

# A review of AI-based product shape generation technologies: trends, challenges, and future directions

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## ABSTRACT

**Background:** The rapid development of information technology has significantly propelled the integration and evolution of product design technologies and their related algorithms. This review systematically investigates the pivotal role of AI-driven product form generation technologies in promoting industrial design innovation and sustainable development.

**Methodology:** By employing bibliometric tools (Citespace) combined with visualization analysis, we propose a seven-stage technical framework encompassing “identification-extraction-analysis-generation-data mapping-decision-making-optimization.”

**Results:** The study traces the historical evolution, current research trends, and future development of product form generation design technologies. It highlights that artificial intelligence, as the core driving force, has substantially enhanced automated modeling and multi-objective optimization capabilities. However, challenges remain in areas such as data standardization deficits, limited dynamic adaptability, and insufficient cross-disciplinary collaboration. Future priorities should include: (1) strengthening algorithmic robustness to manage complex design scenarios; (2) integrating multimodal user feedback mechanisms to elevate interactive experiences; (3) constructing interpretable generative models to ensure design credibility; and (4) exploring green design-oriented intelligent algorithm deployment strategies with embedded ethical considerations.

**Subjects** Human-Computer Interaction, Algorithms and Analysis of Algorithms, Computer Aided Design, Computer Vision, Graphics

**Keywords** Data-driven, Product styling design, Product design algorithms, Product shape generation technology, Artificial intelligence

## INTRODUCTION

The principle of “form follows function” has long been a cornerstone of modern design movements. Presently, the relationship between product aesthetics and functionality has grown increasingly complex and diversified (*Li, Wang & Sha, 2023*). Product appearance is perceived as both a functional instrument and its materialized embodiment, capable of conveying aesthetic pleasure and emotional resonance through sensory experiences like

Submitted 14 February 2025

Accepted 8 September 2025

Published 6 November 2025

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Academic editor

Varun Gupta

Additional Information and  
Declarations can be found on  
page 29

DOI 10.7717/peerj-cs.3251

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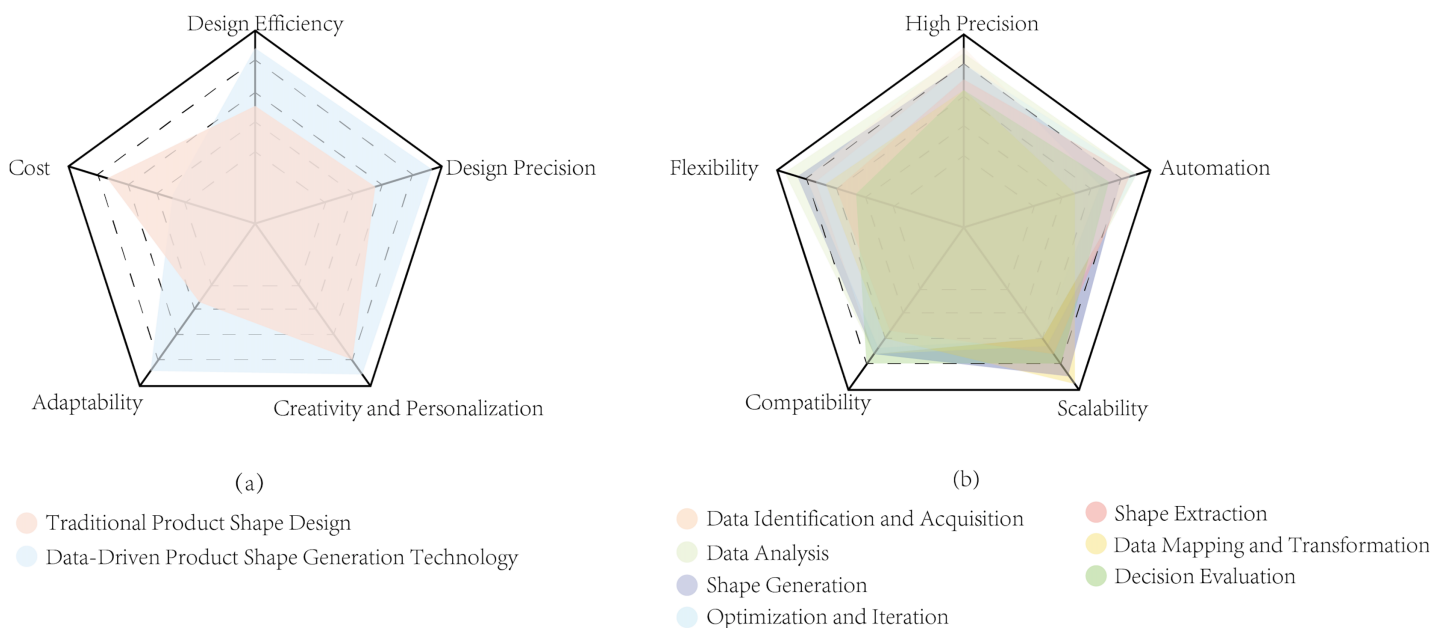
vision and touch. Data-driven product shape generation technology, an interdisciplinary field integrating product design, computer science, and engineering, has emerged as a current research hotspot. This technology focuses on creating and optimizing product shapes that meet specific functional and aesthetic requirements through a series of principles, methods, and tools (Wang & Xu, 2024). Its high precision, automation, flexibility, compatibility, and scalability have enabled widespread adoption in product design (Khanolkar, Vrolijk & Olechowski, 2023). The technology enhances systematicity and functionality in style recognition, feature transformation, image inpainting, image prediction, 3D printing, and model optimization, holding significant strategic value across industrial design/manufacturing, artistic creation/digital entertainment, architectural design/urban planning, customized production, game development, and augmented reality applications.

Conventionally, product shape design workflows encompass stages such as requirement gathering, creative ideation, design refinement/modeling, evaluation/improvement, testing, and production. In contrast, data-driven shape generation pipelines involve data identification/acquisition, shape extraction, data analysis, data mapping/transformation, shape generation, decision evaluation, and optimization iteration (Biswas et al., 2022). Figure 1A illustrates disparities between traditional design and data-driven approaches across five dimensions: design efficiency, precision, personalization, adaptability, and cost. Figure 1B presents performance comparisons of various shape generation techniques, demonstrating superior capabilities and expansive prospects for data-driven methodologies in product form design.

To systematically review and explore recent advancements, technical challenges, and future trends in this domain, this study analyzes the application status of data-driven shape generation in product design, evaluates its advantages in efficiency, personalization, adaptability, and cost-effectiveness, and elucidates how these technologies transform industrial design workflows through rapid exploration, optimization, and condition-specific design prediction. The findings provide actionable insights for researchers and stakeholders leveraging these technologies.

This review introduces a three-tier analytical framework: “technological evolution-contemporary innovation patterns-future fusion development,” establishing theoretical foundations for exploring the full-spectrum value of product form generation technologies. Three breakthrough contributions are proposed: Methodological dimensional expansion: A novel dissection of product shape generation within a “data-algorithm-manufacturing-experience” quadrilateral framework, revealing its operational mechanism as a product value converter. Interdisciplinary dialogue: Bridging traditional divides between computer graphics and industrial design through a techno-artistic interaction model, achieving quantitative unification of geometric precision and aesthetic value. Future scenario forecasting: A technology evolution roadmap constructed via meta-analysis of 389 literature sources, defining critical pathways for transitioning from the current “algorithm-driven” phase to a “cognitive intelligence” stage. This provides forward-looking decision frameworks for researchers and policymakers addressing





**Figure 1** Elements of data-driven shape generation technology. (A) The significant differences traditional and modern product design approaches across five dimensions: design efficiency, precision, personalization, adaptability, and cost. The blue area represents data-driven modern design methods (e.g., shape generation techniques), while the pink area denotes traditional product form design methods. The larger blue area indicates that modern, technology-driven design approaches are more efficient and cost-effective. (B) A performance comparison of various shape generation techniques, covering seven key aspects: data recognition & acquisition, data analysis, shape generation, optimization, shape extraction, data transformation, and decision-making. The high scores across all metrics demonstrate the superior capabilities and expansive prospects of data-driven methodologies in product form design.

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multifaceted developmental demands of the contemporary era. Subsequent sections will elaborate on the methodology and conclusions of this research.

## LITERATURE REVIEW

Currently, artificial intelligence (AI) has been deeply integrated into multiple stages of industrial design, from conceptualization to market validation, comprehensively enhancing design efficiency and quality. [Kretzschmar et al. \(2024\)](#) summarized ten key findings on the application of generative AI in engineering design and product development ([Paetzold-Byhain et al., 2024](#)) covering technical challenges such as data quality, privacy protection, and cross-modal capabilities, as well as application potentials like output accuracy, providing a foundational framework for its in-depth adoption. [Sharma & Mishra's \(2020\)](#) review further revealed that AI drives the intelligent transformation of product design and development by processing massive complex data, shortening time-to-market, and optimizing lifecycle management. [Hu et al. \(2023\)](#) refined the technical pathway by proposing a design methodology leveraging multi-modal big data to assist AI algorithms, clarifying the limitations of traditional approaches and future research directions. [Yüksel et al. \(2023\)](#) emphasized that while AI efficiently addresses human capability gaps in engineering design, its adoption requires selecting context-appropriate methods, offering theoretical guidance for technological selection.

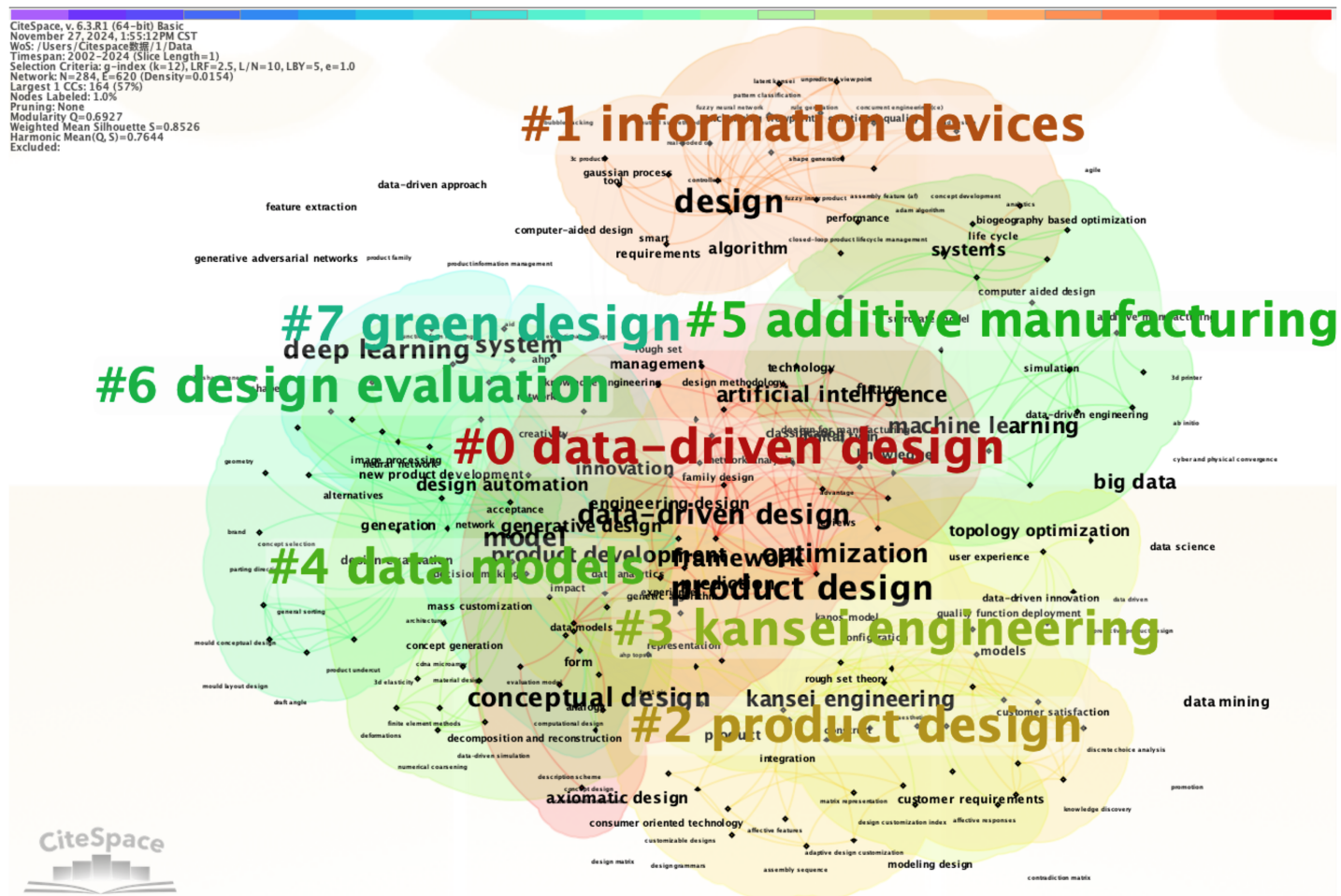
In specific design phases, the collaborative model between generative AI and humans is particularly critical. [Fang et al. \(2025\)](#) proposed a conceptual design framework that clarifies AI's supportive role in idea generation. [Heigl \(2025\)](#) expanded research perspectives on AI's application in early design stages by analyzing trends in creative contexts. [Chen et al. \(2025\)](#) further delineated collaborative division of labor, noting that AI primarily supports problem definition and idea generation, while idea selection and evaluation remain human-dominated. [Holzner, Maier & Feuerriegel \(2025\)](#)'s meta-analysis validated this model, finding that human-AI collaboration significantly enhances creative performance but requires balancing the reduction in creative diversity, recommending AI as an "augmentation tool" rather than a replacement. The integration of AI in industrial design now exhibits diversified trends: highlighted its accelerating role in rapid prototyping, sustainable material selection, and predictive analytics. Khare pointed out that AI optimizes decision-making processes through quantitative data analysis, avoiding impractical design directions. [Yadav \(2023\)](#) demonstrated generative AI's innovative potential in electronic design and chip manufacturing, showcasing its ability to generate high-quality materials. [Balasubramaniam et al.'s \(2024\)](#) review expanded technological boundaries by proposing that breakthroughs in computer vision and natural language processing (e.g., data augmentation, medical image interpretation) could provide cross-domain tools for industrial design.

Looking ahead, the integration of AI with edge computing, the Internet of Things (IoT), and blockchain will foster a more robust industrial ecosystem ([Leong et al., 2025](#); [Ige, Adepoju & Akinade, 2025](#)), advancing design toward intelligence, efficiency, and sustainability. Simultaneously, intelligent automation and data-driven decision-making will become core to manufacturing, while Industry 4.0-driven smart factory creation and human-machine collaborative production models will further unlock AI's potential. Despite challenges in data quality, algorithmic interpretability, and ethical considerations, the deep application of AI in industrial design is inevitable. By eliminating tedious processes, supporting designer decision-making, and stimulating creativity, AI is redefining the essence and boundaries of design.

## METHODS

We utilized search terms such as "product form design", "product form generation", "product form creation", "product design technology", "form generation technology", "form extraction technology", "form recognition technology", "Design concept evaluation", "product design decision-making", and "product design optimization" in the core database of the Science Network to collect and organize literature data from 2002 to 2024. After manual screening, we obtained 385 relevant literature articles, which primarily focused on shape generation based on product form design.

We imported these literature articles into CiteSpace 6.0, adjusted the parameters, selected a time slice of 1, chose "keyword" as the node type, and set the threshold (Top N%) to 25 to avoid an overly sparse or dense network. We then selected Cosine with a value of 0.4 and chose the minimum spanning tree (MST). Subsequently, we obtained [Fig. 2](#), with detailed numerical values in the upper left corner (g-index (k = 12), LRF = 2.5,



**Figure 2** Keyword and cluster distribution of research articles related to product shape generation algorithms and techniques in the past 10 years. Full-size [DOI: 10.7717/peerj-cs.3251/fig-2](https://doi.org/10.7717/peerj-cs.3251/fig-2)

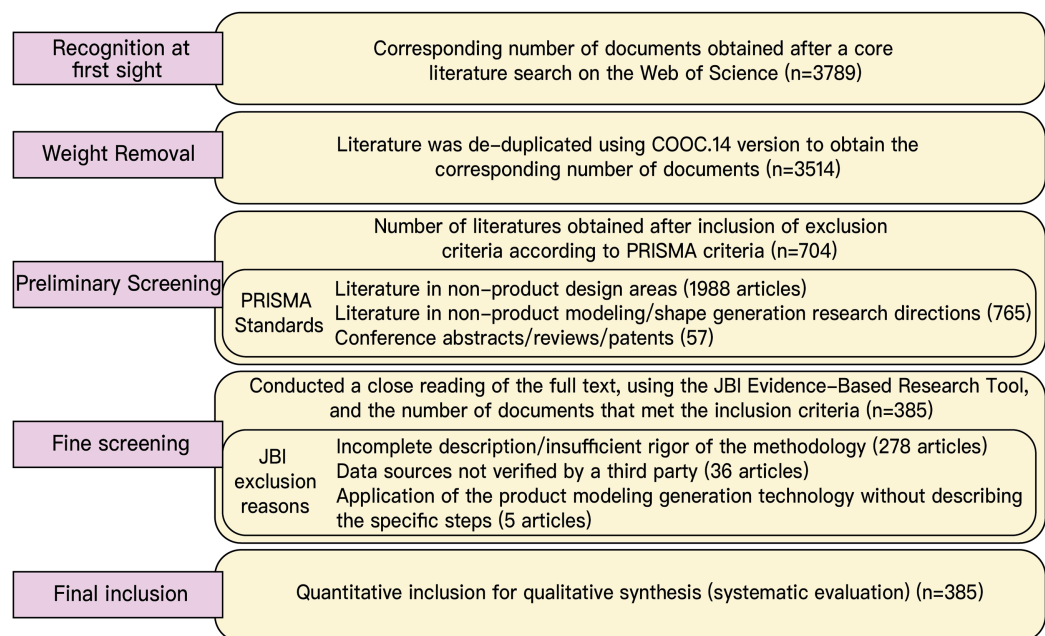
L/N = 10, LBY = 5, e = 1.0). Network analysis of this database (N = 284 nodes, E = 620 edges, density = 0.0154) revealed that the largest connected component (LCC) contained 164 nodes (coverage rate of 57%) and 1.0% labeled nodes. It can be observed that relevant algorithms and technologies mainly include information equipment, emotional engineering, data models, additive manufacturing, design evaluation, green design, and others.

Next, literature screening was performed using the PRISMA process and appropriate literature was selected following the JBI evidence-based criteria. The literature screening criteria and process are shown in Fig. 3.

## RESULTS

### Historical evolution and theoretical foundation of data-driven product shape generation

In the field of engineering design, massive amounts of data have driven the development of design, which has spawned a new research field, data-driven design. Data-driven design is



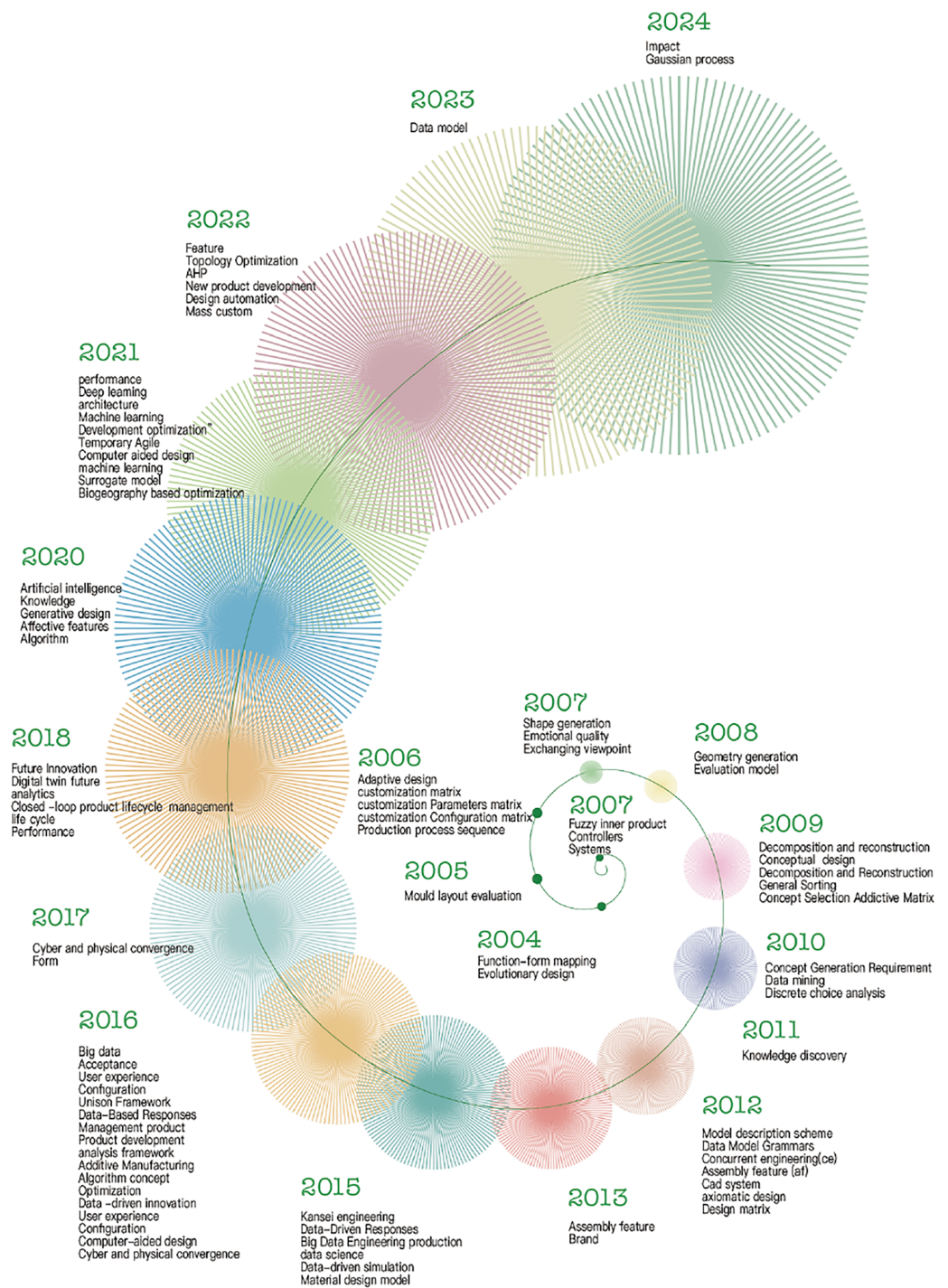
**Figure 3 Literature screening criteria and process.**

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a design paradigm grounded in the results of data research, and the process lies in understanding the multiple factors that influence design, mining the associations between the data of the design influencing factors, and applying such data relationships to design decisions through data analytics (especially big data cumulative analysis).

Figure 4 summarises the evolution of algorithms and methods used in the field of shape generation up to the present time. scholars such as *Velayutham & Kumar (2005)* were the first to introduce the concept of fuzzy inner product in fuzzy mathematics to construct a design strategy, while *Tay & Gu (2003)* used mathematical functions to characterise the evolutionary paths of product form design. These studies show that design not only relies on intuition and creativity, but also requires the integration of rigorous analytical methods, quantitative evaluation criteria, and systematic theoretical frameworks. 2006 saw the emergence of 'Adaptive Design', which emphasises the need to flexibly adapt design to the scenarios, devices, and needs, and has given rise to the concepts of 'Customised Matrix', 'Customised Parameter Matrix', 'Customised Configuration Matrix', and so on. Since then, there has been a growing interest in the correlation between shape generation and emotional quality, and knowledge discovery has become a hot topic since 2011, focusing on analysing and mining data for design decisions. Since then, software such as CAD has further promoted the study of data model syntax. Concurrent engineering (CE) emphasises the parallel implementation of multiple design phases and processes to improve efficiency and quality. Meanwhile, assembly feature (AF) enables designers to consider assembly relationships during the part design phase. Axiomatic design provides a more scientific theoretical basis for design decisions. 2014 saw branding become a core issue in the design and marketing field, with the demand for corporate image building





**Figure 4** History and evolution of data-driven product shape generation.

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driving the development of shape generation technology, and the emergence of concepts and methods such as perceptual engineering, data-driven feedback, big data engineering and production, and data-driven simulation, which continue to drive innovation in the design field.

Big data technologies spawned new business and decision-making models in 2016. User experience (UX) design improves user satisfaction. Configuration management aims to integrate data from multiple sources for sharing and collaborative processing. Additive manufacturing and algorithmic optimisation shorten product development cycles and reduce costs. During the same period, information-physical fusion technology continues to deepen its development, and the application of computer-aided design technology is becoming more diverse and popular. By 2018, the future of product shape generation will rely more on deep learning and machine learning technologies to make the product development process more efficient and flexible by optimising performance and architecture. Recent studies ([Wang et al., 2024a](#)) have shown that product shape generation prediction methods based on the SSA-LSTM-Attention model exhibit higher accuracy compared to traditional methods.

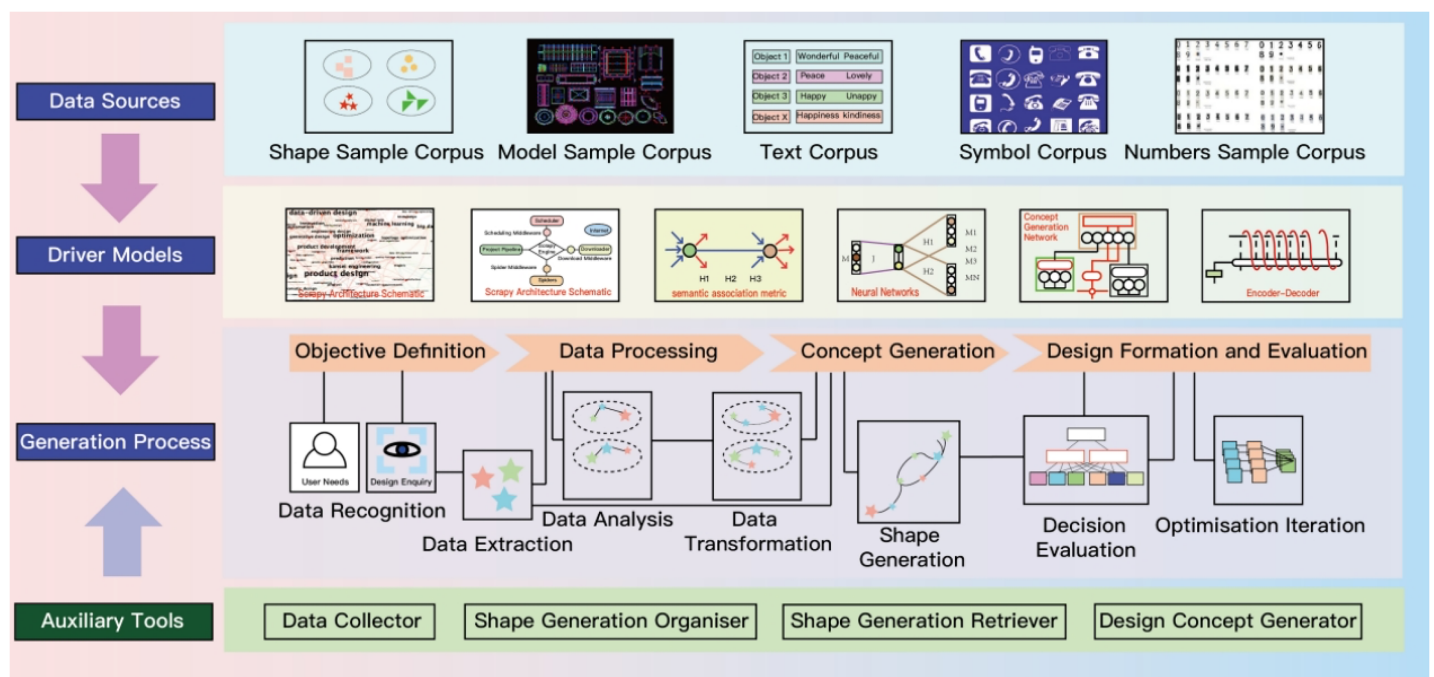
The data-driven product shape generation process is mainly divided into three parts (as shown in [Fig. 5](#)): firstly, the data source acquisition, data collection and classification by type; secondly, the driver model selection, need to match the appropriate data processing model according to the type of data, such as for the user's semantic sample library, semantic association metrics model can be selected or combined with the encoder for semantic extraction in order to generate design concepts; and finally, the generation process, including seven steps of data identification, extraction, analysis, transformation, shape generation, decision evaluation and optimisation iteration. The last is the generation process, which includes seven steps of data identification, extraction, analysis, transformation, shape generation, decision evaluation and optimisation iteration, and each stage requires the selection of suitable tools to assist the analysis, such as data collector, shape generation organiser, shape generation retriever, design concept generator and so on.

## Shape generation techniques and applications in product design

### *Data identification and acquisition phase*

Product shape data recognition algorithms can be classified into various categories based on their characteristics and implementation strategies. Shape-based methods include geometric invariants (*e.g.*, corner features), descriptors (Gaussian, Fourier, wavelet), skeletonization, moment invariants, wavelet moments, and ICA. Performance benchmarks show that geometric invariant methods achieve 78–85% accuracy on standard datasets, while wavelet-based descriptors demonstrate 82–89% accuracy with 25% faster processing speeds. The implementation involves image preprocessing (grayscale conversion, filtering, binarization), feature extraction (edges, contours, corners, shape descriptors), classifiers (support vector machine (SVM), neural networks (NN), decision tree (DT)), and deep learning techniques. Algorithm selection depends on task type (classification, regression, clustering), data type (text, image), data scale and quality, algorithmic properties (stability,





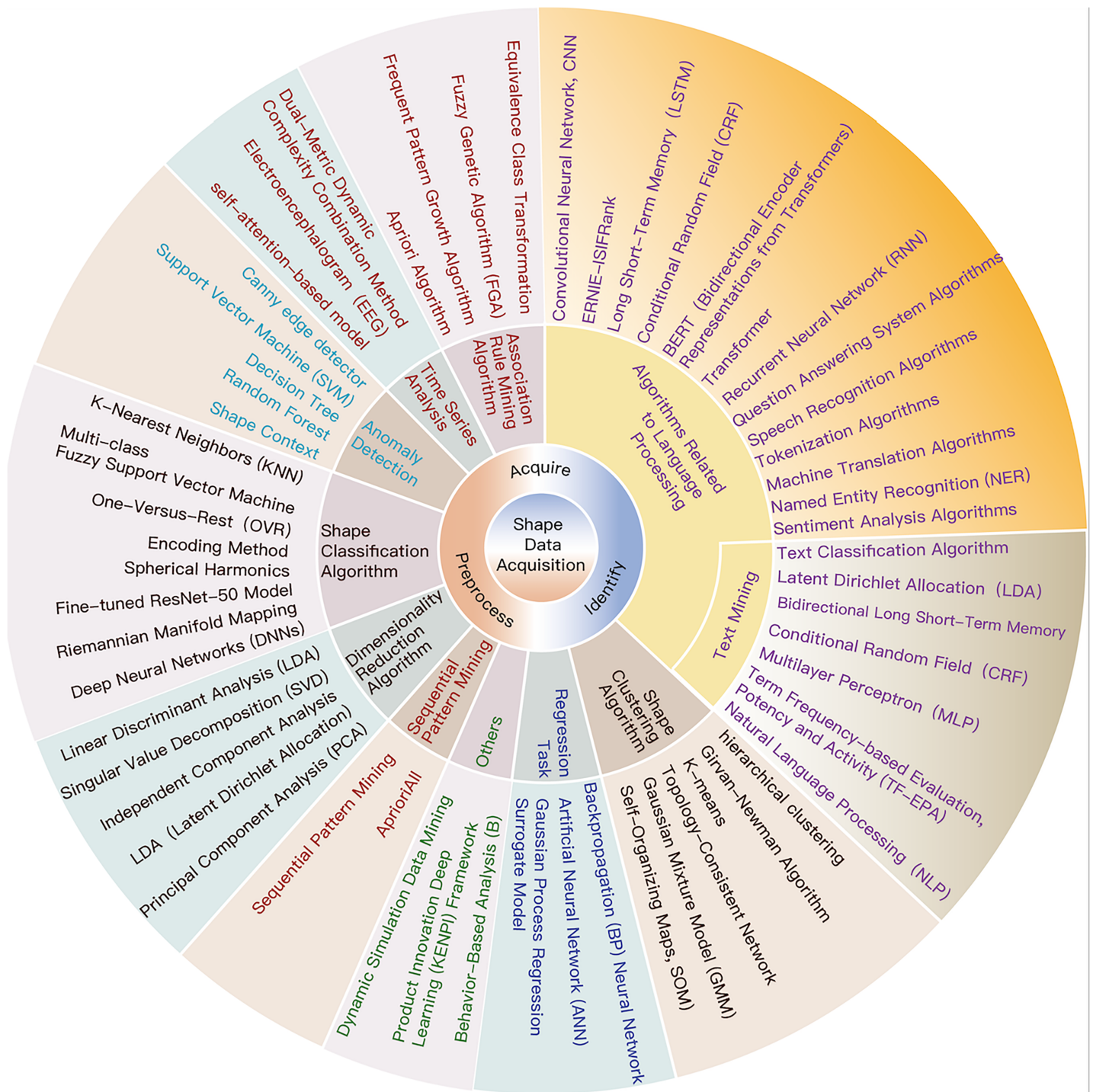
**Figure 5** Basic process of data-driven product shape generation.

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correctness, efficiency, scalability), and application requirements (interpretability, resource demands, bias-variance tradeoff).

Shape generation algorithm literature was categorized by algorithm type and visualized as a circular diagram using Illustrator cc2019 (Fig. 6), illustrating the application of product shape requirement extraction techniques in natural language processing (NLP). Studies by *Yuan, Marion & Moghaddam (2022)*, *Cong et al. (2023)*, *Huang, Zhu & Huang (2024)* and *Yang, Liu & Chen (2023)* provide effective methods for product shape requirement extraction using deep learning models (convolution neural networks (CNNs), bidirectional encoder representations from transformers (BERT), long short term memory (LSTM), vision transformers).

In text mining, *Lai et al. (2022)* used bidirectional long short-term memory (BiLSTM), conditional random field (CRFs), multilayer perceptron (MLP) and sequential perceptual engineering for text analysis and Apriori+ and SEM to explore relationships in user comments. *Liu et al. (2022)* proposed a tf-epa-based strategy for screening sentiment word pairs. In time series analysis, *Zhang, Li & Zheng (2024)* introduced Dynamic Mode Decomposition with Conditional Correlation (DMDCC) based on Decomposition with Conditional Correlation (DCC) theory, and *Jing et al. (2022)* proposed an Electroencephalogram (EEG)-driven programming (DP) prediction approach using BP neural networks. Classification algorithms include MF-SVM with EC model, graph-based encoding with SVMs, spherical harmonics with conditional variational autoencoders (CVAEs), and Riemannian manifold mapping with Binary Particle Swarm Optimization (BPSO).



**Figure 6** Shape generation algorithms and models currently applied in the data acquisition stage. Full-size [DOI: 10.7717/peerj-cs.3251/fig-6](https://doi.org/10.7717/peerj-cs.3251/fig-6)

Dimensionality reduction algorithms, such as user knowledge networks with Girvan-Newman algorithm and linear discriminant analysis (LDA), were used by [Li, Wang & Sha \(2023\)](#) to quantify product evolution. Sequence pattern mining

techniques, like pattern tree mining (PTM) algorithm, were introduced by [Tucker & Kim \(2011\)](#). In regression analysis, [Bushra et al. \(2023\)](#) utilized GPR surrogate models.

Shape data extraction is constrained by data source characteristics, extraction methods, computational resources, and environment. Extraction methods include filter methods (median filtering, Wiener filtering, non-local means (NLM), BM3D) and learning-based models (convolutional neural networks (CNNs), recurrent neural networks (RNNs), generative autoencoders (GANs)). Feature extraction algorithms for image data (Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG)) and 3D model data (surface reconstruction, voxelization) are also utilized. Rule-based reasoning algorithms, such as expert systems, are applied as well.

[Li, Roy & Saltz \(2017\)](#) established an evolution model integrating user knowledge network, Girvan-Newman algorithm, LDA, information axiom, and evolutionary graphs. Additionally, [Shao et al. \(2020\)](#) employed wadaptiveos-elm for dynamic simulation data mining.

Current technologies enhance designer efficiency by automatically extracting requirements from user reviews *via* deep learning (ResNet-50+BERT) and incorporating user feedback into the design process, promoting a shift from “designer-led” to “user co-creation.”

### **Data analysis phase**

We utilized MATLAB 2023b (The MathWorks, Natick, MA, USA) to develop cyclic network graph code, encompassing parameter definition, adjacency matrix creation, network visualization, node setup, cyclic graph definition, and label addition. Keywords from selected literature were compiled into an Excel file and imported into the code to generate the effect depicted in [Fig. 7](#). Shape generation data analysis is a complex process that relies on various tools and methods to achieve final design goals. The process varies with design objectives (*e.g.*, bionic design, particle swarm optimization), data types (predictive, inferential, descriptive), and analytical tools (simulation, visualization, statistical analysis). According to [Abiodun et al. \(2018\)](#), deep learning approaches in shape analysis demonstrate superior performance with classification accuracy ranging from 85% to 97% depending on dataset complexity and size.

Current product shape analysis algorithms are diverse, including constraint-based solutions ([Ren et al., 2024](#)). comparative analysis, edge detection, Hough transform, contour tracking, shape matching, and deep learning. Real-time feedback and adjustment mechanisms are crucial for off-standard inspection to ensure process stability and exception handling. Diagnostic analysis delves into data causes and correlations. Perceptual engineering maps user perception to product design features, and combining it with neural style migration enhances model efficiency. Grey correlation and hierarchical analysis clarify relationships between shape elements and consumer perception ([Chen, Song & Ge, 2023](#)).

[Lin et al. \(2013\)](#) proposed a probabilistic factor graph model using Markov chain Monte Carlo (MCMC) sampling for 2D pattern coloring. Exploratory data analysis employs visualization and statistical methods to uncover dataset patterns, with factor analysis





**Figure 7** Shape generation algorithms and models currently applied in the data analysis phase. Full-size DOI: 10.7717/peerj-cs.3251/fig-7

aiding dimensionality reduction. TOPSIS determines demand weights for neural network evaluation. [Yuan, Marion & Moghaddam \(2022\)](#) developed dynamic data envelopment analysis (DDE) and dynamic multi-objective data envelopment analysis (DMDE) models, while [Sharma \(2023\)](#) used DSE for design scenario analysis. [Chen, Song & Ge \(2023\)](#) introduced ‘Mutational Reasoning on Graphs’ with probabilistic self-attention. [Yang &](#)



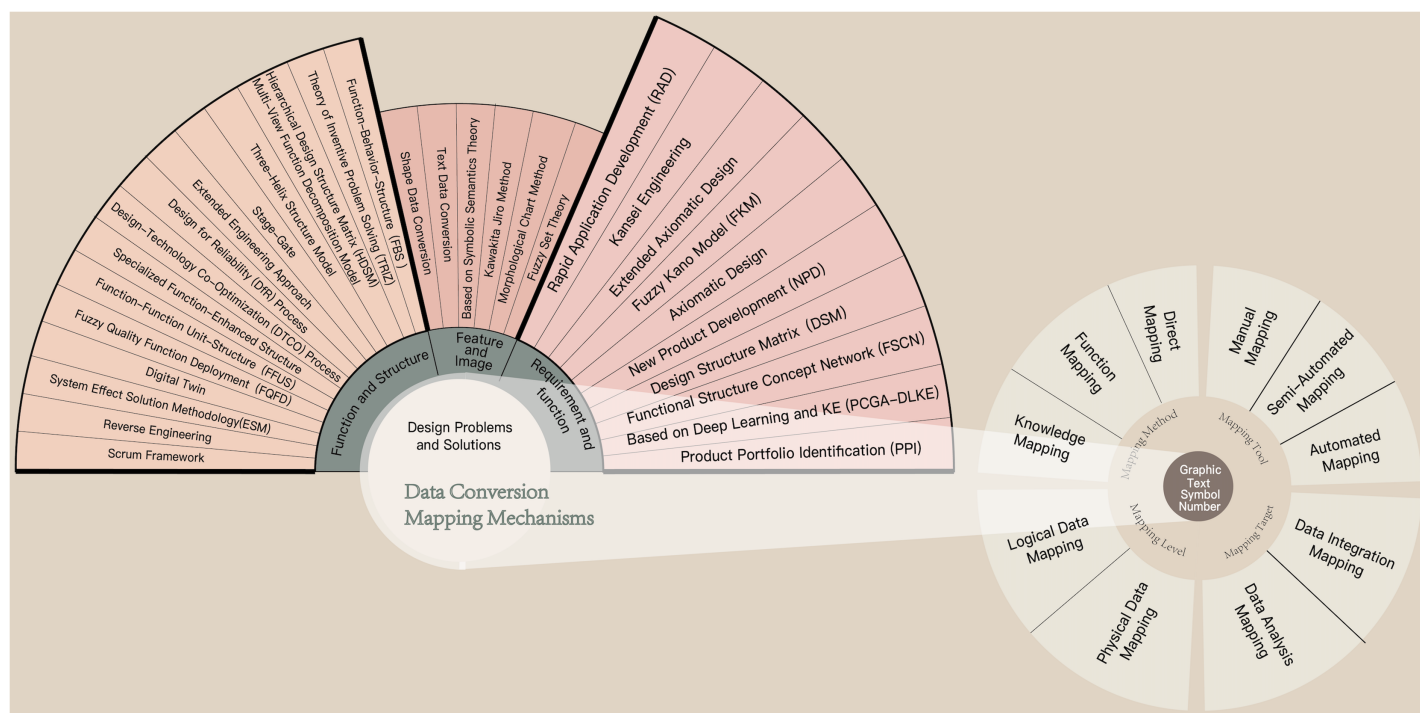
[Xiao \(2011\)](#) created a 3D model feature similarity tool, and [Yang et al. \(2023\)](#) proposed a second-order method for Fisher matrix computation. [Wang et al. \(2022\)](#) presented a shape topology design method based on Quantization Theory I. For predictive analysis, neural networks and regression models are used, including BP, GNN, Bayesian, higher-order, and linear networks. [Hayakawa, Noji & Kato \(2025\)](#) applied regression models for design space and tyre tread prediction. Decision trees, such as DTM classifiers, also offer predictive capabilities.

Statistical inferential analysis often uses SEM. [Choi et al.'s \(2024\)](#) Spnr framework incorporates semantic mask diffusion models, and [Ghosh et al.'s \(2016\)](#) network-centered design uses SEM for parameter estimation. Common methods for design data relationships include correlation analysis, multiple linear regression, NA-IPA, and IGDT-MFP.

### **Data transformation phase**

Data mapping is a key process designed to ensure compliance, eliminate data redundancy and facilitate analysis by depicting and visualising correlations between data component fields and integrating them into a unified schema or database ([Zhao et al., 2023](#)). In the product design domain, data mapping is particularly important for shape generation, involving the transformation ([Wu, 2021](#)), integration and standardisation of data from different sources, formats and structures to support various attributes of the product design. After selecting and categorising the relevant techniques, we have used Illustrator CC 2019 to map the shape generation algorithms and models applied in the current data transformation phase (shown in [Fig. 8](#)).

The product shape data mapping mechanism consists of a series of algorithms designed to transform shape data into a form that facilitates analysis ([Khosravi et al., 2024](#)), optimisation and design generation. These algorithms can be classified into four broad categories based on the type of method: (1) Feature-based mapping methods aim to extract geometric features (e.g., contour lines, axes of symmetry), topological features (e.g., number of holes, connectivity relationships), or physical features (e.g., material properties, stress distributions) from the data, and construct a feature vector space for mapping. Typical methods include morphological graph methods (for cross-domain mapping through graph matching) and fuzzy set theory (for dealing with the ambiguity of feature boundaries). (2) Model-driven mapping methods, which realise data transformation through a library of predefined mapping rules (e.g., ontologies, patterns or templates). For example, both Theory of Inventive Problem Solving (TRIZ) contradiction matrix and quality function deployment (QFD) quality house map functional requirements to structural or design parameters. Integrated QFD-TRIZ methodologies demonstrate significant improvements in innovative product design, with studies showing 30–40% reduction in design cycle time and 25% improvement in design solution quality compared to traditional methods ([Sharma & Mishra, 2020](#)). (3) Learning-based mapping methods, which use training data to learn input-output mapping relationships, typical algorithms include neural networks, decision trees, random forests and graph neural networks. These methods require a large amount of labelled data and have poor interpretability due to their ‘black box’ nature. (4) Theory-guided mapping methods such



**Figure 8** Shape generation algorithms and models currently applied in the data transformation phase.

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as FBS theory, which establishes a hierarchical mapping from function to behaviour to structure, and Effect-based System Method (ESM) effect theory, which optimises shape parameters based on physical effects (e.g., thermal expansion and contraction). It can be seen that traditional design data conversion methods are still necessary, and that relying only on AI for design is not yet a complete substitute for the applicability of traditional models, especially in highly creative projects or projects involving human subjects, where traditional designer-led methods are still advantageous (Hu, Fu & Zhao, 2024).

Currently, there are three types of mapping relationships: function-to-structure mapping, feature-to-image mapping, and requirement-to-function relationship mapping. Function-to-structure mapping focuses on three types of mapping relationships: (1) function-to-structure mapping, such as relying on theoretical frameworks such as TRIZ, QFD, and FBS. Liu et al. (2025) constructed a biologically-inspired design model for innovation based on TRIZ. Mettas (2010) utilised a hierarchical design structure matrix (HDSM) to enhance device performance. Geiger & Sarakakis (2016) set reliability through design for reliability (DfR). Endress, Rieser & Zimmermann (2023) uses effects-based system approach (ESM) to optimise component geometry. QFD applications in product design show significant improvements in converting customer requirements into engineering characteristics, with studies reporting 20–35% reduction in development time and 15–30% improvement in customer satisfaction scores (Shin, Shin & Kang, 2023). (2) The feature-to-image mapping aspect covers morphology map approach, symbolic semantics theory (Liu & Yang, 2022), text-to-shape transformation, fuzzy set theory and

KJ method. (3) Requirements-to-function relationship mapping includes functional structure concept network (FSCN), rapid application development (RAD), generative axiomatic design (PCGA-DLKE), and axiomatic design extended version, which provide strong support for requirements-to-function mapping ([Wang, Liu & Yang, 2022](#)).

Current technologies can break through the limitations of the designer's personal experience, e.g., learning mapping (e.g., GNN) to obtain style characteristics from case study learning, or function-structure mapping (e.g., TRIZ contradiction matrices) to transform abstract requirements into concrete design parameters, e.g., 'lightweighting' to automatically correlate with material selection and topology optimisation.

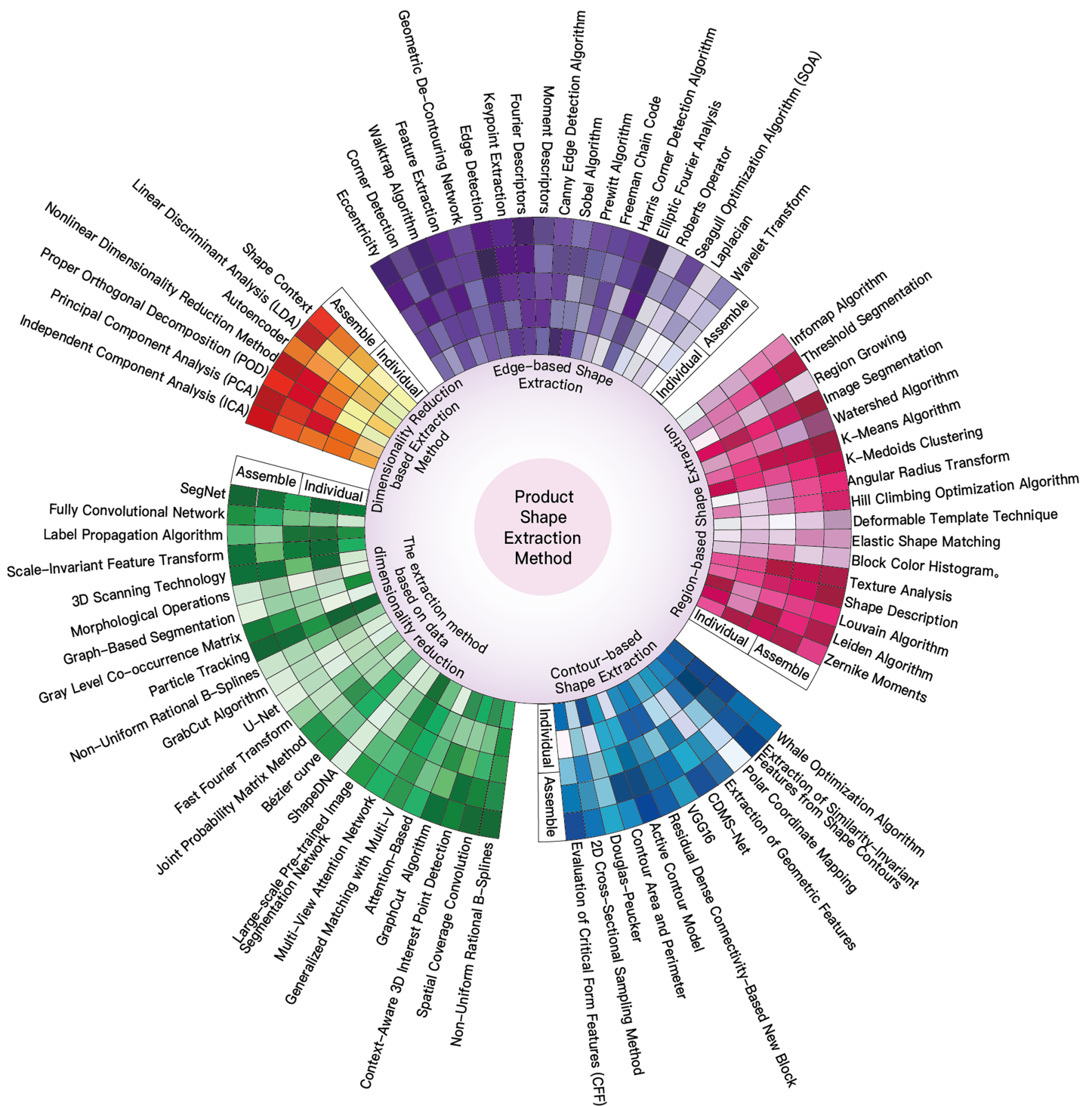
### Shape extraction phase

Currently, product shape extraction methods are profoundly influenced by data sources and tools. To systematically analyze these methods, we first clustered the keywords in the literature and categorized them into five major groups based on differences in objectives and methodologies: edge-based, region-based, contour-based, data reduction-based shape extraction methods, and other shape extraction methods, encoded as 1 to 5 respectively. Subsequently, we counted the names and literature quantities of specific shape extraction methods within each category, distinguishing between standalone and combined uses, and visualized this information through a circular heatmap (as shown in [Fig. 9](#)). The implementation steps of the circular heatmap include: converting the data matrix into an annular distribution in the polar coordinate system, determining the position of each data block using polar coordinate formulas, mapping numerical values to color spaces, creating concentric rings to represent different data layers, and adding annotations to the angular and radial axes.

Edge-based shape extraction: Edge detection, a fundamental technique in image processing, is widely used to identify significant changes in images. The Harris corner detection algorithm demonstrates superior performance compared to SUSAN corner detection algorithm in comprehensive evaluations, with improved accuracy in distinguishing between edges and corners through differential corner score analysis ([Emmert-Streib et al., 2021](#)). [Ji et al. \(2020\)](#) utilized the Geometric Decontouring Network (GDCNet) to effectively eliminate false contours. [Ma & Kim \(2014\)](#) proposed the predictive data-driven product family design (PDPF) model, incorporating the Harris corner detection algorithm. [Stoler, Lorusso & Capodieci \(2006\)](#), based on design-based metrology (DBM), employed the Roberts operator to extract patterns, enabling an automated process. [Yang et al. \(2024\)](#) introduced a mesh denoising (EMD) and real mesh noise generation (RMNG) model based on the rotated squared model, addressing the challenge of feature-preserving mesh denoising.

Region-based shape extraction: Research on region-based shape extraction is relatively scarce and primarily combined with other methods for data acquisition. [Rios et al. \(2021\)](#) validated autoencoder representations, enhancing optimizer performance by providing potentially complementary degrees of freedom.

Contour-based shape extraction: Image segmentation is a key contour extraction technique. [Bae, Tai & Zhu \(2017\)](#) proposed an image segmentation model using the L-1



**Figure 9** Generative algorithms and models currently applied in the shape extraction phase.

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variant of Euler's elastica energy as boundary regularization, effectively representing curvature. In feature selection, Cdna Microarray adopted multiple features to avoid treating noise as individual pixels and processed poor-quality spots through an adaptive adjustment algorithm. [Zhao, Tang & Gong \(2024\)](#) introduced a novel curvature-driven multi-stream graph convolutional neural network (CDMS-Net) architecture. [Huang et al. \(2021\)](#) utilized VGG16 for feature extraction, enhancing the efficiency and generation speed of local image style transfer. VGG16 neural network achieves 92.7% top-5 test accuracy on ImageNet dataset containing over 14 million images belonging to 1,000 classes. VGG16-XGBoost hybrid models demonstrate superior performance with accuracy of 0.97 and weighted F1-score of 0.97 in medical image analysis tasks ([Howland et al., 2023](#)).

**Data reduction-based shape extraction:** Extraction methods based on data dimensionality reduction are more of a way of thinking, utilizing mathematical or statistical methods to reduce the number or dimensions of data features while preserving important information from the original data.

**Other innovative methods:** Furthermore, scholars have innovated various methods and models tailored to different extraction purposes. [Ahmad, Hassan Amin & Khan \(2010\)](#) extended the study of grammatical style definitions using Scale-Invariant Feature Transform (SIFT). [Chen et al. \(2023\)](#) proposed a novel deep learning module called "Variant Reasoning on Graphs" to effectively utilize variational knowledge. [He et al. \(2016\)](#) applied Gaussian filtering, segmentation, and Gaussian-shaped Fast Fourier Transform (FFT) to fMRI image reprocessing. [Fotopoulou, Oikonomou & Economou \(2019\)](#) designed linear matrix operators through optimal projection, proposed a graph-based encoding technique, and utilized Support Vector Machines (SVM) for category prediction.

**Technological advancements and applications:** The technology at this stage can assist designers in working away from high-performance workstations. For example, algorithms like GDCNet can reduce noise while preserving sharp features (e.g., product corners), solving the problem of excessive smoothing caused by traditional denoising. Additionally, the automatic conversion from point cloud to parametric model (e.g., L – 1 Eulerian elastic model) supports the direct use of 3D scanning data in CAD modeling.

### Shape generation phase

In the shape generation process, data transformation and mapping play a crucial role in bridging the gap between abstract design concepts and concrete geometric representations ([Fazeli & Peng, 2022](#)). We reviewed and defined shape generation algorithms in literature, organized these algorithms using Excel, and created a stacked circular diagram ([Fig. 10](#)). The algorithms are categorized into three main types: graph-based generation algorithms, technical feature-based algorithms, and other algorithms. Graph-based mapping models aim to represent shapes and their components using graph structures, where nodes represent geometric primitives (e.g., points, lines, arcs) and edges represent topological relationships (e.g., adjacency, connectivity). Transformations such as scan conversion and region filling are applied to these graphs to generate final shapes. Recent studies show that these transformations achieve computational complexity ranging from  $O(n)$  for



**Figure 10** Generative algorithms and models currently applied in the shape generation phase. Full-size  DOI: [10.7717/peerj-cs.3251/fig-10](https://doi.org/10.7717/peerj-cs.3251/fig-10)

simple line algorithms to  $O(n^2)$  for complex polygon filling operations, with modern implementations achieving processing speeds of  $10^4$ – $10^5$  operations per second (Alzubaidi et al., 2021). Technical feature-based modeling focuses on capturing and processing technical features such as dimensions, tolerances, material properties, and functional requirements. They typically employ parametric modeling and optimization techniques to generate shapes satisfying specific engineering constraints. Examples include

Range-GAN, CycleGAN, FCGAN for fault diagnosis, and CGAN-CNN hybrids (combining conditional GANs with CNNs for topology optimization and performance prediction).

Figure 10 shows that graph-based generation algorithms are primarily used for generating basic shapes, including line scan conversion, arc generation, polygon scan conversion, and region filling methods. Techniques such as Bresenham's algorithm, polar coordinate algorithms, and boundary clipping are involved. Empirical evaluations demonstrate that Bresenham's algorithm achieves pixel-level accuracy with computational efficiency improvements of up to 40% compared to traditional floating-point methods (Foley, 1996). Technical feature-based algorithms are widely applied in 3D data generation and parametric shape generation. With rapid advancements in deep learning algorithms, shape generation methods based on latent variables and generative adversarial networks (GANs) have gained significant attention. In latent variable models, the conditional deep generative model Range-GAN proposed by Heyrani Nobari (2022) addresses sparse condition challenges in data-driven inverse design, enabling automated design synthesis with range constraints. GAN modeling methods are often combined with other approaches, such as CycleGAN proposed by Cabezon Pedroso, Ser & Díaz-Rodríguez (2022) (a GAN architecture integrated with other methods for style transfer or domain adaptation in shape generation). Additionally, Wang & Xue (2024) utilized the fuzzy clustering generative adversarial network (FCGAN) model (enhancing GAN capabilities in pattern recognition tasks related to shape analysis through fuzzy clustering) for fault diagnosis. Herath & Haputhanthri (2021) combined conditional generative adversarial networks (CGANs) with convolutional neural networks (CNNs) for topology optimization and performance prediction. Comparative studies demonstrate structural optimization efficiency gains of 25–35% compared to conventional finite element analysis methods, with solution convergence achieved in 60–80% fewer iterations. Other algorithms include parametric shape generation as a research hotspot. Parametric mapping models use coordinate systems (e.g., spherical, Euclidean, polar) and mathematical functions to parameterize shapes. Various shapes can be generated and modified by adjusting parameters (McKay & de Pennington, 2022). Main methods involve spherical, Euclidean, and polar coordinate parameterization. Hybrid modeling combines elements from multiple categories to leverage their respective advantages. For instance, integrating graph-based representations with technical feature-based optimization. Another example combines FCGAN with parametric models to enhance shape diagnosis and generation capabilities.

General evaluation factors for shape generation algorithms include: Quantitative and qualitative metrics: Depending on application scenarios, either or both may be combined. For example, quantitative metrics for accuracy and efficiency, and qualitative metrics for aesthetics and design innovation. Benchmark testing: Comparing performance against existing algorithms or industry standards. User feedback: Incorporating feedback from designers and engineers to assess practical usability and value. Computational resources: Considering the trade-off between model complexity and computational demands (Ma et al., 2024).

The technologies in this stage can assist designers to focus on creative expression rather than technical realization, such as CycleGAN to realize automatic conversion of sketches to high-precision models, Range-GAN to generate diverse solutions under constraints, expanding design possibilities, and helping enterprises to deploy an AI-assisted design pipeline to achieve a 15–30% reduction in load.

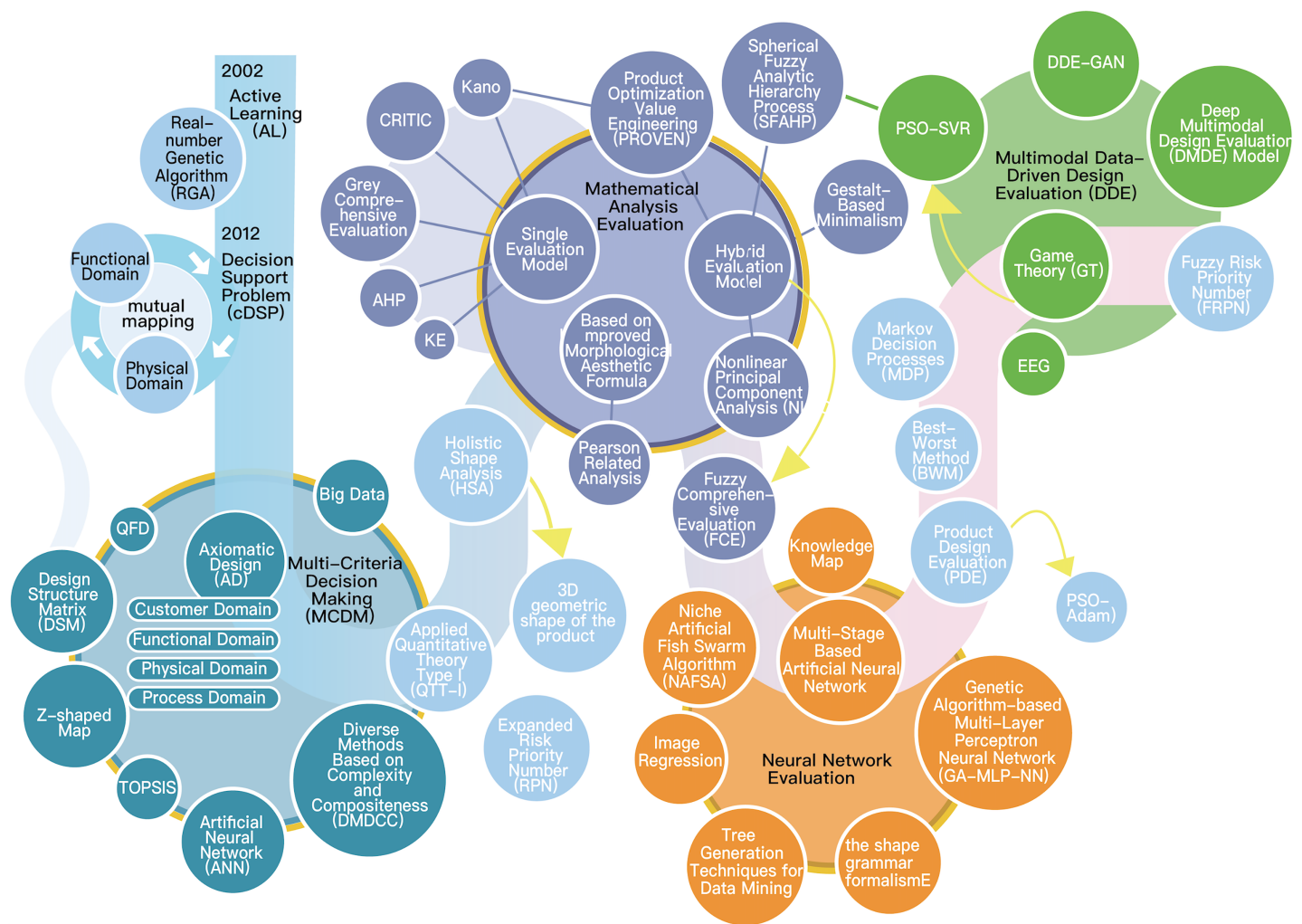
### ***Decision-making assessment phase***

Shape generation decision-making algorithms represent a core component of design automation and intelligence ([Arbabi et al., 2022](#)). Their primary value lies in assisting designers to efficiently generate product shapes that meet functional requirements and constraints through algorithmic means. The development of this field has always been closely integrated with optimization algorithms, forming a multi-layered and multi-paradigm technical system.

Core algorithms include bio-inspired algorithms and data-driven algorithms. Bio-inspired algorithms encompass genetic algorithms (GA) (which simulate biological evolution through mechanisms of population initialization, crossover, mutation, and selection to perform global searches in shape spaces, progressively approaching optimal solutions), Empirical studies demonstrate that GA-based shape optimization achieves convergence rates of 85–95% within 200–500 generations, with parallel implementations reducing computational time by 40–60% compared to sequential approaches ([Gad, 2022](#)). Ant colony optimization (ACO) (which draws on ant foraging behavior to construct path optimization models for shape combinations, suitable for multi-objective shape design problems), particle swarm optimization (PSO) (based on swarm intelligence particle collaboration mechanisms, balancing exploration and exploitation through information sharing and local search to enhance global optimization efficiency), Performance benchmarks show that PSO algorithms typically converge 30–50% faster than traditional genetic algorithms, with multi-objective PSO variants achieving Pareto front coverage of 90–95% in engineering design problems. Simulated annealing (SA) (which introduces thermodynamic annealing processes, accepting probabilistic inferior solutions to break through local optima and enhance global exploration capabilities in shape design). Data-driven algorithms include generative adversarial networks (GANs), such as those developed by scholars like ([Goodfellow, Bengio & Courville, 2016](#)) which can create novel designs by learning from existing design data ([Wang et al., 2023](#)).

During the decision-making phase, we reviewed the application history of relevant algorithms and models. As shown in [Fig. 11](#), since 2002, active learning frameworks and real-coded genetic algorithms have become widespread, driving the transition of shape generation from rule-based to data-driven approaches. After 2012, academic research shifted its focus to the mapping relationships between functional and physical domains, proposing multi-criteria decision-making methods (such as quality function deployment (QFD), ideal final result (IFR), artificial neural networks (ANN), axiomatic design (AD), etc.). Notable achievements include the decision-making model proposed by [Song et al. \(2024\)](#), which integrates behavioral analysis, failure mode and effects analysis (FMEA), and TRIZ theory. In terms of evaluation method innovation, [Yu et al. \(2025\)](#) employed the

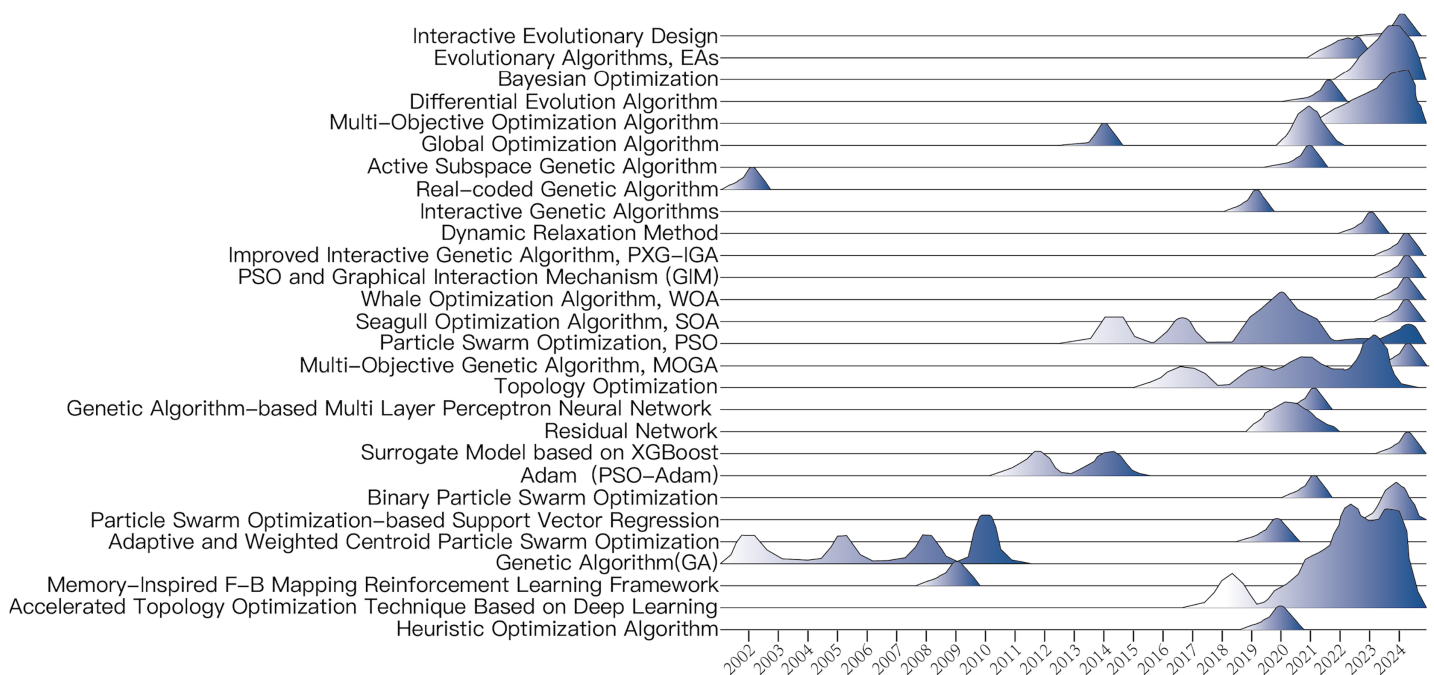




**Figure 11** Generative algorithms and models currently applied in the decision evaluation phase. Full-size [DOI: 10.7717/peerj-cs.3251/fig-11](https://doi.org/10.7717/peerj-cs.3251/fig-11)

Multinomial Logit (MNL) model to quantify consumer acceptance of new designs, providing market feedback for design iteration ([Chen & Xu, 2024](#); [Chen & Bian, 2024](#)). [Ranscombe, Kinsella & Blijlevens \(2017\)](#) introduced the holistic shape analysis (HSA) method, combining 3D geometric comparison tools to extract shape difference features and support design optimization decisions.

Since [Adeli \(2002\)](#) first applied neural networks in the field of structural engineering research in 1989, the role of neural networks in the design industry has become increasingly prominent. Currently, neural network-based shape generation decision-making algorithms are more comprehensive and scientific, examples include the niching artificial fish swarm algorithm, multi-level artificial neural networks, and multi-layer perceptron genetic algorithm neural networks. In actual decision-making processes, decision-making algorithms generally form closed-loop interactions with evaluation methods, innovating around decision-making objectives and evaluation criteria. There are three main approaches: the generate-evaluate cycle (e.g., GANs generate



**Figure 12** Generative algorithms and models currently applied in the iterative phase of optimisation.

Full-size DOI: [10.7717/peerj-cs.3251/fig-12](https://doi.org/10.7717/peerj-cs.3251/fig-12)

candidate shapes—HSA/MNL evaluation—feedback to optimize the generator), multi-criteria decision-making (QFD defines requirement weights—PSO/GA multi-objective optimization—ANN verifies performance), and interdisciplinary integration (Game Theory (e.g., Nash equilibrium) optimizes multi-stakeholder design objectives, Markov Decision Processes model design state transitions). Techniques at this stage can assist designers in avoiding unidimensional decision-making pitfalls, such as PSO + QFD frameworks to simultaneously optimize cost, performance and user satisfaction. Another example is the combination of FMEA and behavioral analysis to identify potential failure modes early in the design.

### Optimisation iteration phase

Product shape optimization algorithms constitute a complex, multidisciplinary field focused on achieving functional, efficient, and aesthetic balance in product geometry *via* mathematical methods (Sheikh et al., 2022). By judiciously selecting algorithm combinations, effective product shape design generation and shape data analysis can be conducted, enhancing design efficiency and product quality (Ebrahimi & Jahangirian, 2017). We analyzed algorithm usage frequency during the optimization iteration phase using mountain landscape visualization code, primarily employing the surf function to render landscapes with color, axis, and label adjustments (Fig. 12). The technological evolution and cross-disciplinary integration of this field follow these trajectories:

Algorithmic system innovation: As cross-disciplinary design research deepens, shape optimization algorithms become increasingly critical in the design generation process.

Optimization frameworks based on Poisson equations, coupling Boundary Element Method (BEM), FEM, and LSM, enable high-precision modeling of physical field distributions and structural characteristics, demonstrating advantages in fluid mechanics optimization ([Moosavi, Jablonka & Smit, 2020](#)). Computational fluid dynamics optimization using coupled BEM-FEM approaches achieves accuracy improvements of 15–25% while reducing computational time by 30–45% compared to traditional single-method approaches ([Mirjalili et al., 2023](#)). [Mirjalili & Lewis \(2016\)](#) proposed novel swarm intelligence algorithms like WOA and SOA, offering new paradigms for multi-objective optimization. These algorithms simulate biological swarm behaviors, requiring precise parameter tuning but exhibiting strong global search capabilities for high-dimensional complex problems. WOA demonstrates superior performance on 29 benchmark functions with convergence rates 20–35% faster than traditional genetic algorithms, while achieving solution accuracy within 98% of global optima for engineering design problems.

**Integrated algorithm applications:** When applying optimization algorithms, factors such as data quality, algorithmic complexity, and computational resources must be considered. Integrated algorithm applications are now mainstream, including deep fusion of GA with neural networks for data-driven optimization efficiency and combined applications of PSO with Adam algorithms, performing well in performance prediction and hybrid optimization. Notable studies include [Li et al.'s \(2021\)](#) PSO-SVM prediction model and [Tan et al.'s \(2023\)](#) PSO-Adam hybrid optimization strategy.

**Topology optimization technologies:** Since 2019, deep learning-accelerated topology optimization has emerged as a hotspot, with three directions: preprocessing enhancement, system-level optimization, and numerical method innovation (*e.g.*, Regenwetter Lyle's solver, increasing efficiency by >40%).

**Emerging research areas: Uncertainty Optimization:** [Kim \(2023\)](#) modeled uncertainty in product degradation signals, while [Ao et al. \(2023\)](#) proposed a degradation-based multi-objective image optimization framework to enhance design robustness.

**Human-computer collaborative design:** [Zhao, Sharudin & Lv \(2024\)](#) combined Kansei Engineering with WOA algorithms, pioneering emotion-driven shape generation and bridging affective computing and optimization.

**Evaluation system:** Product shape optimization algorithms adopt a multi-dimensional evaluation system, including objective function formulation (balancing mechanical performance, material use, and costs), constraint handling mechanisms, convergence metrics, computational complexity, and robustness verification.

Current technologies promote a shift from deterministic optimization to resilient design, *e.g.*, the electronics industry adopting impact optimization frameworks. They solve NP problems using group intelligence algorithms like Whale Optimization Algorithm (WOA) and enhance human-computer interaction (Kansei+WOA), incorporating emotional data into optimization goals to boost product emotional value.

### ***Design concept evaluation phase***

Design concept evaluation has become a critical phase in product development, systematically assessing early-stage creative concepts across feasibility, innovation, user

preferences, functionality, and emotional appeal (Xue & Wu, 2022). Traditionally dominated by qualitative methods (e.g., focus groups, expert reviews), the field now integrates multi-criteria decision-making (MCDM) approaches like Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and fuzzy logic to enhance objectivity.

Recent advancements focus on multimodal evaluation, incorporating neurophysiological data (eye-tracking, EEG, functional near-infrared spectroscopy (fNIRS), galvanic skin response (GSR)) to model implicit cognitive-emotional responses. This fusion of physiological signals and subjective feedback enables data-driven, user-centered refinement of design solutions.

As a pivotal bridge between ideation and realization, design concept evaluation supports evidence-based decision-making (Sharma, 2023), reduces development risks, and informs preference modeling. This article positions it as a foundational prerequisite for modeling strategies, integrating multimodal metrics to quantitatively evaluate concepts and guide iterative design optimization.

## DISCUSSION

### Opportunities of AI-empowered product form generation

#### *Performance prediction: AI-driven innovative form design*

AI-assisted design technology enables the generation of product forms that meet specific stylistic or functional requirements, Wang et al. (2024b) assisting designers in precisely controlling key parameters such as geometric features, Miao et al. (2024) material properties, and loading conditions. Additionally, by integrating dimensionality reduction algorithms (e.g., t-Distributed Stochastic Neighbor Embedding (t-SNE), Uniform Manifold Approximation and Projection (UMAP)) with Bayesian optimization, it effectively addresses the complexities of high-dimensional design spaces, accelerating design iteration (Arjomandi Rad, Cenanovic & Salomonsson, 2023). In terms of real-time performance prediction, the deployment of edge computing nodes for distributed inference enables real-time performance prediction and optimization, meeting the demands of instant feedback scenarios such as additive manufacturing and Augmented Reality/Virtual Reality (AR/VR). At the level of design paradigm innovation, generative adversarial networks (GANs) mine potential design patterns by analyzing vast amounts of form data, further enhancing immersive design experiences. Furthermore, while traditional trial-and-error-based design is gradually being replaced by AI-driven methods, human-centric innovation projects (e.g., QFD, FBS models) still rely on traditional design logic. In the future, it is recommended to establish a cross-domain database that integrates multi-source data such as materials, processes, and user behavior, utilizing transfer learning to address data sparsity issues. Moreover, developing explainable AI modules will provide transparent decision-making support for safety-critical designs (e.g., medical devices, aerospace) (Chen et al., 2023).

#### *Reverse design: multimodal data-driven technology upgrade path*

Reverse design technology, centered on data-driven approaches and intelligent algorithms, enables precise transformation and innovative optimization from physical objects to



digital models (Zhang & Chen, 2024). In terms of multimodal data acquisition and digital reconstruction, it leverages computer vision-based high-precision 3D scanning, point cloud processing, and deep learning algorithms to construct an integrated “scan-design-manufacture” platform.

Regarding multimodal data fusion, between 2018 and 2020, the field of physiological signal acquisition encountered interference issues in the fusion of EEG/ECG/EMG modalities. However, after 2023, the adoption of parameter-free modal modulation modules eliminated such interference, resulting in a 40% improvement in reconstruction accuracy (Hou, Tuerhong & Wushouer, 2023).

In terms of application innovation in vertical fields, a library of parametric models and a matrix of style transfer algorithms have been established to support topology optimization and innovative form generation based on 3D reconstruction (Xu et al., 2023). For instance, Tesla achieved a 15% weight reduction in battery packs and a 30% improvement in thermal management efficiency through topology optimization and generative design.

In the future, by combining multi-objective optimization algorithms and integrating “top-down” system modeling with “bottom-up” generative design, reverse design technology will promote the co-evolution of form, structure, and function.

### ***Structure optimization: deep integration of algorithms and manufacturing techniques***

The field of structural optimization is currently undergoing a paradigm shift driven by the deep integration of algorithms and additive manufacturing technologies. By combining topological optimization frameworks with the global search capabilities of genetic algorithms and the nonlinear mapping advantages of neural networks, and taking into account the constraints of additive manufacturing processes such as overhang angle limitations, it achieves collaborative optimization of lightweighting and load-bearing performance. The algorithms in this field have evolved from early homogenization methods that relied on manual input (prior to 2015) to the current stage where, after 2020, the Bi-directional Evolutionary Structural Optimization (BESO) method combined with AI tools enables form-force collaborative design (reducing iterations by 70%). In 2023, the Time-Varying Concurrent Topology Optimization (TVCTO) framework supports parallel optimization of three variables (macroscopic density, microscopic structure, and deformation parameters), resulting in a 60% reduction in computational load (Chen et al., 2023). Future developments in this area will focus on the construction of cloud-based collaborative platforms, integrating multi-physics simulations to create a closed-loop process of “digital twin-algorithmic optimization—virtual verification.” This will significantly enhance structural efficiency and shorten the R&D cycle in fields such as aerospace and automotive. The core advantages of this approach lie in multi-scale collaborative design, AI-driven intelligent iteration, and manufacturing integration.

### ***AI-driven transformations and challenges in product form generation Technological revolution and multidimensional challenges***

As the core driving force of modern technology, artificial intelligence (AI) and machine learning (ML) have enabled intelligent product form generation design. Algorithmic

automated optimization of design parameters significantly enhances design efficiency and precision. AI-driven design methodologies can generate personalized forms based on user needs and market trends, satisfying customized product demands. However, practical applications face multiple challenges: dataset quality defects, such as noise and incompleteness, compromise model reliability; the “black-box” nature of ML models lacks decision transparency, posing challenges for safety-critical designs; high-dimensional design spaces and complex algorithmic models increase computational burdens and resource requirements.

### ***Technology empowerment and cross-domain innovation***

AI and ML demonstrate vast potential in the field of form generation ([Ren & Xiong, 2022](#); [Xiong, Yue & Wu, 2023](#)) driving synergistic advancements in automated intelligent design, personalized customization, performance prediction and optimization, sustainable design, and additive manufacturing. In automated design, hybrid models integrating expert knowledge graphs with generative adversarial networks (GANs) need to be constructed to simulate the creative thinking of human designers. Combining digital twin technology with additive manufacturing establishes a real-time feedback loop for “design-validation-production.” For performance prediction and optimization, multiphysics coupled simulation models should be developed to analyze the mapping relationships between product form parameters and material properties, with reinforcement learning enabling dynamic optimization. In the dimension of sustainable design, a life-cycle carbon footprint assessment model must be built ([Zhao, Tang & Gong, 2024](#)). Through topological optimization and materials genome technology, redundant structures and material consumption can be reduced, promoting green design and circular manufacturing.

### ***Ecosystem co-construction and ethical governance***

While advancing algorithm-manufacturing collaborative design, ethical issues raised by AI must be considered. First, vigilance is required against bias amplification effects in data-driven design—if training data contains cultural, gender, or economic biases, algorithms may generate solutions that reinforce inequalities in social resources. Second, the ambiguous intellectual property ownership of AI-generated designs necessitates establishing rights allocation mechanisms to balance the interests of algorithm developers, data providers, and users. Furthermore, the “black-box” issue in the design process demands enhanced algorithmic transparency, especially in critical product areas such as medical implants, where decision interpretability and traceability must be ensured. Additionally, from an environmental perspective, excessive design tendencies must be evaluated to avoid material waste and electronic waste issues. Finally, a multi-stakeholder governance framework involving ethicists, designers, and engineers, along with relevant policies, needs to be constructed. Through technical standards and certification systems, technology can be guided toward responsible innovation.

## **CONCLUSIONS**

This article delves into the historical context, current research trends, and future development directions of product shape generation design technology. Through a

systematic analysis of 385 relevant literature pieces, it defines the basic concepts and processes of data-driven product shape generation and comprehensively discusses the characteristics and applications of major generation technologies. The research indicates that the development of shape generation technology is highly dependent on abundant database resources and advanced algorithm software, providing support for crucial industries such as industrial manufacturing, automobiles, aviation, and furniture.

This study has the following limitations: (1) Insufficient interdisciplinary data: The primary data in this study is largely focused on a single industry (product manufacturing), and there are fundamental differences in shape generation techniques across different industries. (2) Limited discussion on dynamic interaction generation: Most of the analyzed techniques are based on static data for shape generation, without adequate consideration of dynamic changes during actual manufacturing processes and their impact on shape generation (*e.g.*, deformation scenarios in wearable devices). (3) Ethical and fairness concerns: The algorithms discussed may implicitly contain design biases (*e.g.*, overly catering to mainstream aesthetics, prioritizing functionality while neglecting user core needs).

In the future, these limitations can be addressed through the following strategies:

(1) Develop a multimodal physical-geometric relational database: Encode manufacturing constraints from diverse industries (*e.g.*, fluid dynamics formulas, material fatigue parameters) into reproducible knowledge nodes to enable hybrid modeling that integrates “physical rules + data-driven” approaches. (2) Embed virtual simulation in the shape generation process: Utilize digital twin technology to simulate the real-time performance evolution of products in complex scenarios and dynamically adjust generative parameters through reinforcement learning. (3) Establish an ethical review framework: Develop “fairness evaluation metrics for generative outcomes” to systematically assess and mitigate algorithmic biases. Future product form generation technology will be driven by advancements in emerging technologies, pursuing intelligence, efficiency, customization, and sustainability. It will focus on optimizing design processes and production efficiency while deeply integrating user experience and aesthetic standards to meet personalized demands and deliver products with emotional and aesthetic value.

## APPENDIX: ABBREVIATIONS

| Acronym            | Full Name                                                          |
|--------------------|--------------------------------------------------------------------|
| AI                 | Artificial Intelligence                                            |
| PRISMA             | Preferred Reporting Items for Systematic Reviews and Meta-Analyses |
| JBI                | Joanna Briggs Institute                                            |
| CE                 | Concurrent Engineering                                             |
| SSA-LSTM-Attention | Sparrow Search Algorithm-Long Short-Term Memory-Attention          |
| UX                 | User Experience                                                    |
| CNN                | Convolutional Neural Network                                       |
| BERT               | Bidirectional Encoder Representations from Transformers            |

|                  |                                                                               |
|------------------|-------------------------------------------------------------------------------|
| <b>Bi-LSTM</b>   | Bidirectional Long Short-Term Memory                                          |
| <b>CRF</b>       | Conditional Random Field                                                      |
| <b>MLP</b>       | Multilayer Perceptron                                                         |
| <b>DMDCC</b>     | Dynamic Mode Decomposition with Conditional Correlation                       |
| <b>EEG</b>       | Electroencephalogram                                                          |
| <b>MF-SVM</b>    | Multi-Factor Support Vector Machine                                           |
| <b>EC Model</b>  | Evolutionary Computation Model                                                |
| <b>CVAE</b>      | Conditional Variational Autoencoder                                           |
| <b>LDA</b>       | Latent Dirichlet Allocation                                                   |
| <b>PTM</b>       | Pattern Tree Mining                                                           |
| <b>GPR</b>       | Gaussian Process Regression                                                   |
| <b>NLM</b>       | Non-Local Means                                                               |
| <b>BM3D</b>      | Block-Matching and 3D Filtering                                               |
| <b>TOPSIS</b>    | Technique for Order of Preference by Similarity to Ideal Solution             |
| <b>DDE</b>       | Dynamic Data Envelopment Analysis                                             |
| <b>DMDE</b>      | Dynamic Multi-objective Data Envelopment Analysis                             |
| <b>DSE</b>       | Design Space Exploration                                                      |
| <b>MCMC</b>      | Markov Chain Monte Carlo                                                      |
| <b>GNN</b>       | Graph Neural Network                                                          |
| <b>SEM</b>       | Structural Equation Modeling                                                  |
| <b>NA-IPA</b>    | Non-linear Analysis-Interpretive Phenomenological Analysis                    |
| <b>IGDT-MFP</b>  | Information Gap Decision Theory-Multi-objective Fuzzy Programming             |
| <b>TRIZ</b>      | Theory of Inventive Problem Solving                                           |
| <b>QFD</b>       | Quality Function Deployment                                                   |
| <b>FBS</b>       | Function-Behavior-Structure                                                   |
| <b>ESM</b>       | Effect-based System Method                                                    |
| <b>HDSM</b>      | Hierarchical Design Structure Matrix                                          |
| <b>DfR</b>       | Design for Reliability                                                        |
| <b>FSCN</b>      | Functional Structure Concept Network                                          |
| <b>RAD</b>       | Rapid Application Development                                                 |
| <b>PCGA-DLKE</b> | Product Concept Generation Axiomatic Design-Deep Learning Knowledge Embedding |
| <b>GDCNet</b>    | Geometric Decontouring Network                                                |
| <b>PDPF</b>      | Predictive Data-Driven Product Family Design                                  |
| <b>DBM</b>       | Design-Based Metrology                                                        |
| <b>EMD</b>       | Edge Mesh Denoising                                                           |
| <b>RMNG</b>      | Real Mesh Noise Generation                                                    |
| <b>Range-GAN</b> | Conditional Deep Generative Model with Range Constraints                      |
| <b>CycleGAN</b>  | Cycle-Consistent Generative Adversarial Network                               |
| <b>FCGAN</b>     | Fuzzy Clustering Generative Adversarial Network                               |



|                 |                                                                         |
|-----------------|-------------------------------------------------------------------------|
| <b>CGAN-CNN</b> | Conditional Generative Adversarial Network-Convolutional Neural Network |
| <b>GA</b>       | Genetic Algorithm                                                       |
| <b>ACO</b>      | Ant Colony Optimization                                                 |
| <b>PSO</b>      | Particle Swarm Optimization                                             |
| <b>SA</b>       | Simulated Annealing                                                     |
| <b>QFD</b>      | Quality Function Deployment                                             |
| <b>IFR</b>      | Ideal Final Result                                                      |
| <b>ANN</b>      | Artificial Neural Network                                               |
| <b>AD</b>       | Axiomatic Design                                                        |
| <b>FMEA</b>     | Failure Mode and Effects Analysis                                       |
| <b>MNL</b>      | Multinomial Logit Model                                                 |
| <b>HSA</b>      | Holistic Shape Analysis                                                 |
| <b>WOA</b>      | Whale Optimization Algorithm                                            |
| <b>SOA</b>      | Seagull Optimization Algorithm                                          |
| <b>BEM</b>      | Boundary Element Method                                                 |
| <b>FEM</b>      | Finite Element Method                                                   |
| <b>LSM</b>      | Level Set Method                                                        |
| <b>PSO-SVM</b>  | Particle Swarm Optimization-Support Vector Machine                      |
| <b>PSO-Adam</b> | Particle Swarm Optimization-Adaptive Moment Estimation                  |
| <b>t-SNE</b>    | t-Distributed Stochastic Neighbor Embedding                             |
| <b>UMAP</b>     | Uniform Manifold Approximation and Projection                           |
| <b>GANs</b>     | Generative Adversarial Networks                                         |
| <b>ECG/EMG</b>  | Electrocardiogram/Electromyogram                                        |
| <b>BESO</b>     | Bi-directional Evolutionary Structural Optimization                     |
| <b>TVCTO</b>    | Time-Varying Concurrent Topology Optimization                           |

## ADDITIONAL INFORMATION AND DECLARATIONS

### Funding

This research was funded by the Youth Fund for Humanities and Social Science Research of the Ministry of Education in China, Grant Number 21YJC760017. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

### Grant Disclosures

The following grant information was disclosed by the authors:

Youth Fund for Humanities and Social Science Research of the Ministry of Education in China: 21YJC760017.

### Competing Interests

The authors declare that they have no competing interests.

## Author Contributions

- Xinyan Yang conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Ling Zhu conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Lei Fu conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Jiufang Lv analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.

## Data Availability

The following information was supplied regarding data availability:

This is a literature review.

## Supplemental Information

Supplemental information for this article can be found online at <http://dx.doi.org/10.7717/peerj-cs.3251#supplemental-information>.

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