design integration

On a system level, a thorough end-to-end design integration should be achieved among humans, machines, SCPs, and other associated objects [13,173,174]. Two potential research directions are highlighted, namely the horizontal integrations of design activities based on product through-lifecycle data to establish a value co-creation design ecosystem [13,28] and the vertical integration of multimodal and cyber-physical data to achieve design contextualization.

(1) Horizontal end-to-end design integration: End-to-end value chain

The horizontal end-to-end design integration connects the accessible product through-lifecycle data to enable the iterative design process with higher data transparency and traceability [33,175], composing an *end-to-end value chain*. By integrating and analyzing the product through-lifecycle data, complexity (i.e., more data sources, entities, and stakeholders with complex interactions) and uncertainty (i.e., dynamics, randomness, and roughness) of the design ecosystem will increase. A basic research question is how to manage complex and uncertain information in the product design system so that the possibility of designing successful product varieties in the market could be expected. One possible solution would be monitoring the dynamics in the product design system, for example, analyzing the dynamics of the customer requirements, the evolutions of the product family design, the changes in the product function-behaviour-structure frameworks, and the transformation of the product modelings [13]. Another possible solution is to achieve the adaptability of a product design system so that the product family design could be easily reconfigurable [176]. Several design activities with advanced abilities are enhanced, such as dynamic requirement management and rapid (even real-time) reconfigurable design.

(2) Vertical end-to-end design integration: Multimodal and cyber-physical data integration

The vertical cyber-physical design integration applies multimodal data collected from multiple sources to describe the same design activities, hence enriching the design contexts [13]. With rich multimodal data, attention and fusion mechanisms can be introduced into the multimodal customer perception analysis, explicit and implicit human intention recognition, AR/VR/MR-enabled prototype validation, multimodal knowledge fusion, and so on. A promising research area would be biometric-based user experience design [177], in which the eye-tracking data, behavioural data, brain data, and speeches could be integrated with the design task descriptions and environmental data. Technically, the multimodal data integration could be achieved by multimodal machine learning techniques.

(3) Cognitive digital twin as the medium of cyber-physical design integration

Both the horizontal design integration and the vertical cyber-physical data integration could be achieved via a cognitive digital twin. Compared with the digital twin that links the physical data with the virtual data of a component/product/system, the cognitive digital twin enhances the computational intelligence to capture and understand the status of a system, as well as how the system interacts with other components in a complex system [178]. The cognitive digital twin presents the characteristics of DT-based, cognitive, full lifecycle-based, autonomous, and continuous evolution [178]. Boschert et al. claimed that the next generation of digital twins should be connected with the knowledge graphs and product lifecycle management system, composing a semantically linked digital artifact [179]. Lu and Zheng proposed a formal definition of the cognitive digital twin, which are “DTs with enhanced semantic capabilities for recognizing the dynamics of the virtual model evolutions, facilitating understanding of interrelationships between the virtual models and enhancing the decision-makings” [180]. In a recent study, Al Faruque et al. proposed the cognitive digital twin framework with cognitive capabilities including perception, attention, memory, reasoning, problem-solving, and learning [181]. An ever-evolving and cognitive product design system could be expected by incorporating the cognitive digital twin with semantic technologies such as ontology modelling, knowledge graph, model-based system engineering, and product lifecycle management system.

(4) AR/VR/MR as the interaction tool for cyber-physical design integration

Augmented reality, virtual reality, and mixed reality not only merge the 3D digital models into the environment, but also allow the users to interact with the digital content in real-time. Shen et al. demonstrated that AR could facilitate the communication and design efficiency among a multidisciplinary design team because AR tools can visualize the product’s structure and information [182]. Tang et al. developed an experiment to prove that MR tools could improve the users’ understanding of geometric relationships and creativity [183]. Ong and Shen developed a system that realizes the bi-directional communication between the MR environment and the CAD system [184]. The visualization and co-modelling of the product models could be achieved among a collaborative design team. Uva et al. presented an AR-based framework that integrates augmented technical drawings, interactive FEM simulation, multimodal annotation and chat tools, web content integration and collaborative client/server architecture [185]. Their proposed framework could support the technical design review with a tangible interface. It is evident that AR/VR/MR is powerful in 3D model visualization and real-time interaction. The product design system can be endowed with higher-level intelligence by combining AR/VR/MR with other technologies, such as combining with mathematical models, empirical design principles, or knowledge learning models.

8.3. Advanced design knowledge support

As a supporting tool, design knowledge has already become a vital and fundamental resource for design practitioners to smoothly complete design tasks. However, it is still not a worry-free and effortless way to manage design knowledge that relies on explosive data.

The approaches to extracting design knowledge from the unstructured and multi-sourced data will be expected. To the authors’ knowledge, the approaches of design knowledge extraction from textual data [43,54,160], pictural data [127], and behavioral data [114] have been separately attempted in product design. Typical approaches contain text mining [43,54,160], CNNs [127], and human factor experiments [114]. It is significant progress that they have been proved effective in customer requirement elicitation, sentiment assessment and prediction, conceptual design, etc. Nevertheless, they mainly devote themselves to the well-developed design tasks that can be derived or adapted from historical paradigms/cases. The knowledge management supporting radical product innovation is still in the infancy stage that is believed with further research interests.

Moreover, design knowledge support is also expected on massive tacit knowledge extraction, which is necessary for DDPD [160,186]. KG is a potential and blooming technique that can support design knowledge management in both well-developed and radical design environments [186]. It has been successfully applied in personalization recommendation [187], biometric and medical field [188] but lacks plentiful publications in the product design field.

8.4. Design for additive manufacturing

Additive manufacturing, as a promising production technology, enables to produce more customized and personalized complex products with lower production costs and shorter product development cycles [189–191]. Design for additive manufacturing that is different with the traditional design for manufacturing and assembly principles has been widely studied in much literature [24,190,192–195], including new approaches to explore large design spaces [191], meanwhile to incorporate hybrid design concerns on material, mesostructure [195,196], and multi-scale design. Existing studies mainly focus on three levels, namely the part level with macro-scale complexity, the material level with micro-scale complexity, and the product level with multi-scale complexity [189]. At the part level, promising research points lie in the combination of multiple materials and colors, free-form geometric design, topology optimization, and personalized product design. At the material level, the research about design for additive manufacturing focuses on custom microstructure, custom material composition, custom surface/texture/porosity, and custom lattice/truss/cellular structures for better functionality. At the product level, researchers and practitioners consider component integration, embedded objects/electronics, and direct production of components during the design phase. More detailed reviews and discussions could be found as [24,189,197].

8.5. Sustainable smart product-service systems

Higher sustainability and extended product lifecycle are the remitting pursuits of product design in manufacturing companies. To realize a sustainable product development process, many research potentials have been studied in both academics and practices, including sustainable strategies [198], circular systems [199], green design strategies [101,200], and product lifecycle management systems [33]. These strategies and approaches aim to effectively reduce non-renewable resource consumption and mitigate environmental impacts. To extend the product lifecycle, product-service system (PSS) appeared as a business paradigm to design the product-service bundles from the product planning phase. PSS could be further enhanced as a smart PSS paradigm based on the widespread ICT infrastructure, digitalization technologies, and intelligent algorithms. Product-sensed data and user-generated data could be collected and traceable via smart products [201], which enables the traceability of the materials/products in the circulation and supports the rapid reconfiguration of future product architectures [104,202]. With hybrid concerns on sustainability, smartness, and PSS, sustainable smart PSS becomes a potential research direction of the DDPD.

A basic research question of the sustainable smart PSS is what sustainable strategies should be applied in each product design phase to reallocate the cyber and physical resources for higher sustainability [203]. Another critical research core is how to perceive the multimodal, large-scale product-sensed data and user-generated data, then encodes them with corresponding design contextual features, achieving the context-awareness of the system [204–207]. As a result, the data analysis technologies and context-aware technologies would incorporate sustainable strategies such as design for reconfiguration, design for remanufacturing, design for redistribution, design for reuse/recycling, and so on [33].

9. Conclusion

DDPD, a powerful design paradigm to conduct design tasks automatically based on big data analysis and computational intelligence, has been ever-evolvingly developed among academics and industry. With advanced technological innovations and marketing transformation, it is critical to comprehensively understand the status of DDPD and further highlight future research potentials in the new Intelligence Age. This survey investigates this research topic from a holistic view, including bibliometric literature analysis, critical concept clarification, driving forces summary, current research status analysis, and future research potentials. The main findings of this study are summarized below.

(1) *Clarified the different design concepts in the current design field*. This study compared the concepts of DDPD with three data-related design terms to clarify the essence of DDPD. Different with data-enabled, data-informed, and data-centric product design, DDPD emphasizes that data is applied as the primary enabler in product design activities.
(2) *Conducted a bibliometric literature analysis on DDPD*. The statistical analysis results of DDPD-related publications show that the DDPD field is vibrant with a significantly increasing research interest since 2015. The top contributing research institutes and journals are also listed. China and North America are the primary districts devoting to the DDPD.
(3) *Provided a holistic review on DDPD about its driving forces, evolution, and status*. Through reviewing 172 relevant papers, this study outlines three technological driving forces and three business driving forces that trigger the development of DDPD. From the technology aspect, it is (1) advanced ICTs and digitalization technologies, (2) big data, and (3) cognitive computing that energize the fundamentals of DDPD. From the business perspective, it is (1) the exact pursuit of mass personalization, (2) the values in big data, and (3) digital integration that motivates the movements towards DDPD. Furthermore, among the DDPD publications, two research interest fluctuations and one recent research interest increase were found via domain keywords analysis, which are separated as (1) DDPD with IT, (2) DDPD with CI, and (3) DDPD with digital transformation. In the recent DDPD with digital transformation stage, DDPD is evolved with the emergence of new technologies such as additive manufacturing and cyber-physical system and new design concerns such as product-service systems, uncertainty, and sustainability.
(4) Summarized the state-of-the-art of DDPD approaches in the stage of product planning, concept design, embodiment design and detail design. The widely used data-driven approaches are machine learning and deep learning algorithms in each design phase. Natural language processing and case-based reasoning have also been applied for ill-defined problems in product planning and concept design stages. In the embodiment design, evolutionary algorithms have been deployed for product family design.
(5) *Proposed the challenges and future perspectives of DDPD*. To fully explore DDPD's potentials, the authors indicated four challenges of current DDPD, namely design analysis paradox between effective data analysis and limited cognitive capability, large quantity of design concept generation/synthesis within a limited time, design based on multimodal data, and design based on tacit knowledge. Towards an advanced DDPD in the Intelligence Age, it is recommended that product design practitioners can further notice the following five possible directions, i.e., cognitive intelligence-enabled design, end-to-end design integration, advanced design knowledge support, design for additive manufacturing, and sustainable smart product-service systems.

The authors hope this study can be regarded as a reference for design practitioners to clarify the entitative meanings of DDPD, understand the evolvement and status of DDPD, and finally offer some insights for the design practitioners to conduct relevant design tasks in the Intelligence Age.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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