Machine learning for engineering design toward smart customization: A systematic review

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Xingzhi Wang
University of Melbourne

Ang Liu
UNSW Sydney

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Review

Machine learning for engineering design toward smart customization: A systematic review

Xingzhi Wang, Ang Liu *, Sami Kara

School of Mechanical and Manufacturing Engineering, University of New South Wales, Sydney 2052, Australia

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ABSTRACT

In today's manufacturing industry, companies are striving to provide customized products to maintain competitiveness. The challenge of design customization lies in the company's ability to balance product variety, responsiveness, and cost-effectiveness simultaneously. Today, the large volume of data in tandem with powerful computation capabilities has made machine learning a promising technology to address various challenges in engineering design, leading to new opportunities for customization. However, few efforts have been devoted to systemically reviewing these new methods, nor to assessing how they are aligned with customization. Against this background, this article presents a systematic literature review on machine learning for engineering design from the customization perspective. A thorough search of relevant works resulted in a total of 116 most relevant articles, based on which, different machine learning applications are mapped to corresponding design stages of an engineering design process. The potential and advantages of machine learning for fulfilling different customization requirements are discussed. Finally, some promising directions for future investigation are outlined.

Introduction

Due to the market competition, customization has become an essential design strategy to help global manufacturers increase market sales. Customization is a particular design paradigm that aims to fulfill individual customer needs while maintaining mass production efficiency [105]. By adopting customization, companies can develop a product family where certain function modules are provided with several variants, allowing customers to make combinations based on their unique needs [40]. In the past few decades, customization has achieved significant commercial success and has been applied in many industries. Typically, a customization system consists of two major parts: a customer configurator at the front-end, and a product family architecture (PFA) at the back-end [105]. For the former one, customer configurator aims to help customer choice what they want quickly without much cognitive burdens. It requires the system can efficiently solicitate customer needs in order to support choice navigation process. For the latter one, an effective PFA should be developed as a product platform to meet different customer needs while maintaining design commonality. Considering customer needs are changing overtime, customization entails a conceptual framework as a generic framework to help companies constantly reconsider the whole value chain and counter-balance product variety, responsiveness, and cost-effectiveness simultaneously [44,105]. Therefore, any technological advances in engineering design should be evaluated to stimulate the development capabilities of customization.

Today, the large volume of data with powerful computation capabilities has made machine learning (ML) a promising technology to address various design challenges, leading to new opportunities for design customization. ML is an artificial intelligence (AI) technology that enables computers to automatically detect meaningful data patterns and make more informed decisions [6]. Considering engineering design is an information-intensive process where a large volume of data can be obtained, many researchers have applied ML to accelerate cumbersome design operations, make informed decisions, and discover hidden knowledge. However, due to the complex nature of engineering design, most existing ML applications are scattered and isolated. There lacks a fundamental survey regarding how ML has been applied in the engineering design domain, how ML can stimulate the development capabilities of customization, and how to restructure customization to embrace ML.

Against the background, this article aims to summarize, analyze, and present the latest research and applications of ML for engineering design, with a particular focus on their implications for customization.

* Corresponding author.
E-mail address: ang.liu@unsw.edu.au (A. Liu).

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The remainder of this article is organized as follows. Section 2 discusses the key requirements of customization in engineering design. Section 3 discusses the evolution from mass customization to smart customization. Section 4 describes the research methodology for retrieving and analyzing relevant articles. Sections 5-7 map relevant articles with their corresponding stages in an engineering design process with respect to research topics. ML applications in each research topic are evaluated against customization requirements to identify research challenges and opportunities. Section 8 outlines future opportunities. Section 9 concludes the main contributions of this work.

Three requirements of customization

As shown in Fig. 1, three unique requirements make customization go beyond the traditional territory of engineering design with aim to balance product variety, responsiveness, and cost-effectiveness [105]. Successful customization lies in the capability to balancing those three requirements simultaneously. In this section, three customization requirements are elaborated as follows.

Product variety refers to a collection of products in a product family. In the front-end, product variety can be increased by identifying individual customer needs (CNs), different kinds of CNs (e.g., functional and non-functional needs), and dynamic CNs. However, identifying CNs is a challenging task. Customers' perceptions of a product depend on various complex factors such as subjective preference, demographics, product usage context, social values, and so on, which differ from person to person. Therefore, any improved way to understand and characterize CNs will result in better customization effectiveness. Besides, in the back-end, advanced design concepts or technologies could also increase product variety. In the current state, product family architecture (PFA) is an essential design concept to realize customization. However, PFA is constrained by manufacturing capabilities therefore can only provide limited freedom of customization. Against the background, one trend in the current research is to increase the flexibility and adaptability of functional modules, product architectures, and manufacturing systems.

Responsiveness refers to the ability to anticipate and adapt to changing socio-technical trends. To achieve sufficient responsiveness, companies firstly should extrapolate CNs on a larger scale by considering various macro-environmental factors (e.g., social, technological, economic, and political factors). By doing this, companies can stay attuned to the latest CNs and think forward toward design opportunities. Besides, engineering design involves numerous time-consuming design operations, so companies should accelerate the process as much as possible. Incorporating appropriate design concepts can eliminate unnecessary design activities, improve information sharing, and facilitate human collaboration. For example, concurrent design concepts can involve designers across departments together to reduce unnecessary design iterations. Identifying the correct technologies that suit companies can also reduce product development time. For example, 3D modeling and rapid prototyping technologies can significantly improve the efficiency of generating and verifying new design concepts.

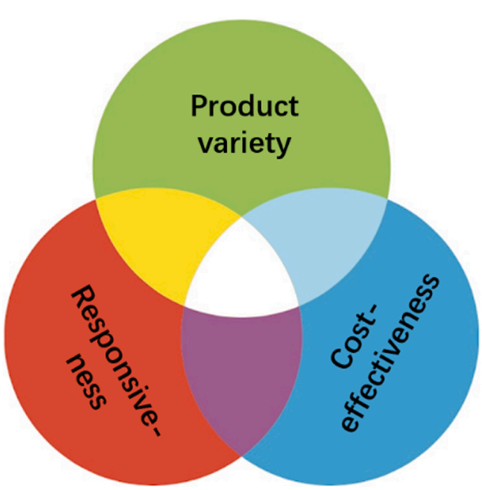

Fig. 1. Venn diagram shows three customization requirements.

Cost-effectiveness measures the effects of products against their relative costs, which is an essential requirement of customization. Although increased variety could increase market sales, it also incurs additional costs from design to production, inventory, marketing, and service. Therefore, companies should define right range of variants that precisely target at customers' value. Traditionally, the study on the cost-effectiveness of customization primarily focused on the economies of scope, which represents the dilemma between flexibility and commonality of product architecture. The flexibility corresponds to the degree of freedom the product can be customized to individual CNs. The commonality represents the number of standardized components built into the product. However, recent advances in manufacturing systems make it possible to increase variety without adding cost. Therefore, one trend in current research is to provide value-added products that outperform their costs. Also, considering engineering design is a cumbersome process that requires various resources, finding low-cost design methods is also an effective way to promote customization. Therefore, companies often investigate new design technologies and resources, to find opportunities to increase cost-effectiveness.

From mass customization to smart customization

Due to several technological advances, customization is evolving from traditional mass customization to smart customization. Compared with conventional mass customization, smart customization is characterized by a more predictive, adaptable, and autonomous paradigm in terms of soliciting and fulfilling individual customer needs. The driving force behind smart customization is multi-sourced big data. Although data has been an integral part of mass customization, they are mainly obtained through traditional methods such as surveys or planned maintenance based on designers' experience. Due to time and budget constraints, data are collected in a reactive or time-based manner, and the sample size is relatively small. Therefore, traditional customization practice is insufficient to explore smaller market niches and fulfill emerging customer needs.

Recently, with the sweeping trend of data-driven smart manufacturing, design and manufacturing processes are becoming more digitalized than ever before [100]. Large volume of multi-sourced heterogeneous data is readily available, which can greatly enhance the intelligence of design customization. Based on our preliminary research, three potential benefits are identified. Firstly, data generated from customer-end reflects more diversified and dynamic customer needs, allowing companies to capture design opportunities and adjust customization strategies in a more predictive fashion. Secondly, data collected from company-end are also analysed to improve resource utilization efficiency, as a result, make customization system more responsive. Thirdly, data could be used to optimize product family architecture, making customized products more adaptable [111,125].

Specifically, in the smart customization paradigm, companies are more connected with end-users through smart products. On the one hand, products can predict individual customer needs, adapt functionalities, and provide value-added services through user-product interactions. On the other hand, product usage data will guide companies to reconsider design customization strategies according to market fluctuations, value chains, and social trends. ML-based data analytics will play a pivotal role in supporting the development of smart customization. Nevertheless, there is a lack of fundamental research to investigate the most cutting-edge ML technologies and state-of-the-art applications in the engineering design domain. Motivated by the background, this article is dedicated to exploring the frontiers of ML in engineering design, summarizing their implications for design customization, and highlighting future directions.

Research methodology

To review the state-of-the-art of the research and applications of ML for engineering design, and investigate their implications to customization, a structured research methodology has been followed to conduct the review in a thorough, systematic, and unbiased manner [103]. As illustrated in Fig. 2, the systematic review process in this article consists of four steps.

In the first step, based on the research scope and motivation, a robust search query is developed to identify potentially relevant literature. A search query refers to the string of keywords used to identify potentially relevant literature in a literature database. To identify as many relevant literatures as possible, in this article, the search query is developed as follows:

(TITLE-ABS-KEY ("machine learning" OR "deep learning") AND TITLE-ABS-KEY ("engineering design" OR "product design" OR "product development" OR "customization" OR "personalization")) AND PUBYEAR > 2000 AND PUBYEAR < 2022 AND (LIMIT-TO (LANGUAGE, "English")).

The literature database used for literature identification is Scopus. Scopus is recognized as one of the most comprehensive databases, which contains the majority of papers in the engineering domain [8]. Based on the application of the search query in Scopus, 2723 articles were identified as potentially relevant.

In the second step, the inclusion and exclusion criteria for literature selection are specified as follows:

- The research domain should lie in mechanical, manufacturing, and production engineering. Besides, only the articles that focus on the design of industrial and consumer products were selected. The articles focused on other research domains (e.g., chemical process design, building structure design, and software design) were filtered.
- The literature should focus on the technical aspect of ML for engineering design. Therefore, literature that focus\ on personal opinions or philosophical aspects of ML, such as review articles and opinion articles, were excluded from the future review.

Based on this, the authors read through the title, abstract, and content of potentially relevant literature for further screening. In the end, 116 publications were selected for convergent review. Fig. 3 shows the number of publications each year. It can be seen that there is a noticeable increase trend in research on ML for engineering design, especially in recent five years. This trend indicates that ML has enormous potential to influence engineering design process.

In the third step, a literature analysis process was followed to map, summarize, and analyze the selected publications systematically. The analysis began with characterizing the specific design operations and research topics of ML in each selected publication. This research followed the Axiomatic Design theory to divide an engineering design process into three stages (i.e., functional design, conceptual design, and technical design) [96]. Each stage involves a series of interrelated research topics. The selected publications were firstly classified according to their positioning in different design stages. In every design stage, articles are synthesized by research topics and ML applications. Next, the authors further explored the motivation and justification of adopting ML for the research topic in question. Finally, the analysis was regarding the advantages of ML and their alignment with different customization requirements. Specific research topics in each design stage were evaluated to determine whether, how, and to what extent customization requirements were met.

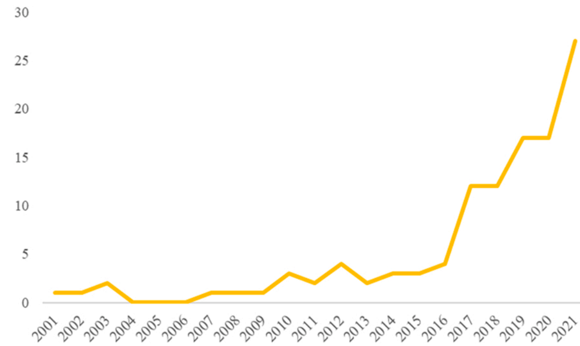

Fig. 3. Number of publications by year from 2001 to 2021 reviewed.

In the last step, based on the above analysis process, not only some unresolved challenges and insufficiently explored areas were identified, but also some future opportunities were illuminated.

ML for functional design

The functional design aims to generate design targets based on customer voices, market strategies, and competitive benchmarking. The input of functional design is a set of ambiguous and inconsistent CNs, whereas the output is a set of clear and consistent functional requirements (FRs). There are four topics summarized in this stage. Articles in each research topic are evaluated against three customization requirements. To be specific, each customization requirement is further decomposed into several factors to clarify how articles can meet customization requirements. Product variety in this stage evaluates whether an article can identify individual-level CNs, diverse types of CNs, and dynamic CNs. Responsiveness evaluates whether an article can reduce design time or makes companies more adaptable to change. Cost-effectiveness measures whether an article can help reduce design cost, generate additional product value, and improve design resource reuse.

As shown in Fig. 4, 51 articles are summarized into four research topics in this stage. Among all the research topics, the most popular two research topics are ML-based UGC analysis for customer research, and ML for function formulation and classification. Those two topics collectively accumulated 78 % of articles. Although ML for macro-environmental factors hasn't attracted much attention from researchers, it is a rising topic and is becoming popular recently. The evaluation result shows that generally applying ML can help to reduce the time and cost of specific design tasks in functional design. For

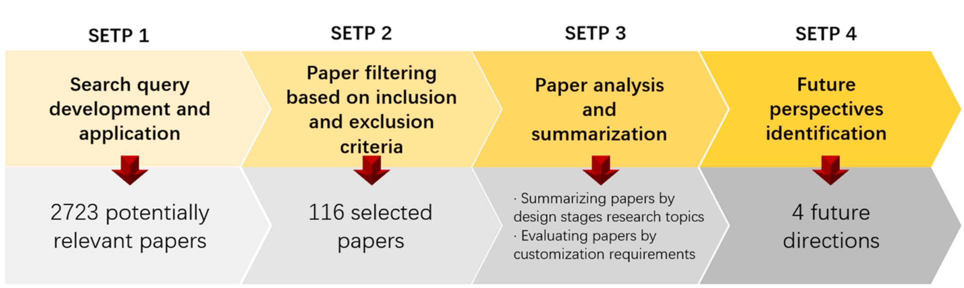

Fig. 2. Literature review process.

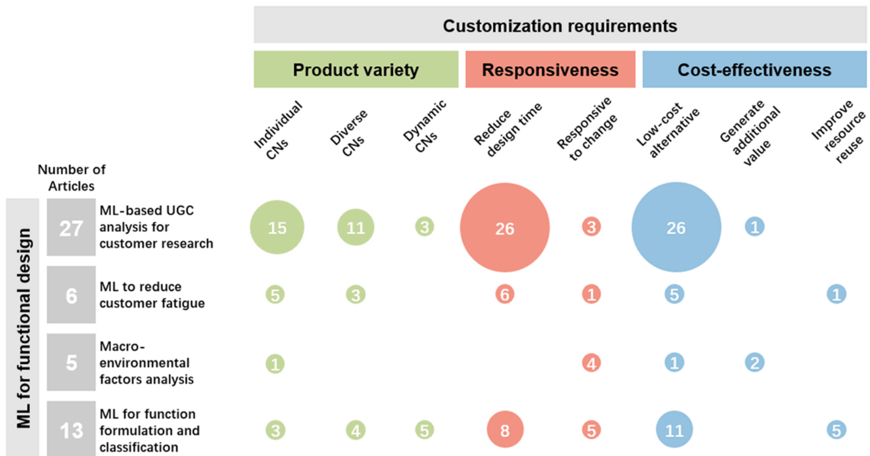

Fig. 4. Research topics in functional design stage and their evaluation against customization requirements.

customer research, it is believed that ML and UGC can identify smaller market niches and individualized CNs, which will significantly benefit customization. Also, ML can support the constant monitoring of several macro-environmental factors, and the market performance of product functions. This capability can make functional design tasks more responsive to changes and dynamic CNs.

ML-based UGC analysis for customer research

Knowing customers is the key to a successful design. Conventionally, customer research methods (e.g., survey, interview, focus group, consumer ethnography) are characterized as highly time-consuming, labor-intensive, and expensive activities. With the massive growth of the Internet, a large volume of user-generated content (UGC) is considered a promising alternative for customer research. Besides, ML has shown its efficacy in processing UGC with reasonable effort. Therefore, there are in total of 27 ML-based UGC analysis articles are identified. Literature analysis shows that using ML to analyze UGC can significantly reduce design time and is considered a low-cost alternative. This is mainly because the volume and generating speed of UGC is much higher than that of conventional methods, and UGC are publicly available online with no or little cost. In addition, literature analysis also indicates that ML-based UGC analysis can identify individual-level CNs and classify different types of CNs. Based on individual CNs, ML can further identify large amount of lead users, or perform customer segmentations. The details of different research topics are elaborated in below:

Customer needs assessment

This research topic aims to analyze customer opinions regarding product features, either qualitatively or quantitively. The qualitative analysis aims to convert unstructured UGC into brief but structured keywords of CNs. For example, Lee proposed a ML-based text summarization model to automatically convert unstructured sentences into a list of subject-verb-object (SVO) triples [54]. The SVO triples can be classified based on the contents of their subjects (e.g., personal pronouns, product names, brands, or product features) to reflect different types of CNs. Subsequently, several ML-based CNs summarization models are proposed for different design purposes, including design innovation, product planning, quality improvement, sustainable design, etc [101,116,119,25,34,39,5,85]. Quantitative analysis refers to the computational study of a customer's attitude towards product features, which can be achieved through sentiment analysis or product rating analysis. Sentiment analysis is an NLP method that focuses on the polarity (i.e., positive, negative, neutral) classification of UGC texts. As a negative sentiment is typically coupled with undesirable or unsatisfactory product features [43], sentiment analysis is widely adopted to assess product performance [131,17,19,22,29,35,43,46,86,98]. Besides sentiment analysis, correlation analysis between a product's overall rating and product features is also a practical quantitative approach to reflect CNs. For example, Singh and Tucker classified product features into different categories (i.e., form, function, behavior, service), and assessed their correlation coefficient to product's overall rating to identify the most important product features that affect product overall rating [94].

Assessing user experience (UX) is also a critical CNs assessment topic. UX design emphasizes uncovering appealing design elements to boost users' psychological and emotional feelings. While current research has widely acknowledged that UGC contains essential information about UX, there lacks unified models to represent UX factors holistically. Yang et al. proposed a faceted model to describe UX as the combination of product, user cognition, situation, and user sentiment factors [121]. Based on this, the authors further proposed a ML-based computational method to model UX using UGC. Kansei attributes and product usage context (PUC) identification are also important topics. Kansei attributes refer to the physical traits of a product that can emotionally attract customers. In UGC, Kansei attributes are often expressed by adjectives (e.g., soft-hard, handy-bulky, reliable-shoddy). Based on this, Wang et al. proposed a ML model that integrates adjective extraction and WordNet to identify Kansei attributes mentioned by customers [108]. Besides, sentiment analysis is also employed to quantify customers' affective feelings toward Kansei attributes [60]. PUC refers to all the application and environmental factors that affect CNs. In traditional design practices, PUC is pre-determined by designers subjectively, as it is difficult for designers to anticipate all the factors that are contextually relevant to the product. However, UGC provides an alternative data source to help designers understand PUC in a more objective, holistic manner. Against the background, Suryadi and Kim defined three grammatical rules to help the ML identify product tasks and applications from UGC [99].

Fig. 5 summarizes different types of CNs focused on by designers. The horizontal axis represents the publication year, and the vertical axis represents different aspects of CNs. Seven articles are screened in the figure since they represent the first article that applied ML to related topics. Priority to 2018, research primarily focused on customers' function needs. A variety of text summarization and named-entity recognition models are proposed to convert unstructured UGC into structured qualitative data. Since 2018, owing to the emergence of sentiment analysis, design researchers can perform quantitative analysis of CNs accordingly. As a result, research topics are gradually shifting toward product usability and UX, such as Kansei attributes, usage context, customer preference, etc.

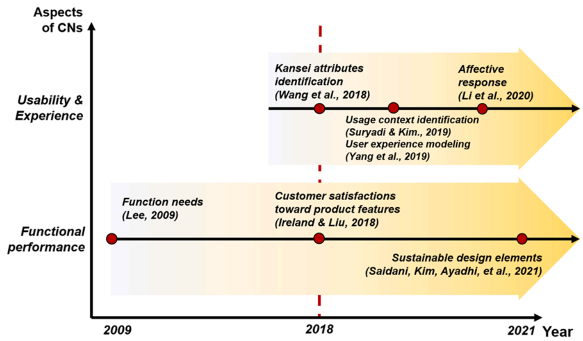

Fig. 5. Different types of CNs focused by designers.

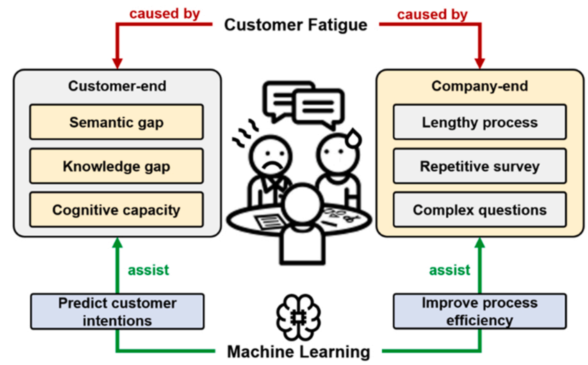

Fig. 6. Causes of customer fatigue and ML capabilities.

Lead user identification and customer segmentation

Lead user identification and customer segmentation are two important activities for customer analysis and management. Lead users are advanced users who own rich knowledge regarding product use, CNs, and demand trends. Their contributions to product innovation have been widely recognized by researchers. However, traditionally it's difficult to find a sufficient amount of lead users. To address this challenge, Pajo et al. proposed a UGC-based lead user identification model [73], where ML was adopted to differentiate lead users and non-lead users. The method used sets of searching bigrams to seek potentially relevant users on a social network platform. For each user, the authors retrieved his/her UGC and followers list for analysis. The authors first analyzed user engagement by measuring posting frequency, trend, relevance, and sentiment. Afterward, the authors analyzed each user's centrality in the social network by analyzing followers list. A ML classification model is developed to classify lead and non-lead users based on user engagement and social centrality. Customer segmentation is the process of dividing customers into smaller groups based on shared attributes (e.g., demographics, behaviours, preferences). Traditionally, attributes used for customer segmentation are pre-defined by designers [95]. However, UGC provides an alternative approach to segment customers based on customer-defined attributes. As a customer neglects to mention an attribute unless he or she cares about it, Jiang et al. proposed a method to segment customers based on the customer-mentioned product features [47].

In summary, ML-based UGC analysis can meet all three customization requirements. Traditional customer research methods are characterized as highly time-consuming, costly approaches. Moreover, constrained by time and cost, they cannot obtain sufficient customer samples to identify smaller market niches. In comparison, three advantages of UGC are recognized in the literature. First, UGC enables designers to understand different aspects of needs (function needs, user experience), which could facilitate increasing product variety [99]. Second, UGC is an open data source for free and is considered a cost-saving alternative for customer research [94,99]. Third, adopting ML to process UGC and other types of survey data is proven more time-efficient than conventional approaches.

ML to reduce customer fatigue

Many design operations in the functional design stage require intensive participation of customers. However, over-participation will disappoint customers quickly and result in customer fatigue. Customer fatigue refers to the level of mental exhaustion felt by customers. It can be caused by both customers and companies. Fig. 6 shows the causes of customer fatigue from both customer-end and company-end. From customer-end, fatigue is caused by semantic gap: customers and companies cannot understand mutually due to different language domains; knowledge gap: customers cannot be aware of what they want; and cognitive capacity: customers cannot formulate their needs holistically in one go. From company-end, lengthy, repetitive and complex customer research can easily result in customer fatigue. Due to fatigue, customers will reduce their motivation to exercise by increasing the perceived effort required. Customer fatigue has become a major concern in threatening the quality of many design operations. In the literature, ML is adopted to reduce customer fatigue in survey and configuration operations in two ways. First, ML can make survey process adaptable, reducing the overall process time. Second, ML can assist with clarifying CNs, and configuring products using natural language to reduce the semantic gap and cognitive burden involved in the customization process. The analysis of articles indicates that ML can significantly improve the communication efficiency, or even eliminate the participation of designers, to accelerate the overall process.

Designers have been using various methods to conduct survey. In the past decade, web survey has become one of the most popular modes of conducting surveys. Compared with telephone-based or land survey, web survey has several advantages, including lower delivery cost, shorter transmitting time. However, intensively conducting web survey could result in a lowering of response rate [30]. This problem is becoming more prominent in the engineering design domain. With product complexity increases, respondents are usually required to answer a lengthy questionnaire to obtain sufficient information. To address the problem, designers could firstly improve survey efficiency by reducing the length of questionnaire. Besides, designers could propose more consistent and logical CNs analysis methods to avoid repetitive survey. Against the background, an active learning approach was introduced to make surveying process more adaptable. Active learning can enable the automatic adjustment of questions for respondents based on their previously answered questions to shorten the time required to collect holistic CNs. Huang and Luo incorporated active learning in the surveying process, making their model can rapidly and efficiently elicit CNs for products equipped with 70–100 attributes [41]. Besides, to make a more logical and consistent CNs analysis method, ML were widely adopted to provide comprehensive questionnaire analysis. For example, Shimomura et al. used clustering algorithms to automatically convert survey data into a well-organized persona and scenario of customers [92].

In customization process, configuration is a critical design operation enabling customers to co-design products with companies. Generally, configuration can be regarded as the mapping between CNs and product specifications, where customers have to make selection in a lengthy configuration list based on their own needs. However, several research have discussed the concern of "mass confusion" caused by configuration interaction process. The term "mass confusion" described the situation that customers get overwhelmed and frustrated by a large number of options during configuration. Due to lack sufficient product knowledge, CNs are often expressed vaguely and imprecisely. Therefore, it's imperative to develop a method that can fill the semantic gap between CNs and product specifications to ensure consistency and coherence in design communication practices. Against the background, Wang et al. developed a deep learning-based model to translate vaguely expressed

CNs into viable combination of product specifications [114,115]. In addition. A multi-task learning approach is adopted to resolve the semantic gap between CNs and product specifications [113], and transfer learning is used to increase adaptability of configurations in different product domains [112].

Macro-environmental factors analysis

Macro-environmental factors (e.g., political, economic, social, and technological) often imply new design opportunities. Past research has shown that the ability to extrapolate design objectives in the macro-environmental context could help designers develop products more effectively. ML has enabled designers to anticipate and respond to changes in macro-environmental factors efficiently. And macro-environmental changes also put forward new requirements for applying ML in design domain. The analysis of articles shows that applying ML will make companies more adaptable to social trends, market fluctuations, and technological changes. Topics of current research include: online social network analysis, market performance prediction, and data privacy protection.

The rapid development of Internet has broken geographic boundaries and connected people with similar preferences and values, leading to the emergence of online social networks. Compared with traditional social networks, online social networks are more dynamic. For example, news about a product malfunction could rapidly spread over the Internet and change users' purchase decisions. Therefore, analyzing online social trends has become a popular topic in design domain. Biliri et al. proposed a social data analysis method to help companies catch the market realm, prevent reputation damage, and detect social trends [14]. In another study, social network analysis (SNA) is adopted to analyze keywords extracted from UGC to highlight customers' shared interests in product features [110]. The main advantages of current studies are: Firstly, methods proposed in current research are domain-independent, therefore can be easily applied to different types of products. Second, current research allows for the real-time streaming of social trends, making companies more responsive to several changes. However, existing research can only monitor general social changes, such as popular social topics and so on. Those methods cannot detect unique social changes led by niche social groups. To address the problem, design researchers should apply more advanced ML models, such as anomaly detection and novelty detection, to develop social monitoring methods. Besides, some fundamental research should be conducted to investigate specific product domains with social trends.

Predicting the market performance of new products at the early design stage is a problem that has plagued designers for a long time, as market performance is affected by multiple factors that are difficult to identify. Nevertheless, ML's ability to handle multi-dimensional data makes it a promising technology for market performance prediction. For instance, an ML-based prediction model is proposed to analyze product characteristics and predict market performance based on product similarity [123]. Another research applied ML to analyze customers' previous purchase patterns and predict next-to-be purchased products [68]. The results of two research show ML methods have two advantages over previous methods. Firstly, ML-based method is more accurate in predicting product sales, especially for short life cycle products. Second, ML can find unknown patterns that cannot be explained by previous methods. Considering market uncertainty and complexity are high, researchers should continue to use ML models. The main disadvantage of current research is the market is assumed to be static. However, other social-technical factors such as global competition and innovation diffusion will affect the market potential of the same product over time. It is therefore important to characterize those factors and develop more advanced ML models to make better predictions.

Data privacy is becoming a significant social problem for product design. Many smart products (e.g., smartphones and wearable devices) require customers to share highly sensitive data for analysis [102]. In order to address the dilemma between the performance of ML and data privacy, a new paradigm of ML called federated learning has emerged. Federated learning is a new ML paradigm that enables numerous edge devices to collaboratively train a model using decentralized data. Aiming at developing smart products that possess privacy-preserving capabilities, a process framework is proposed to integrate federated learning with product design [63]. This research aligns with the recent trend in ML research, that is, making ML more responsible and ethical. Although relevant research is rival in the computer science domain, they have not attracted much attention from design researchers. The responsibility of ML concerns not only data protection, but also ML explainability, model bias and so on. In that sense, researchers should devote more effort to investigating how to develop more responsible ML models when performing design tasks.

ML for function formulation and classification

Formulating appropriate product functionalities has always been a challenge for designers as it needs to address the dilemma between CNs and manufacturing capabilities. In conventional approach, it's time consuming to collect and analyze relevant data. In addition, it requires the participation of experienced designers, which is costly. ML, on the other hand, can accelerate the collection and analysis of data while reducing or eliminating involvement of designers, to save time and cost. In current research, ML is used to facilitate function formulation and classification. The former research topic aims at fulfilling CNs and boost customer satisfaction, while the latter topic aims at determining design priorities and resource allocation.

Existing research on ML for function formulation has two streams. The first stream aims to recommend new functions for product innovations. Inspired by the recommender systems in eCommerce platform, function recommender systems are proposed to recommend new functions from peer products to boost customer satisfaction [62,130]. Another stream aims to facilitate knowledge reuse by extracting FRs from descriptive documents [2–4,75]. Function classification helps designers determine design priorities and resource allocation in product design. Using ML to analyze real-time data can improve the responsiveness of function classification. Conventional classification methods (e.g., Kano Model, Long Tail Model) depend on data from surveys, which are time-consuming and costly. However, ML can enable companies to analyze crowdsourced UGC, making function classification more efficient. Against the background, an intelligent Kano classification model was proposed to automatically classify and monitor the evolvement of functions [21]. The proposed model can classify product features into different categories based on customer satisfaction. In addition, the model can also track the evolvement of product features through time series analysis to help designers adjust their design strategies. Similarly, another study integrates ML with the importance-performance analysis (IPA) model to categorize product attributes [49]. Li et al. proposed a rating model to quantify the importance of FRs based on the priority of CNs [57]. Zhang et al. used sales data to predict customer preferences on different combinations of product features [128]. ML can also be used to analyze customer preferences on design elements or technical specifications to predict the rating of a new design [23,61]. Besides, today there are several independent rating companies determine the rank of products. If designers can retrieve the evaluation criteria behind ranking model, they can allocate design resources more effectively to achieve higher rating. Based on this, Chang et al. proposed a ML model to reverse-engineer quality rankings [20].

ML for conceptual design

Conceptual design is a challenging yet rewarding phase of engineering design, where designers must transform FRs into more concrete and tangible design parameters (DPs), such as technologies, working principles, and shape in the physical domain. Three research topics are discussed in this stage: ML-based design concept management, concept evaluation, and concept visualization. Articles in each research topic are evaluated against three customization requirements. In this stage, product variety require a ML application can facilitate design innovation, handle multiple concepts, and identify individual CNs. Responsiveness requires a ML application to reduce design time or makes companies more adaptable to change. Cost-effectiveness requires a ML application to reduce design cost, improve target value setting, and improve design resource reuse.

The general statics of result is shown in Fig. 7. A total of 34 articles are summarized. Among all the research topics, ML-based design concept management is the most popular one and has accumulated 60 % of articles. And ML-based concept visualization is a rising topic and is becoming more popular these two years. Evaluation of literature shows that applying ML can enhance concept management efficiency by enabling designers to generate, evaluate, and manage increasing number of design concepts. ML-based design knowledge management can improve concept knowledge reuse to save design costs. Besides, ML-based concept evaluation methods can help designers make more informed decisions by evaluating design concepts against different design objectives. The detailed summarizations and discussions of different research topics are shown in Section 6.1–6.3 as follows.

ML-based design concept management

When generating new design concepts, the knowledge required to perform this task is often acquired through many years of experience and is often at a premium. In addition, every increasing pressure on inventive design has forced designers to explore broader knowledge fields to achieve inspirations. These situations have led to a number of attempts to use ML to manage design concepts to facilitate knowledge acquisition and reuse. Through article analysis, ML technologies in this stage are used to reduce time of summarizing and organizing crowd-sourced design concepts, improve resource reuse and recommend new ideas when generating concepts. Generally, current research can be classified as concept clustering and classification, concept knowledge organization, knowledge representation, and concept recommendation.

Classification and clustering are semantically similar terms as they both aiming at grouping a given set of objects into meaningful classes. However, in design concept management, there are significant differences. Classification is the task of assigning a design concept into predefined classes to facilitate concept management, whereas clustering is the task of narrowing down crowd-sourced design concepts into smaller number of clusters to indicate design team with divergent concept generation. Considering design concepts are primarily represented in the format of free texts (e.g., design logbook, patent) and images (e.g., concept sketch, CAD drawing), concept classification and clustering can be classified as text-based approach and image-based approach. Text-based approach perform clustering and classification primarily through text similarity computation. For example, a variety of patent retrieval models are proposed to analyze patents by defining design problem similarity [59,64,69,88]. Besides, text-similarity-based concept summarization and clustering models are also proposed to manage descriptive documents [7,76,126,127]. For image-based concept classification methods Krahe et al. proposed a CAD management model to represent similar CAD designs based on multi-viewed shapes [52]. Through the proposed model, CAD data are classified by measuring shape similarity. Jiang et al. proposed a design feature vector approach to represent design images, which can classify image data by measuring their cosine similarity in the vector space [48].

Concept organization refers to the process of integrating scattered design concepts into a holistic system to represent product architecture. To organize design concepts, a conceptual map extraction method is developed to identify the interrelationship between different team member's design tasks based on their design documents [70]. Documents for a design project are used as the data source. The Latent Dirichlet Allocation (LDA) algorithm is used to extract topics from documents, followed by the bottom-up hierarchical clustering method to induce topic hierarchy. By doing so, the concept structure can be visualized. The proposed method provides a time-efficient way to find the inter-dependencies of various concepts. This model reduces the time required for manual organization, so introducing ML for concept organization can shorten the product development time.

Knowledge representation for conceptual design require the methods to deal with evolving, multi-sourced heterogeneous data. Therefore, a unified representation method is required. Against the background, Chunli and Hao proposed a subject-oriented and multi-dimensional knowledge model to represent various kinds of design knowledge from different data sources [26]. Another research introduced knowledge graph to support patent knowledge management [88]. By analyzing keywords of patent, the proposed method can significantly reduce human effort for concept querying. In addition, knowledge graph is a self-extendable and upgradable knowledge representation model, so the proposed method is more flexible and adaptable.

Recommender system is also employed to recommend suitable design concept [31]. Since most of concepts are generated by modifying previous design, modification-based design synthesis models are proposed to retrieve constraints and design parameter values to provide modification suggestions [67,106]. In addition, considering designers must keep abreast of the most cutting-edge technologies to prevent technological obsolescence. A patent-based innovative knowledge extraction model is proposed to identify the latest technologies [91]. Obieke et al. also proposed an emergent technology-based innovative design method to assist the generation of new design concepts [71]. Similarly, an obsolescence forecasting model is developed to classify product parts into active, in production, or obsolete [45]. Besides, reinforcement learning is used to ensure that the choice of technologies is aligned with corporate goals [83].

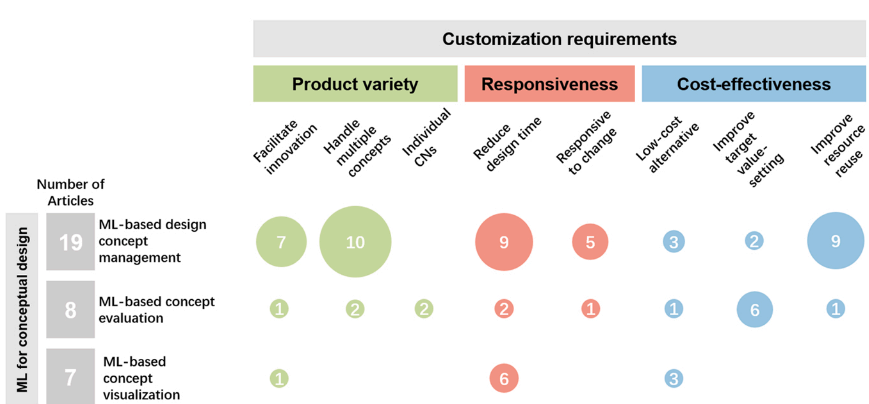

Fig. 7. Research topics in conceptual design stage and their evaluation against customization requirements.

ML-based concept evaluation

In concept evaluation, designers need to compare and select the most feasible concept against the elevation criteria. In practice, in order to develop sufficient novel products in this increasingly competitive market, it may be advantageous to generate as large number of design concepts as possible. As a result, there are two challenges associated with concept evaluation. First, it can be difficult for designers to compare thousands of design concepts. Second, quantitative metrics for concept evaluation is becoming more complex due to changes in company goals and design objectives. ML-based computational concept evaluation methods have been investigated by various researchers. There are totally 7 articles concerning this topic, and most of articles agreed that ML is a promising approach to improve design value setting by selecting the best concept. Based on the design objectives, concept evaluation models can be classified into aesthetic design, function-based design, and innovative design. The summary of concept evaluation research is shown in the Table 1.

Visual aesthetic is an important determinant of design concept evaluation, and a high aesthetic quality of design appearance can promote commercial sales significantly. Two types of aesthetic evaluation models can be found in current research. The first type of model is constructed using the explicit cause-and-effect relationships between product form features (PFFs) and customer's affective response (CARs). Such relationship can be obtained through systematic customer survey [87,122]. Another type of model aims to retrieve the implicit criteria from image data directly. To achieve this, Wu et al. proposed a method that can learn aesthetic quality from the appearance of award-winning products [117]. By annotating awarded design scheme images and eliminated design images, machine can be trained to automatically learn the evaluation model for determining visual aesthetic quality. In another study, He and McAuley trained a ML model to analyze the implicit relationships between product visual appearance, customer purchase history and browsing logs [36]. The main difference of two methods is, in the former one, visual factors are pre-determined by designers based on their design experience. For the latter one, visual factors are not pre-determined, and ML models are encouraged to explore implicit preference factors.

In function-based design, design concepts are evaluated against functional and engineering performance. Traditionally, design team has to build and test large amount prototypes for each concept to select feasible one. As this process is iterative and costly, designers start to find efficient alternatives for concept evaluation. Against the background, Yoo et al. proposed a two-stage framework that uses ML to predict the engineering performance of 2D sketches. In the design generation stage, a ML model is trained to convert 2D sketches into 3D CAD drawings automatically. In the design evaluation stage, ML was trained to predict the 3D CAE simulation result automatically [124]. As a result, the proposed framework has enabled designers to select feasible concepts more quickly. With the development of information communication technology (ICT), product usage data is also becoming an important data source to populate value model for concept evaluation. As shown in Fig. 8. Bertoni et al. proposed a framework that can analyze product usage data and generate a design value model for concept evaluation. Based on which, the selected design can generate more value-in-use to customers in reality [13].

Novelty is also a criterion to assess when evaluating design concept. Camburn et al. developed a ML inferable design concept ontology to assess novelty level using crowdsourced design concepts [18]. The ontology defines a design concept includes category (i.e., high level categorization of subject), topic (i.e., overarching sentence topic), and entity (i.e., keywords of product features or functions). Then, ML-based ontological analysis is performed to identify category, topic and entities from design concept. Finally, level of novelty is measured by the relevance between core entity and other entities in the design concept.

ML also enabled evaluation of new products with predicted market demands. Considering in an incremental design improvement, a new product often shares some commonality with the predecessor product, and designers can use ML to weigh design differentiation factors between new products and predecessors and use historical sale volume to predict the market performance of the new product. Afrin et al. developed a transfer learning model to analyze the correlation between product differentiation and product demand, aiming to optimize the parameter setting to increase market performance [1].

ML-based concept visualization and sketching assistance

In the conceptual design stage, the product's form and user interfaces are also created to convey the overall design vision before goes into technical design. There are several mediums to visualize a concept, such as sketches, CAD drawings, soft models and so on. A good visualization will facilitate communication between stakeholders and will promote market sale. The article analysis indicates that ML provides a scalable means to generate novel designs, or can intelligently assist designers with the sketching process professionally. Therefore, ML can improve the time and cost efficiency of related design tasks. And there are two topics can be identified: ML-based concept visualization, and ML-based sketching assistance.

As shown in Fig. 9, visualizing design concepts using ML has long been investigated by design researchers. In 2011, Wang used product stylistic features database and Kansei words database to train a ML model to generate sketches that conform to human aesthetics [109]. In 2012, Tseng et al. also proposed an intelligent parametric design model that automatically generate product form based on stylistic and functional goals [104]. However, due to technological limitations, traditional ML models can only generate 2D parametric representations or shape grammars. The drawback of these visualization methods are: Firstly, visual effects are often of limited realism. Second, ML in those methods cannot proactively generate design concepts. In recent years, the rapid development of deep generative models, such as generative adversarial networks (GAN), has enabled computers to generate visual content proactively. In some research domain, machine-generated contents are already indistinguishable from human-generated ones. As a result, an increasing number of deep generative design methods are

Table 1
Summary of design concept evaluation research.

Design objectives	Evaluation metrics	Data source	Research aim	Articles
Aesthetic quality	User preference	Survey questionnaire	Predict consumers' affective responses to a new design	[87, 122]
	Visual aesthetic features	Award-winning design cases	Obtain a unified aesthetic evaluation model	[117]
Functionality	Engineering performance	2D sketch, CAE simulation data	Generate 3D CAD drawing based on 2D sketch, and predict engineering performance simultaneously	[124]
	Additional product usage value	Product usage data	Populate value models for concept evaluation	[13]
Design innovation	Novelty and detailedness	Crowdsourced design concepts (natural language)	Perform ontological analysis to analyze novelty of a concept	[18]
Market performance	Product differentiation level, demand differentiation level	Predecessor design, historical demand data	Use market demands of predecessor designs to predict market performance of new design	[1]

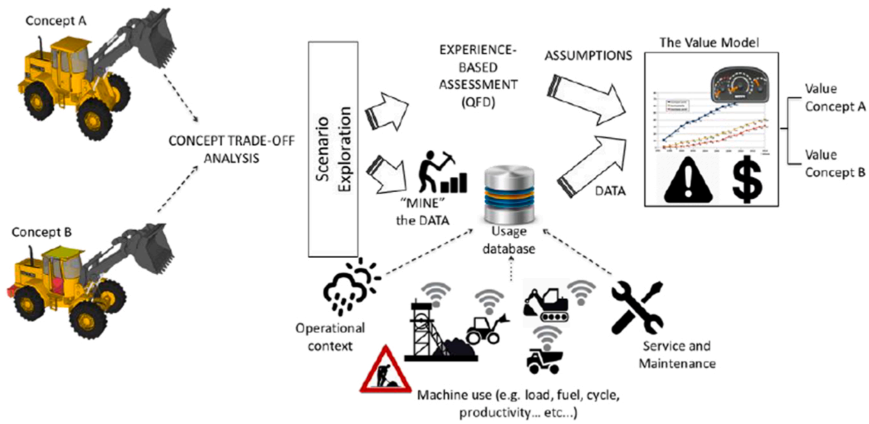

Fig. 8. Product usage data-driven concept evaluation [13].

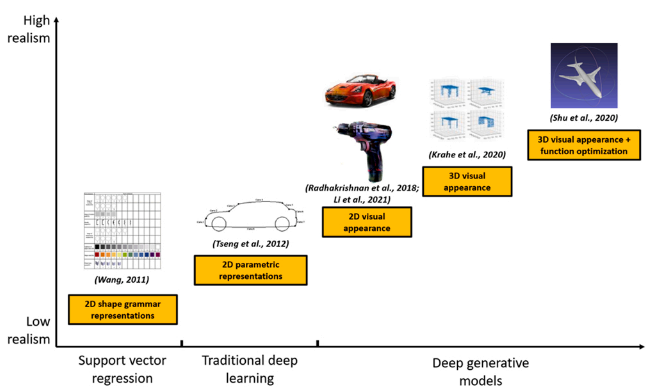

Fig. 9. Different ML-based concept visualization methods.

being proposed. Based on training data, deep generative models can perform both 2D design and 3D design. 2D design models are trained with image data, and only focus on the visual aspect of design, such as form and colors [58,79]. 3D design models are trained with point cloud data [51,93]. Compared to 2D design models, 3D design models capture not only the visual appearance of products, but also their functionalities. For example, Shu et al., proposed a model that can generate 3D aircraft with high visual quality and aerodynamic performance [93].

Although research on ML-based concept visualization is sparce, this topic is becoming more and more popular. In our reviewed literature, most generative design research were published in recent four years. In recent years, different types of deep generative models are also proposed. Many studies have shown that new deep generative models can significantly outperform traditional ones. For example, new deep generative models such as VAE and diffusion models can not only generate higher realistic visual content than GAN, but also can generate visual content based on human language. Considering deep generative models are a relative new technology and is continuously growing, researchers should devote more effort to exploring their full potential.

ML-based sketching assistance aims to analyze designers' behaviors, supporting them with sketch drawing without limiting their creative roles. The challenges of this work can be characterized as solution variety and participant's expertise. Solution variety means there are more than one correct way of solving a design task. Participant's expertise means design experience might hinder the ML model's attempt to analyze designers' behavior during the process. To address above-mentioned challenges, Kaloskampis et al. integrated ML with computer vision and knowledge-based systems (KBS). By tracking designer's activities using camera, KBS can predict design progress and flag potential mistakes [50].

ML for technical design

At the technical design stage, the design concepts are further transformed into complete product systems, subsystems, as well as details and specifics. In the past decades, although mass customization has been successfully adopted to increase product variety, it also caused several technical challenges. Firstly, designers should deal with a variety of design objectives simultaneously, making it more difficult to obtain optimal design parameter values. Secondly, mass customization has led to increased design variants, which has challenged the way to reuse design knowledge from historical design. Third, large volume of data generated in the product usage stage has made it possible to continuously improve product performance. Therefore, as shown in Fig. 10, five research topics are found in this stage: ML for design optimization, crowd-sensing for continuous product improvement, ML-based simulation data mining, ML-assisted commonality design, and ML-based manufacturing process prediction. There are 30 articles summarized in this stage, ML for design optimization is the most popular research topic. The evaluation result shows that specific design operations can be accelerated and saved due to the advances in ML. As design operations at technical design stage are more concrete and detailed, their focus is becoming less relevant to product variety. However, with the rapid development of product-equipped sensors, smart products can monitor the real-time status of product operations and continuously optimize product functionalities. This topic has become a rising topic in technical designs stage.

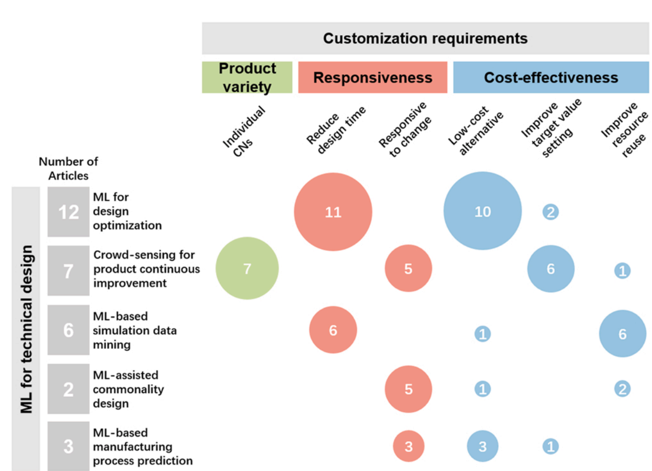

Fig. 10. Research topics in technical design stage and their evaluation against customization requirements.

ML for design optimization

In current technical design practices, designers should deal with product quality as well as multiple manufacturer's decision objectives (e.g., unit production cost, market performance, sustainability). The trade-off between multiple design objectives is difficult to be handled by traditional design optimization models as a large number of possible solutions can be obtained. Therefore, design optimization problems were gradually transformed into ML-based fashion. Qu et al. proposed an active learning-based framework to determine the optimal design parameters under multi-objectives (i.e., unit production cost, quality, market response, and sustainability) [78]. Bodendorf and Franke proposed an ML approach to predict the cost of design based on a number of variables (e.g., product information, material, process parameter, tooling invests) to help manage overall product development costs [15]. Romeo et al. proposed a ML-based support system to guide designers toward the best possible technical choice [84]. Pilarski et al. introduced ML into the design of a complex system to resolve constraints between subsystems [74]. Lee et al. introduced reinforcement learning (RL) for flow sculpting of microfluidic devices. The article emphasizes RL-based approach is more data-efficient and accurate than average optimization approaches [55]. However, a significant challenge associated with ML is the high cost of labeling. To address the problem, Ren and Papalambros proposed an active learning-based iterative query process to train the ML model with a small set of training data and efficiently refine the estimation based on current knowledge [82].

During design optimization process, a variety of computational simulations are used. Simulation often involves the trade-off between result accuracy and resource consumption (e.g., time and cost). The approximation models, also known as surrogate models, are widely used to improve simulation efficiency. The application of ML for constructing surrogate models can be found in the aerospace industry [11,12,28,9]. Another research combined clustering and nonlinear dimensionality reduction to reduce the computing resource required to analyze finite element data. The model is applied in the automotive industry for car crash simulation [16]. In ship design, a ML-based approximation modeling method is developed to construct a statistical approximation model for ship resistance analysis [56].

Comparing with traditional optimization practices, ML-based approaches have several advantages. Firstly, ML-based approaches are more adaptive to the changing design objectives. A well-developed ML model can be quickly adapted to deal with different objectives for different products. Second, ML-based approaches are more predictive; they could approximate optimal design with restricted available data. Third, ML-based approaches can achieve higher resource utilization as data from previous designs are efficiently reused to optimize new designs.

Crowd-sensing for continuous product improvement

Traditionally, product data from the use phase have few feedback to facilitate product improvement. However, due to the advances in IoT and smart products, a large amount of environment data (e.g., time, location, weather, use frequency, use longevity) and user behavior data (e.g., walk, stand, run) are aggregated in product usage stage, enabling continuous improvement of product performance. Generally, product improvement goals can be divided into product-centric goals (e.g., robust operability, fault avoidance) and customer-centric goals (e.g., usability, user experience). The product-centric approach aims at adapting the optimal setting to improve product performance. For example, Voet et al. proposed a ML-based framework to capture and analyze the usage data (e.g., RPM, grinding force, workpiece material) of a handheld grinder to predict the optimal settings to enable higher machining quality [107]. Chin et al. proposed a predictive preconditioning model to provide personalized vehicle's interior air conditioning service [24].

Customer-centric approach aims at modeling personalized behaviors to improve product performance and avoid customer inconvenience. Many research have adopted ML to demystify the relationship between customer attributes, usage behaviors, and product performance [10,32,80]. However, several challenges are involved in personalized behavior modeling. First, it is difficult to directly create personalized ML models as it usually requires a large amount of individual data. To address the problem, Xu et al. leveraged a collaborative-filtering approach [120]. A ML model is trained with population's behavior data, and a behavior relevance metric is proposed to leverage individual users' behavioral similarities and differences to impute missing data. Second, individuals may also behave differently subject to changing contexts in real-world life. To address this problem, Sarker and Kayes proposed a context-behavior rule approach to improve prediction accuracy [89].

ML-based simulation data mining

Today, manufacturers are stive to provide a wider variety of products. However, due to the lack of design commonality, product variety has increased the number of distinct designs and part types. For every new product, designers are likely to start a new design each time rather than use as many of existing designs as possible. As a result, a lot of designs are evolved in an inconsistent and non-uniform manner, which introduces significant variations in design cases. Reusing historical design will significantly improve resource utilization and design change efficiency, simulation data mining has become a popular topic to achieve this. Generally speaking, simulation data mining can exploit how design changes can affect product performance, which is an important method to improve design knowledge reuse.

Through the extensive literature review, current research on simulation data mining can be classified as single performance evaluation and global performance evaluation. Single performance evaluation deals with the interrelationship between a single design parameter and a single performance parameter. For example, the shape and force-displacement of the automotive rubber bumper [42]. While ML can be used to perform single performance evaluations, the value of ML lies in ML's capabilities in performing global performance evaluations (i.e., exploiting the interrelationships between multiple design parameters and global performance parameters). By training ML with the initial design and idealized design, ML model will automatically produce the logic to identify the set of design parameters being most relevant to the performance and generate optimized design accordingly. For example, Ramnath et al. trained ML with idealized model (i.e., the design that has undergone multiple evolutions and has been massively produced, which is close to the perfect design) to study the hidden parametric sensitivities of pocket features on frame surfaces [81]. Through this approach, the ML model can automatically suggest the most suitable pocket features for each given design to achieve light-weight structure while maintaining crash worthiness. This process will significantly reduce the experiment design and trial-and-error process. However, a challenge associated with global performance evaluation is it requires same-engineered and uniform simulation data. To analyze heterogeneous simulation data with different mesh distributions, two challenges should be resolved. First, there requires a unified representation of heterogeneous data. Second, it requires a global performance evaluation indicator for prediction. To address the challenges, Shao et al. proposed a cross-parameterization algorithm to convert heterogeneous simulation data into the intermediate parameter domain. In addition, the Extreme learning machine (ELM) model was adopted to exploit the relationship between design parameters and performance parameters [90]. As the boundaries between design, material, and manufacturing are increasingly blurred, a consistent way to handle knowledge among different domains is also becoming essential. Therefore, a domain knowledge search system is developed to summarize knowledge from design cases through ML, and provide guidance for future design [72]. Design knowledge can be extracted from CAD models to support faster product development [53]. The challenge lies in how to predict and resolve constraints caused by module configurations. To predict design constraints imposed by a particular architecture, ML is applied to learn configuration knowledge [33].

ML-assisted commonality design

Commonality design is a bottom-up product platform development approach that aims to consolidate a group of distinct products to improve economies of scale by standardizing components [65]. Due to mass customization, large variety of part proliferation is regarded as one of the most serious issues in technical design stage. For example, in the aircraft manufacturing industry, the brackets to join parts, strengthen joints and hold wires are yet to be standardized. Therefore, it is necessary and important to perform commonality design. However, standardizing component parts is a complex problem that need to account for the functionalities, dimensions, interface, use frequency, and cost. Considering ML can cluster a large set of component part data to identify a relatively small number of component parts to approximately represent the entire component part sets, Clark et al. proposed a ML-based framework to cluster a particular type of aircraft part (i.e., brackets) based on their geometrical and hole variables, the research claims the full set of brackets on a commercial aircraft can be reduced by 30 % [27].

ML can also be incorporated to find effective ways of non-default geometrical partitioning. Geometrical partitioning is a design operation that decomposes a complex shape into independent features or surface portions to support manufacturing. Due to part proliferation, many component parts are too unique to be decomposed into default classes (e.g., planar, cylindrical, helical). Therefore, non-default partitioning is required to create compound features for coarser partitions. To address the problem, Qie and Anwer proposed a rule-based and deep learning method to detect compound features on a part [77]. In the proposed framework, default partitioning is firstly applied to classify single surfaces into default classes. Second, non-default partitioning is performed based on relative positioning searching and invariance subgroup reasoning.

ML-based manufacturing process prediction

The final output of engineering design involves a set of process variables (PVs) to represent the final embodiment of CNs. Typically, PVs are manufacturing processes, resources and financial support needed to satisfy DPs [97]. Therefore, designers need to evaluate manufacturability by carefully assessing the process against resources. ML can be used to connect design with manufacturing or assembly processes. A ML model is proposed to automatically identify required processes to produce product [38]. The proposed model introduced three groups of metrics (i.e., aggregate geometry, slice-based machining, facet-based orientation) along with manufacturing process to train the ML model to recognize a design's required process. Wu et al. introduced RL to solve the assembly sequence planning problem, from which it cannot only determine the assembly sequence for product, but also identify the tool required for assembly [118]. Zhang et al. proposed an ML-based fixture configuration method. Given that fixture is an essential support device that needs to be reconfigured based on the shape of workpiece, accelerating fixture configuration using ML will undoubtedly reduce product time-to-market [129].

Future perspectives

Incorporate product usage context into customization

Incorporating product usage context (PUC) will improve customization capabilities from both the front-end and back-end. In the front-end, PUC could help to reduce perceived uncertainties in the customer co-design process. Perceived uncertainty is one of the reasons customers hesitate to select customized products. As customers don't have sufficient product experience and cannot test products in advance, they may be uncertain about the functional performance and utility of their design. To reduce perceived uncertainties, customization calls for new methods to help customers reveal needs holistically, foresee potential design failures, and be more confident with their designs. Incorporating product usage context (PUC) into the customization process is a possible yet practical solution. Given that CNs are context-dependent, referring to personal PUC in the co-design process will help customers better reveal their needs without much cognitive burden. It also helps customers foresee risk factors in the environment in order to develop robust products.

In the back-end, considering context-aware smart products are becoming new mediums to provide customized functions and services, better PUC models are needed to help designers develop advanced smart product architectures. In the current research, PUC models used to train smart products are pre-defined by designers. Those models are imprecise, inaccurate, and incomplete. As a result, many customized smart functions fail to perform in usage environments [37]. In order to develop a more robust architecture and more advanced context-awareness capabilities, designers should devote more effort to analyzing and understanding PUC.

UGC is considered an efficient data source for PUC knowledge extraction. Many customer complaints in UGC have exemplified what, how, and to what extent a PUC factor may affect specific products, which are unknown by designers. To extract PUC from UGC, several research gaps are listed. First, it is essential to propose product-specific PUC ontology models to clarify the categories, properties, and relations of PUC in different product categories. Second, ML-based PUC identification methods should be developed. Researchers should find more unique language patterns (e.g., units of words, dependency relations) to identify different types of PUC. Third, researchers should map PUC with product features (e.g., form, function, behavior, structure) for design target value setting.

Identify and manage dynamic customer needs

CNs assessment using UGC has become a popular research topic. However, most of current research treat CNs statically and ignore their dynamic nature. According to Kano Model, due to customer preference changes, an attractive product feature could gradually become a basic feature as it matures over time [66]. Moreover, owing to the Internet, such preference change is becoming more prominent. For example, some social trends could spread quickly across populations and fundamentally change customer preference. In that case, the ability to capture dynamic CNs can help manufacturers seize market opportunities ahead of competitors. Three important topics should be considered in future research.

First, designers can propose new methods to detect and monitor dynamic customer needs. Given that UGC is timestamped, it's possible to develop time-series analytical models to provide more in-depth analysis. In a meanwhile, CNs assessment models can integrate with macro-environment assessment models to explore hidden patterns between social-technical trends and CNs. Second, given that CNs are constantly and dynamically changing, it is important to propose more advanced customer knowledge management method to accommodate enormous amount of UGC from multiple sources with different formats. In order to incorporate latest dynamic into design and customization practice, new customer knowledge management methods should also be efficient in supporting knowledge querying, representation, updating and reasoning. Third, new product platform should also be adaptable and flexible enough to make sure new products can be quickly developed.

Manage complexities in ML

Although ML has facilitated design operations in many ways, it also introduced additional complexity in three ways. Firstly, owing to ML, the number of solutions to a specific design problem has increased significantly, resulting in an increased design process diversity. For example, in the functional design stage, a variety of models are proposed to represent CNs and UX. Secondly, ML has made design operations intensively inter-connected. Design tools and methods across different design stages were integrated to propose ML-based design frameworks. For example, detailed parametric design documents were served to generate design concepts and predict market performance in the conceptual design stages.

In this situation, it is necessary to manage and reduce ML-related complexity. Firstly, there is a need to develop a uniform reference model to accommodate a wide range of ML applications and design paradigms. Secondly, merging ML applications into an integrated solution is important. Third, an extendable, upgradable data management method should be deployed to promote storage, representation, and reasoning of multi-sourced heterogeneous design data.

Increase the responsibility of ML for customization

In current studies, ML has been extensively adopted to improve design efficiency and effectiveness. Nevertheless, many ML applications have caused negative impacts on society and have triggered intense concerns about ethical issues. For example, smart products often breach data privacy, unfairly splurge computing resources, discriminate prices against customers, and so on. These facts suggest that it is now urgent to address certain ethical issues and improve the trustworthiness of ML for engineering design. The following challenges are frequently discussed in the design domain:

- Bias: A ML model can perpetuate discrimination when trained with biased data. And a biased model could lead to undesirable or even unfair outcomes, such as price discrimination.
- Explainability: A ML model is a black box decision-making system that typically nobody can understand the reasons underlying its decisions. And it is difficult to gain trust from people if they cannot explain the rationale behind it.
- Accountability: Behind a ML model, whether there are entities or humans identified to e accountable for the outcomes of AI system.

There are two research streams to increase the responsibility of ML for engineering design. First, researchers can focus on how to develop more advanced product and design mechanisms to ensure designers can use ML responsibly. Second, researchers can also focus on how to use new ML technologies as means to achieve a more responsible ML system end.

Conclusion

Engineering design is evolving towards a more data-rich and technology-intensive paradigm, and in every design stage, ML has made significant contributions to many design challenges. Also, as manufacturers are keen to offer more customized products, ML is becoming a fledgling research field with much potential. To identify the advances and limitations of current research and suggest some future research directions, this paper conducted a systematic literature review of ML for engineering design and selected 116 relevant articles. The major findings are summarized based on design stages.

- *Functional design.* The current ML for functional design can enhance customization in three ways. Firstly, a variety of ML-based UGC analysis models are proposed to reflect the latest individual CNs from multiple aspects, which provides more design customization opportunities. Secondly, ML has significantly accelerated CNs mapping process, making design configuration more customer-friendly, predictive, and adaptable. Thirdly, ML enabled a more accurate product function recommendation, which can further enhance the modular design for customization. However, there are still some opportunities for future research. Firstly, UGC not only contains CN, but it also contains sufficient individual-granularity PUC information that is yet to be explored. Customizing products based on PUC could further eliminate the cognitive burden involved in the configuration process. Second, researchers can further focus on the evolutions and dynamics of customer opinions in UGC to capture the latest customization opportunity. Thirdly, considering responsible ML has attracted much attention, designers should focus on the individual customer's ethical ML needs when providing customized product functions and services.
- *Conceptual design.* The current ML for conceptual design can promote customization in two ways. Firstly, a variety of ML-assisted expert systems for concept generation can help designers quickly convert individual customers' requirements into sound design concepts. Second, ML can improve the efficiency of concept clustering and configuration evaluation, resulting in improved customization responsiveness. Nevertheless, considering there are multiple formats of design concepts (e.g., text statement, concept drawing, CAD model), it is essential to find an effective design concept management method to enhance design knowledge retrieval, representation, and reasoning.
- *Technical design.* ML for technical design primarily focused on design optimization and space exploration. In addition, current research on product architecture generation and production process prediction also provide customization with more cost-efficient means to achieve economies of scope. However, future research still needs to further optimize and manage design complexity introduced by multidisciplinary design and design couplings.

Some limitations should be considered in interpreting the review outcomes. Firstly, customization is a multifaceted notion concerning design, manufacturing, supply chain, marketing, and business strategy, while this research only focused on the engineering design facet of customization. Second, this research mainly focused on the applications and advantages of ML instead of technical aspects. It is hoped that this research will serve as the fundamental basis to motivate more in-depth research in design customization in the future.

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.

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