Patent Data for Engineering Design: A Critical Review and Future Directions

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ABSTRACT

Patent data have long been used for engineering design research because of its large and expanding size, and widely varying massive amount of design information contained in patents. Recent advances in artificial intelligence and data science present unprecedented opportunities to develop data-driven design methods and tools, as well as advance design science, using the patent database. Herein, we survey and categorize the patent-for-design literature based on its contributions to design theories, methods, tools, and strategies, as well as the types of patent data and data-driven methods used in respective studies. Our review highlights promising future research directions in patent data-driven design research and practice.

KEYWORDS

Patent, Engineering Design, Data-Driven Design, Artificial Intelligence, Data Science

1 Introduction

In the engineering design field, mining patent data to develop design theory and methodology has a long history, dating back to the 1950s. Altshuller and his colleagues developed the theory of inventive problem solving (TRIZ) by manually examining thousands of patent documents [1]. Over the past few decades, advancements in artificial intelligence (AI) and data science have developed new and growing opportunities for mining and analyzing big data related to engineering design for supporting design research and practice. In contrast to human-curated design repositories [2,3], patent databases provide several advantages for data-driven engineering design.

First, patent databases are large-scale repositories that accumulate over time as inventors file patent applications for their inventions. For example, from 1963 to 2020,
the United States Patent and Trademark Office (USPTO) database contained over 7.7 million granted patents. Second, patents contain massive design information on technologies, systems, or processes from all domains in both textual and visual forms, the innovation activity footprints and collaboration information of inventors and organizations in bibliometrics, and their relations to prior or future designs in the form of citations. Moreover, every patent is assigned to a domain class(es) by multiple patent examiners, making patent data ready for both supervised and unsupervised machine learning applications.

In recent years, several engineering design research groups have actively explored cutting-edge data science techniques to mine patent databases for diverse applications (hereafter referred to as patent-for-design studies) such as design representation, design space exploration, design prior art searching, stimuli recommendation, idea generation, and evaluation [4–10]. These patent-for-design studies relied on a broad collection of methods ranging from classic statistical analysis to network analysis, natural language processing (NLP), machine learning, deep learning, and data visualization. To the best of our knowledge, there has been no systematic review of patent-for-design research literature despite its rapid growth. Therefore, we conducted this review to elucidate the state of the art and reveal the trends. We also benchmarked the status quo with frontiers of data science to identify future research opportunities and directions.

The remainder of this paper is organized as follows. Section 2 describes literature retrieval methodology. Section 3 introduces the patent data structure and summarizes
the use of patents in engineering design research field. We then present a nuanced review of all patent-for-design literature categorized by their research applications, namely, design theories, design methodologies, design tools, and design strategies in Section 4. Section 5 provides a structured and integrated analysis of the methods and algorithms used in the patent-for-design publications. Section 6 maps feasible directions for future research. Finally, Section 7 concludes the paper.

2 Literature Retrieval Methodology

To retrieve prior patent-for-design publications, we used the following search process to ensure comprehensiveness and relevance (retrieval date: Oct 23, 2021). Because this review study aims to contribute to the engineering design field, we started a literature search from eight leading engineering design journals: (1) ASME Journal of Mechanical Design (JMD); (2) ASME Journal of Computing and Information Science in Engineering (JCISE); (3) Research in Engineering Design (RIED); (4) Journal of Engineering Design (JED); (5) Design Studies; (6) Design Science; (7) Artificial Intelligence for Engineering Design, Analysis and Manufacturing (AI-EDAM); (8) Computer-aided design (CAD); and three conferences: (1) International Conference on Engineering Design (ICED), (2) International Design Conference (DESIGN), and (3) International Design Engineering Technical Conferences & Computers and Information in Engineering Conference (IDETC/CIE). All authors of the present study reached an agreement after discussing the journals and conferences for inclusion and conducting literature search.
To search for journal papers, in the first round, we ran a query search in Web of Science. The following query was used: (TI="patent" OR AB="patent") AND (SO=X) AND (PY=1950-2021), where X represents one of eight engineering design journals. The search returned 46 articles. We manually checked these papers and identified 32 that met the scope of this review. The inclusion criteria (with an AND condition) are as follows: (1) patent data are used as research data in the body text of the paper; (2) the paper contributes to the support of engineering design-related processes. These 32 papers formed the initial core paper list.

In the second round, we browsed the journal websites to search for any missing relevant literature in the first round, including recently accepted manuscripts that are relevant to our topic but not yet included in Web of Science. We queried the search engines of the journal websites using the keyword “patent”. In this round, we found 18 additional relevant papers, bringing the list to 50.

In the third round, we removed journal restraint in the query to conduct a global search in Web of Science. The following query was used: (TS=(“patent” AND “engineering design”)) AND (PY=1950-2021). Selecting the document type as "article" returned 36 papers. Among them, 13 have already been included in the list from previous searches, and 6 are about using patent data as engineering design cases for education, which are beyond the scope of this review. From the remaining papers, we identified 5 relevant papers and added them to the list, resulting in a total of 55 papers.

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2 In this Web-of-Science query, TI stands for title, AB stands for abstract, SO stands for publication name, and PY stands for publication year.

3 In this Web-of-Science query, TS stands for topic, and PY stands for publication year.
Finally, in the fourth round, we further checked the forward and backward citations of the papers in the core list using a snowballing process and found another three relevant papers to add to the list, resulting in a total of 58 journal papers.

We used a slightly different method to search conference papers. Because the index of these conference proceedings in Web of Science was rather ambiguous, in the first round, we directly queried “patent” as the keyword in the titles and abstracts of the papers using the search engines in conference websites. The searches returned 22, 2, and 73 papers in the ICED, DESIGN, and IDETC/CIE proceedings, respectively. Using the same inclusion criteria that we used for journal papers, we reduced the set to 12, 2, and 18 papers, totaling 32 conference papers. We further checked whether we had already identified and collected the journal versions of these papers. Consequently, we removed 11 papers from our set, reducing the list to 20 conference papers. Finally, we checked the forward and backward citations of these papers. Although we found some relevant papers in this step, these papers have already been identified in previous searches for journal papers. Therefore, we identified 20 conference papers related to the focus of this review.

In summary, we curated a patent-for-design literature list of 78 papers (including 58 journal papers and 20 conference papers) for review⁴. Table 1 summarizes the literature search process.

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⁴ The entire list of patent-for-design literature is presented in Fig. 4 (Section 4).
Table 1: Entire literature search process

| Step | Journal/Conf. | The Operation of Each Step | Number of Retrieved Papers (Accumulated) |
|------|--------------|-----------------------------|----------------------------------------|
| 1    | Journal      | Search in Web of Science and then manually identify relevant literature. *Query:* *(TI=“patent” OR AB=“patent”) AND (SO=X) AND (PY=1950-2021)* | 32                                      |
| 2    | Journal      | Search in each journal’s website (using “patent” as keyword) to search for possible missing literature. | 50                                      |
| 3    | Journal      | Search in Web of Science and then manually identify relevant literature. *Query:* *(TS=(“patent” AND “engineering design”)) AND (PY=1950-2021)* | 55                                      |
| 4    | Journal      | Manually check the forward and backward citations of the papers in the core list using a snowballing process | 58                                      |
| 5    | Conf.        | Search in each conference’s website (using “patent” as keyword), and remove the non-relevant ones and the conference-version ones of previously retrieved journal papers. | 78                                      |

Fig. 1 reports the distribution of these papers: A) publication years and B) journals and conferences. Fig. 2 shows the co-occurrence of keywords in all the retrieved literature. To create the keyword co-occurrence figure, we conducted lemmatization to reduce inflectional forms of similar keywords, and then removed all keywords that appeared only once in the literature. In addition, we removed the keyword “patents” because all papers had it. The co-occurrence of keywords forms a map to illustrate the leading research topics in patent-for-design literature.
3 Patent Data

The patent documents are formally semi-structured. Patent documents contain bibliometric information (inventor, assignee, and publication time), classification information (IPC: International Patent Classification; USPC: US Patent Classification; CPC: Cooperative Patent Classification), citation information (patent and non-patent citations), text (title, abstract, claims, and detailed descriptions), and images (drawings
and their descriptions). Fig. 3 shows an example of a patent document. In addition to the full document as a holistic representation of an invention, each specific part of the patent document has its own value in engineering design research. In the following section, we introduce how patent data are mined and analyzed.

Table 2 summarizes the use of different information items of patent documents in engineering design literature. Almost half of these studies have used all fields of patent documents. Textual information received the most attention among all information items. Design information and knowledge were extracted from the patent titles, abstracts, and descriptions using various NLP techniques. Claims texts have also
been mined to extract knowledge tuples for creating knowledge graphs [4,11,12]. Classification information, which contains categorical knowledge from patent examiners, can be viewed as annotations or labels for use in supervised machine learning tasks [5,13]. A few studies have also used classification information to cluster and manage existing design solutions and support design ideation [7,8,14].

Table 2: Parts of patent documents being used for engineering design research

| Parts of patent      | Used in                  |
|----------------------|--------------------------|
| Bibliometric information | [15–21]                  |
| Texts                | Titles [6,9,22–24]        |
|                      | Abstracts [6,8–10,14,22–25] |
|                      | Claims [4,8,10–12,23,26–28] |
|                      | Descriptions [8,10,14,25,28–32] |
|                      | Unspecified [17,33–52]    |
| Images               | [5,11,21]                 |
| Classification information | IPC [5,7,9,15,16,50,53–58] |
|                      | CPC [8,10]                |
| Citation information | [7,17,19,21,38,53–57]     |
| Full document        | [36,53,56,58–82]          |

Table 3 lists several popular patent databases used by design researchers. The two leading patent offices (i.e., USPTO and EPO) provide researchers with various datasets of patent applications and granted patents. Researchers can directly download original US patent datasets from the USPTO Bulkdata website or PatentsView website in tab separated value (TSV) format for program readability. Both databases contain several patent documents and can be used in machine learning or deep learning pipelines that typically require big data for training and testing.
To promote data science research based on patent data, several communities have curated collections based on original patent documents and released some open tasks. NTCIR workshops, which were designed to support research in information access technologies [83], have been organizing patent-related campaigns and providing international patent collections since 2001. The topics of the campaigns included prior art search, patent classification, evaluation, and machine translation. Similarly, the CLEF-IP forum organized a series of shared tasks between 2009 and 2013, including patent retrieval, structure recognition, image classification and recognition, and novelty search, and provided the corresponding EPO datasets for benchmarking [84]. These curated patent collections can potentially support the development of relevant methods or tools to assist engineering design tasks such as design precedent search [17] and design novelty evaluation [57].

**Table 3: Patent datasets**

| Dataset | Source |
|---------|--------|
| USPTO   | [https://bulkdata.uspto.gov](https://bulkdata.uspto.gov) | [https://patentsview.org/download/data-download-tables](https://patentsview.org/download/data-download-tables) |
| EPO     | [https://www.epo.org/searching-for-patents/data/bulk-data-sets.html](https://www.epo.org/searching-for-patents/data/bulk-data-sets.html) |
| NTCIR   | [http://research.nii.ac.jp/ntcir/data/data-en.html](http://research.nii.ac.jp/ntcir/data/data-en.html) |
| CLEF-IP | [http://www.ifstuwien.ac.at/~clef-ip/download-central.shtml](http://www.ifstuwien.ac.at/~clef-ip/download-central.shtml) |
4 Engineering Design Research Based on Patent Data: A Detailed Review

During our review of patent-for-design literature, four themes emerged based on the contributions of individual publications: (1) design theory, (2) design methodology, (3) design tool, and (4) design strategy. These themes resonate with recent special issue topics in the data-driven engineering design journals [85–87]. Here, we provide a brief description of the four themes, which will serve as the basis for categorizing our literature review later in this paper.

**Design theory** refers to the fundamental understanding of the design process and design rules as well as the causalities among designer traits, design preferences, behaviors, and performances. Design theory research often aims to identify the factors influencing design outcomes [53]. Spillers and Newsome [88] claimed that design theory is a meta-theory of existing theories of structures, machines, and aesthetics.

**Design methodology** refers to a method or framework that can be repeatedly used to assist designers in carrying out design activities in one or multiple design phases, including: design need analysis, conceptual design, embodiment design, detailed or optimal design, and design evaluation [89]. Most design methodologies can be implemented manually or (semi-)automatically in computer-aided design tools.

**Design tool** refers to a tool that is developed based on one or more specific design methods to facilitate the design process. These tools typically have their own UI interfaces (web-based or software-based), such as TechNet [22] and InnoGPS[90]. In this study, we classified the works that the authors claimed to be practical tools in this category.
**Design strategy** refers to a plan, policy, or process heuristic [91] that designers can use to guide design activities and processes [92]. For example, a design team can integrate the engineering design process with scientific research and entrepreneurship activities to achieve innovation [93]. The design strategy is macro, often motivated by the designers’ own goals and intents, and in principle, need to be rationalized and guided by design theories.

Our literature analysis was organized into four categories [88]. Specifically, the first author of this paper categorizes these papers. The second author reviewed the categorization results in detail and proposed several changes. All authors discussed the categorization and reached a final agreement. Fig. 4 summarizes the literature distribution based on categories. It is noteworthy that alternative categorizations (e.g., different design phases [89]) can be used for different focuses and interests, whereas our categorization addresses the types of research contributions to design. In addition, one paper may contribute to one or more categories, as shown in Fig. 4B. Thus, the sum of the ratios of publications in each category over the total number of publications (78) is greater than 1, as shown in Fig. 4A.
Figure 4: Distribution of patent-for-design publications by their research contribution types
4.1 Design Theory

Patent data serves as the empirical basis for research on various design theories. For example, Busby et al. [79] performed an experiment on the factors that influenced design solution search activities and used the patent database as the searching pool. Weaver et al. [75] and Singh et al. [76] developed transformation design principles by examining patents, products, and biological cases, assisting engineering designers in developing products by transforming or reconfiguring design knowledge between multiple states. Qureshi et al. [81] proposed a patent dissection method to discover product flexibility principles from a patent database.

Later, many researchers studied design-by-analogy (DbA) using patent databases as sources of design stimuli for drawing analogies [94]. They examined how analogical distance[34,36,53,56,73], commonness[73], and the modality of examples [73] influence DbA-based ideation outcomes. Similarly, Saliminamin et al. [61] used patents as idea triggers to explore the effect of precedents and design strategies on idea generation. Parvin et al. [82] used TRIZ contradiction models derived from specific patents to stimulate novel solutions for design problems.

In addition to the influencing factors on design outcomes, a few recent studies have mined bibliometric, citation, and classification information of patent documents to reveal the fundamental patterns in designers' exploratory behaviors[18], causality between design novelty and potential impact, [57] and growing complexity of the design and invention process[16]. Luo and Wood [16] used a set of patent-based metrics to discover the constantly increasing complexity of inventions and invention processes.
over time. According to their analysis inventions have been increasingly requiring larger and more diverse teams, as well as integrating a larger base of prior technologies to deliver more systemic and integrative new technologies. Alstott et al. [18] observed that most inventions are created by inventors who move between different technological domains during their careers, based on their analysis of 2.8 million inventors patenting records. They also identified that knowledge distance conditions inventors’ abilities and performance in exploring new domains away from their prior domains. He and Luo [57] analyzed 3.9 million patents’ citations as a proxy for prior art combinations and identified that the most valuable patented inventions are based on the integration of moderate mean novelty and high extreme novelty in the combination space. By analyzing non-patent literature in patent documents, they observed that the use of scientific and broader knowledge beyond patentable technologies increases the value of patented inventions.

4.2 Design Methodology

As shown in Fig. 4, most patent-for-design studies aim to develop new design methodologies. The earliest study relied on human expertise and manual efforts to extract design rules or heuristics from patents or use patents as design cases to illustrate design methods [19,34,36,53,59,61–63,65,66,68,71,73,79]. Recent studies have used NLP to identify innovative solutions from patent databases to design problems to facilitate the use of TRIZ [27,38,42,70]. For example, Cascini and Russo [42] proposed a method to automatically identify the design contradictions underlying a
patented invention to support TRIZ. Li et al. [38] proposed an NLP-based methodological framework to classify patents based on invention level, as defined in TRIZ. Li et al. [27] presented an innovative design process that combines TRIZ and patent circumvention to develop new design solutions. On this basis, they further defined several rules for trimming technical features to avoid infringement during the design process and developed a TRIZ-based trimming method for patent design [70].

Another strand of research has developed design methodologies that leverage the design knowledge in patents for design representation and reasoning. For instance, Van Wie et al. [28] presented engineering products based on the function-behavior-structure (FBS) ontology [95] by analyzing patent documents. Bonaccorsi and Fantoni [47] expanded the functional basis by retrieving verbs from patents sampled from various IPC classes and classifying them to preserve the ontological function structure. They also developed a patent text analysis tool to demonstrate the usefulness of the expanded functional basis. Li and Tate [32] proposed a rule-based methodology to automatically retrieve functional requirements and design parameters from patent text using NLP techniques. Subsequently they introduced an enhanced study to represent a patent as a rule-based tree by combining NLP techniques and ontologies [52]. Jiang et al. [48] introduced a framework for building domain-specific ontologies based on a function analysis diagram to avoid patent infringement in the product development process. Yamamoto et al. [41] extracted subject-verb-object (SVO) tuples from patent texts for function division in conceptual design. Fantoni et al. [37] proposed an approach for extracting function–behavior–state information from patents. Liang et al. [39] and Liu et
al. [40] proposed a methodology to discover design topics (or design rationales) from patent documents by combining text mining, clustering techniques, and term similarity metrics. Valverde et al. [67] developed a discovery matrix in which physical phenomena and technologies are matched by patents to inspire engineers. Hwang and Park [64] developed design heuristic sets for X (DHSfXs) from products and patents to facilitate concept design for specific goals. Atherton et al. [11] proposed a functional representation method using the annotation of geometric interactions derived from patent claims, which assists designers in better understanding prior designs. Chiarello et al. introduced NLP based methods to extract “advantages” and “drawbacks” from patent texts and a classification framework to organize the extracted knowledge [49], as well as introduced various methods to retrieve affordances from patent texts [44]. Melluso et al. [31] proposed an NLP-based methodology that leverages keyword search and rule-based entity matching techniques to discover patents that contain information about bad designs and design bias. Jiang et al. [45] introduced an NLP-based method to automatically extract design entities and the hierarchical and functional relations between them from patent text to identify the invention working principle.

Because patent databases are natural repositories of design precedents, methods of retrieving patents as inspirational stimuli to augment design ideation are of central interest to conceptual design researchers. For example, Verhaegen et al. [30] retrieved candidate patents as product precedents for analogical design by distilling product features. Rios-Zapata et al. [58] presented a creative design method that fuses combination and mutation models to support patent prior art search and analysis it in
the early design stages. Russo and Montecchi [50] introduced a method that uses a prebuilt thesaurus of physical effects, WordNet for the abstraction of functions, and FBS ontology to search for prior art in a patent database. Similarly, Russo et al. [23] used the FBS ontology to build systematic queries to retrieve prior art patents for a given design problem by leveraging subject-object-action structures. Song et al. [56] proposed a method for patent stimuli searching based on community detection within a patent class network. Song and Luo [17] proposed a method for retrieving patent precedents for data-driven design by integrating searches through keywords, citations, and co-inventor networks. Jiang et al. [12] presented a framework that can assist designers in comparing prior arts and obtaining inspiration from them. Their framework is built on a functional knowledge graph with human-created ontologies. Liu et al. [9] proposed a method to extract functional terms from a patent database and processed them using clustering algorithms for design ideation. Luo et al. [7] used patent citation-based metrics to measure knowledge distance among different technology domains, and proposed workflows to search and retrieve design stimuli for analogy and synthesis across domains based on knowledge distance. Chan et al. [21] investigated whether visually similar design patents could be clustered together using a citation network of design patents.

Specifically, a group of studies has focused on patent data retrieval to support DbA. Linsey et al. [72] proposed the WordTree method to semantically re-represent design problems based on WordNet and guide designers to find potential analogies for innovative design from a set of patents. Fu et al. [14,25] used the combination of
Bayesian model and latent semantic analysis (LSA) to map a set of patent documents in a network structure to guide patent searches for analogical inspirations. Murphy et al. [35] proposed a functional vector method based on the bag-of-words to encode patent documents into high-dimensional vectors for supporting an analogy search. Sanaei et al. [51] proposed an ensemble model to retrieve analogical solutions for a given problem in the entire patent database. Their ensemble model includes a word embedding model, graph matching model based on syntactic trees of sentences, transformation-based model that scores the similarity between sentences by measuring the partial transformations required, and long short-term memory (LSTM) model for deriving sentence embeddings.

The latest advances in data science and AI have enabled the development of automated or semi-automated design methods that process massive patent data. Koza [77] developed a genetic programming algorithm to solve design problems automatically and used a patent database to examine the novelty of the newly generated solutions. Wodehouse et al. [68] presented a clustering method for analyzing design opportunities using crowd intelligence. Song et al. [33] proposed a data-driven product platform design method based on core-periphery structure detection within functional word co-occurrence networks created from patent texts. Jiang et al. [5] proposed a convolutional neural network-based representation method for design images from patent documents to facilitate a visual DbA. Sarica et al. [6] presented an idea generation methodology based on a large technology semantic network of over
four million technical terms using a word embedding model trained on a patent database [22].

4.3 Design Tool

Recent studies have leveraged patent data to develop data-driven design tools and facilitate and automate relevant design methodologies. Fitzgerald et al. [74] developed a design-for-environment (DfE) tool to manage and facilitate the analysis and reuse of successful products for conceptual design. Their DfE tool was a rule-based system built on TRIZ and DbA. Vandevenne et al. [29] developed a tool called scalable search for systematic biologically inspired design (SEABIRD), which enables designers to perform a scalable search for biological stimuli. SEABIRD uses rule-based text mining techniques to extract and map the product aspects of technical systems in patent documents and the organism aspects of biological systems in academic papers to identify candidate analogies. Chang et al. [46] introduced a methodology for design-around using TRIZ contradictions and text mining techniques. Hsu et al. [80] introduced a design process that represents patents with a design matrix inspired by axiomatic design theory, and uses matrix operations and TRIZ contradictions to develop innovative solutions by using a patent design-around process. They also developed a tool to assist designers develop innovative designs by using a design matrix. McCaffrey [96] developed Analogy Finder, a DbA support system, to identify adaptable semantic analogies from a patent database. Later, McCaffrey and Spector [69] devised a visual and verbal problem-solving representation to support human-machine collaboration in
innovative design. Luo et al. [55] developed InnoGPS, a cloud-based tool that uses an empirically built interactive network map of all patent technology classes, to guide the search for design inspiration (from patent texts) and innovation opportunities in different domains. Using InnoGPS as the basis, Luo et al. proposed a series of data-driven design applications, including design opportunity identification [54,55] and analogical conceptual design [7,90]. Siddharth and Chakrabarti [65] developed IdeaInspire 4.0 and validated it on patents. Idea-Inspire represents both engineering concepts and biological ideas using SAPPhIRE model ontology [97] for biologically inspired design. Based on the Idea-Inspire tool and SAPPhIRE model, they developed an automated novelty evaluation method for engineering design solutions [60]. Song and Fu [8] used a topic modelling algorithm to structure a repository of mechanical design patents with three facets: behavior, material, and component. They developed a visual interaction tool for seeking design inspiration, named VISION [8]. Sarica et al. [22] applied word embedding techniques to patent data and constructed a large-scale technology semantic network of over four million terms called TechNet, which is accessible through API and a public web portal. TechNet has been used for design representation [98], prior art retrieval [24], idea generation [6], and concept evaluation [99]. Siddharth et al. [4] developed a large and scalable engineering knowledge graph based on the USPTO database, which can be used to support design inference, reasoning, and representation in engineering design applications.

4.4 Design Strategy
Patent databases also enable researchers to design strategies in both manual and automated ways. For example, Jugulum and Frey [78] studied a large number of inventions and summarized several general strategies used in these inventions as a taxonomy of concept design for improved robustness. Koh et al. [59,62,71] studied the proper methods and repercussions of reviewing patent documents during the early design stage. Kokshagina et al. [66] proposed the design-for-patentability’ strategy to guide the innovation of engineering designers.

Several researchers have studied how to mine and analyze patent data to identify potential design directions and opportunities, and formulate long-term strategies for innovation at a higher level than the design process at an operational level. For example, Luo et al. proposed a series of patent-data-driven methods to enable macro-level design opportunity identification [54], strategic direction planning [7,55], and technology road mapping [15], using a total technology space map (TSM) based on the patent classification information. Smojver et al. introduced methodologies to develop longitudinal patent networks of specific design domains using bibliographic and citation data [19], and text mining [43] to support the visual analysis of technological change and evolution, which may inform macro-level design strategies.

5 Analysis of Methods and Algorithms

The patent-for-design literature has used a variety of research methods ranging from qualitative analysis and reasoning to the latest network analysis, data science, and
machine learning techniques. Table 4 presents the categorization of papers according to the methods used.

**Table 4: Methods and algorithms used in the patent-for-design publications**

| Methods                                      | References                               |
|----------------------------------------------|------------------------------------------|
| Human-involved Study                         | [34,36,53,59,61–63,65,66,68,71,73,79,81]|
| Rule-based Expert System                     | [11,12,17,23,26–28,31,42,46,58,60,64,65,67,69,70,72,74–76,78,80,82]|
| Statistical Analysis                         | [14,16,18,20,57]                         |
| Genetic Programming                          | [77]                                     |
| Machine Learning (Classification and Clustering) | [9,21]                                   |
| Network Science                              | • Network visualization [7,8,10,14,15,19,33,43,54–56]                                     |
|                                             | • Network-based metric analysis [7,15,33,43,56,57]                                           |
| Vector Space Method                          | • Functional vector space [34,35]                                   |
|                                             | • Technology space map [7,54,55]                                |
|                                             | • SAPPhIRE-based vector space [60]                              |
|                                             | • PA and OA space [29,30]                                   |
| Deep Learning (Neural Networks)              | • Artificial Neural Network [38]                               |
|                                             | • Convolutional Neural Network [5]                              |
|                                             | • Recurrent Neural Network [22,51]                             |
| Text Mining                                  | • Text pre-processing [4,9,22–24,29,30,32,34,35,37–40,42–46,49–52,75,76]            |
|                                             | • Syntactic analysis [4,32,37,41,44,45,49,51]                     |
|                                             | • Word co-occurrence analysis [33]                               |
| Topic Modelling                              | • Non-Negative Matrix Factorization [8,10]                      |
|                                             | • Latent Semantic Analysis [14,25,36]                            |
| Ontology, Semantic Network and Knowledge Graph | • Ontology [47,48]                                      |
|                                             | • Semantic network [6,22,45,72]                                  |
|                                             | • Automated or semi-automated constructed knowledge graph [4,37,39,40]          |
|                                             | • Manually curated knowledge graph [11,12,26]                   |
Fig. 5 shows the co-uses of the methods and different information items of the patent data in the reviewed studies. Multiple methods can be used for various data sources. Each item was counted to ensure that each method matched the corresponding part of the patent data. The decomposition of classification information and text in Fig. 5 also refers to the summary in Table 2. Different line colors denote different parts of the patent data and the width of a line indicates the number of corresponding studies.

**Figure 5:** Methods in relation to different parts of patent data

Human subject experiments have primarily been used to develop theories and scientific understanding. In these studies, full patent documents were often directly provided to designers as design aids, such as prior art solutions [59,62,63,66,68,71,79,81] or design stimuli [34,36,53,61,65,73] for engineering design. In addition, a group of qualitative studies used knowledge-based rules or strategies to
boost computer aided engineering design, and developed rule-based expert systems [11,12,17,23,26–28,31,42,46,58,60,64,65,67,69,70,72,74–76,78,80,82]. These expert systems typically require designers to collaborate with algorithms to address specific problems.

A wide range of data science techniques have been used in the patent-for-design literature. As shown in Fig. 6, patent-for-design studies using data science surpassed those without using data science in the past 10 years, and the gap is still expanding. For instance, complex network analysis has been used to mine relational information from citations or measure proximities of semantic content among patents [7,8,10,14,15,19,33,43,54–56]. Using network-based metrics such as centrality, entropy, and coherence, prior studies have developed new scientific understandings of design artifacts and processes [15,57] and proposed patent data-driven design methodologies and strategies [7]. Some design tools, such as InnoGPS [7,55] and VISION [8], use network visualizations to guide designers in exploring design or technology spaces constructed on patent data or patent classification labels.
NLP techniques are increasingly being used to retrieve design knowledge from patent texts. Fig. 7 shows different types of semantic information extracted from the patent text, including specific semantic information (such as TRIZ contradictions), functional semantic information (such as functional verbs), and general semantic information (such as word embeddings).

Figure 6: Growth of data science-based patent-for-design publications

The data science-based patent-for-design publications stand for those that used advanced data mining and analysis techniques (including statistical analysis, network science, machine learning, deep learning, etc.) instead of directly using patent documents as design stimuli or case studies.

Figure 7: Information extraction from patent texts
A few studies have used standard text pre-processing pipelines, including lemmatization, stemming, and stop-word removal techniques, for cleaning the raw text for further processing steps. In addition, design knowledge is extracted in certain forms of templates from a given patent text, using syntactic dependencies to support the automation of TRIZ [41] and the construction of knowledge graphs [4,37]. In addition, topic modelling algorithms, such as non-negative matrix factorization [8,10] and latent semantic analysis, [14,25,36] have been applied to patent texts to represent design repositories in a more structured form.

Semantic networks and knowledge graphs have long been used to support engineering design research [100]. Several early studies leveraged pre-trained common-sense semantic networks [72] or manually curated ontology-based knowledge graphs [11,12,26] to support design innovation and problem-solving. Until recently, the patent database was mined to construct large-scale cross-domain engineering semantic networks and knowledge graphs [4,22], serving as a knowledge infrastructure to support data-driven engineering design research and practice.

Deep neural networks, because of their ability to learn complex patterns from big data, have been used in patent-for-design literature. For instance, Li et al. [38] trained a neural network to classify patents based on the novelty level of an invention, as defined in TRIZ. Recently, researchers have developed design methodologies based on convolutional neural networks [5] and language models [22,51] trained on datasets of patent images and text, respectively. Other machine learning models, such as the naïve Bayes classification method [9], clustering methods[21], and advanced statistical
analysis methods [14,16,18,20,57], have also presented their values in the patent-for-design literature. It is worth mentioning that all parts of patent documents have the potential to support engineering design research using diverse data science techniques, as shown in Fig. 5.

6 Future Opportunities and Directions

In this study, we reviewed and analyzed the patent-for-design literature to elucidate the status quo of this field. A clear increasing trend of using patent data in engineering design research (Fig. 2A) and a similar upward trend of using advanced data science techniques in the same literature (Fig. 6) can be observed. Although existing studies have already shown the value of patent databases for data-driven engineering design research and practice, there are still several challenges and opportunities regarding 1) patent data, 2) data science algorithms, and 3) design applications. In the following section, we discuss research opportunities and map the course of feasible directions for future studies.

6.1 Research Opportunities Regarding Data

Patent databases are natural benchmark datasets for supervised machine learning applications because every patent is rigorously labelled by patent offices regarding its technological domain(s). The classification information and citation-based metrics of patents can serve as the gold standard that enables training, benchmarking,
testing, and comparison of the performance of different supervised learning algorithms [13].

Patent texts contain rich design information that can be used to create datasets for NLP-related tasks such as entity recognition and detailed analysis of functions, behaviors, and structures of engineering designs. However, these datasets require heavy labelling and annotation to curate, and thus, are laborious human tasks requiring considerable expertise, time, and resources.

In Fig. 5, we can see that bibliometrics, images, citations, and classification information of patents are not mined as commonly as textual information for design support. It is recommended that researchers use multimodal patent information instead of a single modality to develop a more systemic understanding of design artifacts and processes or more intelligent design methods and tools.

Furthermore, the current patent-for-design literature focuses on USPTO and EPO patents as data sources (primarily because they are written in English). We believe that patents from other countries such as Japan⁶ and China⁷ are also useful for supporting engineering design research.

6.2 Research Opportunities Regarding Algorithms

Owing to their large volume, patent databases are suitable for implementing modern deep learning techniques for specific tasks that typically require massive

⁶ China National Intellectual Property Administration: https://english.cnipa.gov.cn/
⁷ Japan Patent Office: https://www.jpo.go.jp/e/
amounts of data for model training. Rapidly advancing data science technologies have also empowered the research community to work on patent databases, and many statistical, graph theoretical, and deep learning methods have been developed or adopted for various tasks and produced state-of-the-art results. Some of these studies may shed light on new research opportunities for engineering design researchers to better use patent data. For instance, retrieving prior art or relevant patents to derive design inspiration or to prevent patent infringement is an important step in product development. Engineering design researchers may adopt or adapt deep learning methods developed in computer science literature for patent prior art search \[101,102\], classification \[103–105\], and representation \[103,106–108\].

Specifically, the latest deep learning capabilities for natural language understanding (NLU) have great potential for enhancing design-knowledge representations. Large language models, such as bidirectional encoder representations from transformers, if trained on massive patent data, can enable high-dimensional statistics to derive accurate semantic relations and meanings of engineering concepts, and support the creation of comprehensive design knowledge bases \[109,110\]. In turn, such semantic knowledge bases may offer not only structural and explicit information in patent texts but also latent causal relations and working mechanisms in technical inventions, and complement the existing common sense knowledge bases for use in design \[100\].

In addition, recent progress in graph neural networks (GNN) has enabled us to extract relational information among patents and derive high-dimensional
representations for downstream tasks [111], such as design repository restructuring and
design stimuli identification. Provided that patent documents normally contain
multimodal information on design, we can take advantage of multimodal deep learning
techniques to develop more systematic and informative design representations [112],
such as multimodal knowledge graphs and resultant graph embeddings. The multimodal
deep learning of patent data has tremendous potential for engineering design
applications.

Finally, in the past five years the AI community has seen rapid development of
powerful deep generative models (e.g., VAE [113] and GAN [114]) and large pre-trained
language models (e.g., GPT-3 [115] and BERT [116]) for image and text generation.
These generative models can also be used to develop AI-aided creative ideation or
design-generation methods. Researchers can develop generative models [117]
specifically for design synthesis and analogy by learning engineering design-related
knowledge from the patent data. For instance, Zhu and Luo [118] recently used patent
text data in different design domains to fine-tune the OpenAI GPT-2 model to train
virtual domain experts, and then used them to generate novel design concepts with
knowledge from specific target domains.

6.3 Research Opportunities Regarding Applications

Fig. 4 shows that patent data are mostly used to develop design methods and
tools, whereas applications in design theory and strategy research at higher levels
deserve further exploration. Large-scale patent databases that contain detailed
multimodal content and rich bibliometrics, citations, and classification information offer unprecedented opportunities for design theory building. For example, big patent data analysis, in contrast to small-sample human subject studies, may offer statistically significant findings that explain the behaviors and performances of design agents across diverse technological domains [18] and the conditions for achieving highly valuable designs and breakthrough innovations [57]. However, only a few studies have used big data-driven methods to build theories in the field of design science.

Moreover, although the literature has reported several design tools developed based on corresponding design methodologies, only a few are open-sourced and publicly accessible, and can be directly used by other engineering designers or researchers. To generate greater real-world impact and foster improvements of such tools, we recommend researchers to open source their developed tools (such as uploading the codes on GitHub) and provide open tool access to the public to use, test, and provide feedback.

In addition, we believe that the statistics of the big multimodal patent database could substantially deepen our fundamental understanding of design teamwork, designer behaviors and rationales, design impact dynamics, etc. Existing patent-for-design studies have demonstrated the potential of mining patent databases to explore white space and identify feasible directions for the R&D activities of designers, design teams, and large companies [55]. Several patent data providers, such as Patsnap⁸ and

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⁸ Patsnap Pte. Ltd.: https://www.patsnap.com/
Incopat⁹, have begun to provide patent analytics to inform innovation strategies and management decisions. Thus, we recommend that researchers explore and experiment with various AI methods on billions of patent documents and unlock the potential of data-driven design strategy, management, and innovation decisions [119].

6.4 Inspiration from Patent Analytics in Other Fields

This study focuses on engineering design research. Meanwhile, research in other fields also mined and analyzed patent data from different perspectives and for other interests beyond those in the engineering design community. For example, a global search in the Web of Science database using the keyword “patent data” would also return publications from journals such as Management Science, Research Policy, Scientometrics, and World Patent Information which use patent data as the empirical basis. These studies may also provide inspiration for design research opportunities.

For instance, management researchers have mined patent data to inform financing and capital decisions [120] and analyze market dynamics [121] by correlating the patenting behaviors of companies and businesses, as well as the economy. Some studies have aimed to establish the relationship between a company’s patent records and its future growth and success [122]. Analogically, engineering design researchers may also analyze designers’ patent records to infer their innovation-related behaviors and performances, and predict their career prospects [18].

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⁹ Incopat Co. Ltd.: https://www.incopat.com/
Patent value estimation and prediction are of interest in scientometric and econometric research. For example, Bakker [123] identified a linear relationship between patent citations and patent value. Bass and Kurgan [124] used machine learning techniques to identify the key factors influencing patent value, including the past performance of inventors, assignees, and the number of referenced patents. Du et al. [125] developed a recommendation system for high-quality patent trading based on the hybrid analytics of patent texts, classifications, and citations. Similarly, data-driven design evaluation (employing patents as a proxy for designs or evaluation benchmarks) is also of central interest to engineering design researchers [57].

Furthermore, several researchers have leveraged patent data to characterize and classify product designs. For instance, Chan et al. [126] combined clustering methods with experimental validation to identify product styles from over 350,000 US design patents. Huenteler et al. [127] extracted the hierarchy level in a product’s design (system, subsystem, and component) from patent citation networks. Patents have also been studied as proxies for intellectual property. For instance, Lee and Hsiang [128] fine-tuned the OpenAI GPT-2 model to automatically generate patent claim text for patent filing. Inspired by these studies, engineering researchers may mine patent data to gauge trends in design innovation [16] and train generative neural networks to generate novel designs for innovation [118].

7 Conclusion
Patent databases are ideal resources for engineering design researchers to develop design theories, strategies, methods, and tools based on manual efforts and various data science techniques because of the richness of the design information contained in patent documents. The past decade has witnessed a growing trend in the use of data science techniques to mine and analyze patent databases to support engineering design research and practice. This study contributes to the patent-for-design literature by elucidating the status quo of this field and identifying the potential research opportunities and directions. We believe that our review and propositions can serve as a guide for design researchers and practitioners in discovering the greater value of patent databases for engineering design research, developing more powerful and intelligent patent data-driven design methods and tools, and advancing our scientific understanding and theories of design.

There are several limitations in using patent data to support the engineering design process. First, some patents fields for IP strategies by companies (such as patent fence strategy) might not represent actual engineering design outcomes and lead to bias when researchers count them in the statistics. In addition, the correctness of the detailed information in patent documents may not be checked by examiners who primarily focus their analysis on the patentability, novelty, and inventive steps of patent applications. For comparison, the validity of the technical information in published scientific papers will be checked by peer reviewers. Although this review paper has only focused on leveraging patent data for engineering design research and practice, the AI and data science techniques that we analyzed can be used to mine and analyze a wider
range of data for data-driven design and innovation [127], such as scientific papers, reports, books, products, and CAD databases[129].

Owing to the richness of patent data, researchers from various fields have used patent data to acquire indicators related to economics, technology, and innovation management [130–133]. In addition, the vast amount of technical knowledge accumulated in patents has created a basis for automating parts of the design process or the discovery of new materials and drugs [134,135]. Researcher may find inspiration from these studies in other fields and leverage their insights into engineering design. In addition, several recent startups and companies that focus on AI- and data-driven innovative designs have attracted much attention from venture capitalists, such as Small Design\(^{10}\) (as of Jan 01, 2022, it raised $15M in total) and Tezign\(^{11}\) (as of Jan 01, 2022, it raised $150M in total). In this case, the commercial value of mining patent databases for automated engineering design may exist.

In conclusion, given the continual accumulation of patent data and rapid advancements in data science, machine learning, and artificial intelligence capabilities, the value and importance of patent data-driven approaches to engineering design and innovation are expected to grow in the future. Our review addresses this trend and aims to stimulate and guide future efforts to exploit and explore opportunities for patent data-driven engineering design and make the design process more intelligent.

\(^{10}\) https://www.smalld.cn/

\(^{11}\) https://www.tezign.com/
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REFERENCES

[1] Altshuller, G. S., and Rafael, B. S., 1956, “Psychology of Inventive Creativity,” Issues of Psychology, (6), pp. 37–49.

[2] Fuge, M., Tee, K., Agogino, A., and Maton, N., 2014, “Analysis of Collaborative Design Networks: A Case Study of OpenIDEO,” Journal of Computing and Information Science in Engineering, 14(2).

[3] Bohm, M. R., Vucovich, J. P., and Stone, R. B., 2008, “Using a Design Repository to Drive Concept Generation,” Journal of Computing and Information Science in Engineering, 8(1).

[4] Siddharth, L., Blessing, L. T. M., Wood, K. L., and Luo, J., 2022, “Engineering Knowledge Graph from Patent Database,” Journal of Computing and Information Science in Engineering, pp. 1–36.

[5] Jiang, S., Luo, J., Ruiz-pava, G., Hu, J., and Magee, C. L., 2021, “Deriving Design Feature Vectors for Patent Images Using Convolutional Neural Networks,” ASME Journal of Mechanical Design, 143(6), p. 061405.

[6] Sarica, S., Song, B., Luo, J., and Wood, K. L., 2021, “Idea Generation with Technology Semantic Network,” Artificial Intelligence for Engineering Design, Analysis and Manufacturing, pp. 1–19.

[7] Luo, J., Sarica, S., and Wood, K. L., 2021, “Guiding Data-Driven Design Ideation by Knowledge Distance,” Knowledge-Based Systems, 218, p. 106873.

[8] Song, H., Evans, J., and Fu, K., 2020, “An Exploration-Based Approach to Computationally Supported Design-by-Analogy Using D3,” Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 34(4), pp. 444–457.

[9] Liu, L., Li, Y., Xiong, Y., and Cavallucci, D., 2020, “A New Function-Based Patent Knowledge Retrieval Tool for Conceptual Design of Innovative Products,” Computers in Industry, 115, p. 103154.

[10] Song, H., and Fu, K., 2019, “Design-by-Analogy: Exploring for Analogical Inspiration With Behavior, Material, and Component-Based Structural Representation of Patent Databases,” ASME Journal of Computing and Information Science in Engineering, 19(2), p. 021014.

[11] Atherton, M., Jiang, P., Harrison, D., and Malizia, A., 2018, “Design for Invention: Annotation of Functional Geometry Interaction for Representing Novel Working Principles,” Res Eng Des, 29(2), pp. 245–262.

[12] Jiang, P., Atherton, M., Sorce, S., Harrison, D., and Malizia, A., 2018, “Design for Invention: A Framework for Identifying Emerging Design--Prior Art Conflict,” Journal of Engineering Design, 29(10), pp. 596–615.

[13] Jiang, S., Hu, J., Magee, C. L., and Luo, J., 2022, “Deep Learning for Technical Document Classification,” IEEE Transactions on Engineering Management.

[14] Fu, K., Cagan, J., Kotovsky, K., and Wood, K., 2013, “Discovering Structure in Design Databases through Functional and Surface Based Mapping,” ASME Journal of Mechanical Design, 135(3), p. 031006.

[15] Song, B., Yan, B., Triulzi, G., Alstott, J., and Luo, J., 2019, “Overlay Technology Space Map for Analyzing Design Knowledge Base of a Technology Domain: The Case of Hybrid Electric Vehicles,” Research in Engineering Design, 30(3), pp. 405–423.
[16] Luo, J., and Wood, K. L., 2017, “The Growing Complexity in Invention Process,” Research in Engineering Design, 28(4), pp. 421–435.
[17] Song, B., and Luo, J., 2017, “Mining Patent Precedents for Data-Driven Design: The Case of Spherical Rolling Robots,” Journal of Mechanical Design, 139(11).
[18] Alstott, J., Triulzi, G., Yan, B., and Luo, J., 2017, “Inventors’ Explorations across Technology Domains,” Design Science, 3.
[19] Smojver, V., Štorga, M., and Potočki, E., 2016, “An Extended Methodology for the Assessment of Technical Invention Evolution,” International Design Conference (DESIGN2016), pp. 1135–1144.
[20] Ishii, T., Parque, V., Miura, S., and Miyashita, T., 2017, “Definition and Support of Differentiation and Integration in Mechanical Structure Using S-Curve Theory and Wavelet Transform,” International Conference on Engineering Design (ICED17), pp. 355–364.
[21] Chan, T., Mihm, J., and Sosa, M., 2012, “A Structured Approach to Identify Styles in Design,” ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE 2012), pp. 1–10.
[22] Sarica, S., Luo, J., and Wood, K. L., 2020, “TechNet: Technology Semantic Network Based on Patent Data,” Expert Systems with Applications, 142, p. 112995.
[23] Russo, D., Montecchi, T., and Liu, Y., 2012, “Functional-Based Search for Patent Technology Transfer,” ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE 2012), pp. 1–11.
[24] Sarica, S., Song, B., Low, E., and Luo, J., 2019, “Engineering Knowledge Graph for Keyword Discovery in Patent Search,” International Conference on Engineering Design (ICED19), The Netherlands, Aug. 5–8, pp. 2249–2258.
[25] Fu, K., Chan, J., Schunn, C., Cagan, J., and Kotovsky, K., 2013, “Expert Representation of Design Repository Space: A Comparison to and Validation of Algorithmic Output,” Design Studies, 34(6), pp. 729–762.
[26] Hagedorn, T. J., Grosse, I. R., and Krishnamurty, S., 2015, “A Concept Ideation Framework for Medical Device Design,” J Biomed Inform, 55, pp. 218–230.
[27] Li, M., Ming, X., Zheng, M., Xu, Z., and He, L., 2013, “A Framework of Product Innovative Design Process Based on TRIZ and Patent Circumvention,” Journal of Engineering Design, 24(12), pp. 830–848.
[28] Van Wie, M., Bryant, C. R., Bohm, M. R., McAdams, D. A., and Stone, R. B., 2005, “A Model of Function-Based Representations,” AI EDAM, 19(2), pp. 89–111.
[29] Vandevenne, D., Verhaegen, P.-A., Dewulf, S., and Duflo, J. R., 2016, “SEABIRD: Scalable Search for Systematic Biologically Inspired Design,” Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 30(1), pp. 78–95.
[30] Verhaegen, P., Joris, D., Vandevenne, D., Dewulf, S., and Duflo, J. R., 2011, “Identifying Candidates for Design-by-Analogy,” Computers in Industry, 62(4), pp. 446–459.
[31] Melluso, N., Pardelli, S., Fantoni, G., Chiarello, F., and Bonaccorsi, A., 2021, “Detecting Bad Design and Bias from Patents,” *International Conference on Engineering Design (ICED21)*, pp. 1173–1182.

[32] Li, Z., and Tate, D., 2010, “Automatic Function Interpretation: Using Natural Language Processing on Patents to Understand Design Purposes,” *ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE 2010)*, pp. 443–452.

[33] Song, B., Luo, J., and Wood, K., 2019, “Data-Driven Platform Design: Patent Data and Function Network Analysis,” *ASME Journal of Mechanical Design*, 141(2), p. 021101.

[34] Fu, K., Murphy, J., Yang, M., Otto, K., Jensen, D., and Wood, K., 2015, “Design-by-Analogy: Experimental Evaluation of a Functional Analogy Search Methodology for Concept Generation Improvement,” *Research in Engineering Design*, 26(1), pp. 77–95.

[35] Murphy, J., Fu, K., Otto, K., Yang, M., Jensen, D., and Wood, K., 2014, “Function Based Design-by-Analogy: A Functional Vector Approach to Analogical Search,” *ASME Journal of Mechanical Design*, 136(10), p. 101102.

[36] Fu, K., Chan, J., Cagan, J., Kotovsky, K., Schunn, C., and Wood, K., 2013, “The Meaning of ‘near’ and ‘Far’: The Impact of Structuring Design Databases and the Effect of Distance of Analogy on Design Output,” *ASME Journal of Mechanical Design*, 135(2), p. 021007.

[37] Fantoni, G., Apreda, R., Dell’Orletta, F., and Monge, M., 2013, “Automatic Extraction of Function--Behaviour--State Information from Patents,” *Advanced Engineering Informatics*, 27(3), pp. 317–334.

[38] Li, Z., Tate, D., Lane, C., and Adams, C., 2012, “A Framework for Automatic TRIZ Level of Invention Estimation of Patents Using Natural Language Processing, Knowledge-Transfer and Patent Citation Metrics,” *Computer-aided Design*, 44(10), pp. 987–1010.

[39] Liang, Y., Liu, Y., Kwong, C. K., and Lee, W. B., 2012, “Learning the ‘Whys’: Discovering Design Rationale Using Text Mining—An Algorithm Perspective,” *Computer-Aided Design*, 44(10), pp. 916–930.

[40] Liu, Y., Liang, Y., Kwong, C. K., and Lee, W. B., 2010, “A New Design Rationale Representation Model for Rationale Mining,” *Journal of Computing and Information Science in Engineering*, 10(3).

[41] Yamamoto, E., Taura, T., Ohashi, S., and Yamamoto, M., 2010, “A Method for Function Dividing in Conceptual Design by Focusing on Linguistic Hierarchal Relations,” *J Comput Inf Sci Eng*, 10(3).

[42] Cascini, G., and Russo, D., 2007, “Computer-Aided Analysis of Patents and Search for TRIZ Contradictions,” *International Journal of Product Development*, 4(1), pp. 52–67.

[43] Smojar, V., Potočki, E., and Štorga, M., 2017, “A Visual Analysis of Technical Knowledge Evolution Based on Patent Data,” *International Conference on Engineering Design (ICED17)*, pp. 307–316.

[44] Chiarello, F., Cirri, I., Melluso, N., Fantoni, G., Bonaccorsi, A., and Pavanello, T., 2019, “Approaches to Automatically Extract Affordances from Patents,” *International Conference on Engineering Design (ICED19)*, pp. 2487–2496.
Jiang, P., Atherton, M., and Sorce, S., 2021, “Automated Functional Analysis of Patents for Producing Design Insight,” *International Conference on Engineering Design (ICED21)*, pp. 541–550.

Chang, H. T., Chang, C. Y., and Yang, Y. P., 2013, “Combining Surveying Patent Information, Reappearing Problem and Discovering Breakthrough for Design-Around,” *International Conference on Engineering Design (ICED13)*, pp. 417–426.

Bonaccorsi, A., and Fantoni, G., 2007, “Expanding the Functional Ontology in Conceptual Design,” *International Conference on Engineering Design (ICED07)*, pp. 1–12.

Jiang, P., Atherton, M., Harrison, D., and Malizia, A., 2017, “Framework of Mechanical Design Knowledge Representations for Avoiding Patent Infringement,” *International Conference on Engineering Design (ICED17)*, pp. 81–90.

Chiarello, F., Fantoni, G., and Bonaccorsi, A., 2017, “Product Description in Terms of Advantages and Drawbacks: Exploiting Patent Information in Novel Ways,” *International Conference on Engineering Design (ICED17)*, pp. 101–110.

Russo, D., and Montecchi, T., 2011, “A Function-Behaviour Oriented Search for Patent Digging,” *ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE 2011)*, pp. 1111–1120.

Sanaei, R., Lu, W., Blessing, L. T. M., Otto, K. N., and Wood, K. L., 2017, “Analogy Retrieval through Textual Inference,” *ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE 2017)*, Cleveland, USA, Aug. 6–9, p. V02AT03A007.

Li, Z., and Tate, D., 2013, “Interpreting Design Structure in Patents Using an Ontology Library,” *ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE 2013)*, p. V005T06A004.

Srinivasan, V., Song, B., Luo, J., Subburaj, K., Elara, M. R., Blessing, L., and Wood, K., 2018, “Does Analogical Distance Affect Performance of Ideation?,” ASME Journal of Mechanical Design, 140(7), p. 071101.

Luo, J., Song, B., Blessing, L., and Wood, K., 2018, “Design Opportunity Conception Using the Total Technology Space Map,” Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 32(4), pp. 449–461.

Luo, J., Yan, B., and Wood, K., 2017, “InnoGPS for Data-Driven Exploration of Design Opportunities and Directions: The Case of Google Driverless Car Project,” Journal of Mechanical Design, 139(11).

Song, B., Srinivasan, V., and Luo, J., 2017, “Patent Stimuli Search and Its Influence on Ideation Outcomes,” Design Science, 3(e25), pp. 1–25.

He, Y., and Luo, J., 2017, “The Novelty ‘Sweet Spot’ of Invention,” Design Science, 3.

Rios-Zapata, D., Duarte, R., Pailhès, J., Mejia-Gutiérrez, R., and Mesnard, M., 2017, “Patent-Based Creativity Method for Early Design Stages: Case Study in
Locking Systems for Medical Applications,” International Journal on Interactive Design and Manufacturing (IJIDeM), 11(3), pp. 689–701.

[59] Koh, E. C. Y., 2020, “Read the Full Patent or Just the Claims? Mitigating Design Fixation and Design Distraction When Reviewing Patent Documents,” Design Studies, 68, pp. 34–57.

[60] Siddharth, L., Madhusudanan, N., and Chakrabarti, A., 2020, “Toward Automatically Assessing the Novelty of Engineering Design Solutions,” Journal of Computing and Information Science in Engineering, 20(1), p. 11001.

[61] Saliminamin, S., Becattini, N., and Cascini, G., 2019, “Sources of Creativity Stimulation for Designing the next Generation of Technical Systems: Correlations with R&D Designers’ Performance,” Research in Engineering Design, 30(1), pp. 133–153.

[62] Koh, E. C. Y., and De Lessio, M. P., 2018, “Fixation and Distraction in Creative Design: The Repercussions of Reviewing Patent Documents to Avoid Infringement,” RESEARCH IN ENGINEERING DESIGN, 29(3), pp. 351–366.

[63] Wodehouse, A., Vasantha, G., Corney, J., Jagadeesan, A., and Maclachlan, R., 2018, “Realising the Affective Potential of Patents: A New Model of Database Interpretation for User-Centred Design,” Journal of Engineering Design, 29(8–9), pp. 484–511.

[64] Hwang, D., and Park, W., 2018, “Design Heuristics Set for X: A Design Aid for Assistive Product Concept Generation,” Design Studies, 58, pp. 89–126.

[65] Siddharth, L., and Chakrabarti, A., 2018, “Evaluating the Impact of Idea-Inspire 4.0 on Analogical Transfer of Concepts,” Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 32(4), pp. 431–448.

[66] Kokshagina, O., Le Masson, P., and Weil, B., 2017, “Should We Manage the Process of Inventing? Designing for Patentability,” Research in Engineering Design, 28(4), pp. 457–475.

[67] Valverde, U. Y., Nadeau, J.-P., and Scaravetti, D., 2017, “A New Method for Extracting Knowledge from Patents to Inspire Designers during the Problem-Solving Phase,” Journal of Engineering Design, 28(6), pp. 369–407.

[68] Wodehouse, A., Vasantha, G., Corney, J., Maclachlan, R., and Jagadeesan, A., 2017, “The Generation of Problem-Focussed Patent Clusters: A Comparative Analysis of Crowd Intelligence with Algorithmic and Expert Approaches,” Design Science, 3.

[69] McCaffrey, T., and Spector, L., 2018, “An Approach to Human--Machine Collaboration in Innovation,” AI EDAM, 32(1), pp. 1–15.

[70] Li, M., Ming, X., He, L., Zheng, M., and Xu, Z., 2015, “A TRIZ-Based Trimming Method for Patent Design Around,” Computer-Aided Design, 62, pp. 20–30.

[71] Koh, E. C. Y., 2013, “Engineering Design and Intellectual Property: Where Do They Meet?,” Research in Engineering Design, 24(4), pp. 325–329.

[72] Linsey, J. S., Markman, A. B., and Wood, K. L., 2012, “Design by Analogy: A Study of the WordTree Method for Problem Re-Representation,” ASME Journal of Mechanical Design, 134(4), p. 041009.

[73] Chan, J., Fu, K., Schunn, C., Cagan, J., Wood, K., and Kotovsky, K., 2011, “On the Benefits and Pitfalls of Analogies for Innovative Design: Ideation Performance
Based on Analogical Distance, Commonness, and Modality of Examples,” ASME Journal of mechanical design, 133(8), p. 081004.

[74] Fitzgerald, D. P., Herrmann, J. W., and Schmidt, L. C., 2010, “A Conceptual Design Tool for Resolving Conflicts Between Product Functionality and Environmental Impact,” ASME Journal of Mechanical Design, 132(9).

[75] Weaver, J., Wood, K., Crawford, R., and Jensen, D., 2010, “Transformation Design Theory: A Meta-Analogical Framework,” ASME Journal of Computing and Information Science in Engineering, 10(3, SI).

[76] Singh, V., Skiles, S. M., Krager, J. E., Wood, K. L., Jensen, D., and Sierakowski, R., 2009, “Innovations in Design Through Transformation: A Fundamental Study of Transformation Principles,” ASME Journal of Mechanical Design, 131(8), p. 081010.

[77] Koza, J. R., 2008, “Human-Competitive Machine Invention by Means of Genetic Programming,” Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 22(3), pp. 185–193.

[78] Jugulum, R., and Frey, D. D., 2007, “Toward a Taxonomy of Concept Designs for Improved Robustness,” Journal of Engineering Design, 18(2), pp. 139–156.

[79] Busby, J. A., and Lloyd, P. A., 1999, “Influences on Solution Search Processes in Design Organisations,” Research in Engineering Design, 11(3), pp. 158–171.

[80] Hsu, Y. L., Hsu, P. E., Hung, Y. C., and Xiao, Y. D., 2010, “Development and Application of a Patent-Based Design around Process,” ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE 2010), pp. 91–100.

[81] Qureshi, A., Murphy, J. T., Kuchinsky, B., Seepersad, C. C., Wood, K. L., and Jensen, D. D., 2006, “Principles of Product Flexibility,” ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE 2006), pp. 1–31.

[82] Parvin, M., Cascini, G., and Becattini, N., 2017, “Information Extracted From Patents As Creative Stimuli For Product Innovation,” International Conference on Engineering Design (ICED17), pp. 297–306.

[83] Lupu, M., Fujii, A., Oard, D. W., Iwayama, M., and Kando, N., 2017, “Patent-Related Tasks at NTCIR,” Current Challenges in Patent Information Retrieval, Springer, pp. 77–111.

[84] Piroi, F., and Hanbury, A., 2017, “Evaluating Information Retrieval Systems on European Patent Data: The CLEF-IP Campaign,” Current Challenges in Patent Information Retrieval, Springer, pp. 113–142.

[85] Campbell, M. I., Hölttä-Otto, K., and Linsey, J., 2016, “Special Issue on Design Theory and Methodology,” Journal of Mechanical Design, 138(10), p. 100301.

[86] Goel, A. K., and de Silva Garza, A. G., 2010, “Special Issue on Artificial Intelligence in Design,” Journal of Computing and Information Science in Engineering, 10(3).

[87] Allison, J. T., Cardin, M.-A., McComb, C., Ren, M. Y., Selva, D., Tucker, C., Witherell, P., and Zhao, Y. F., 2022, “Special Issue on Artificial Intelligence and Engineering Design,” Journal of Mechanical Design, 144(2).
[88] Spillers, W. R., and Newsome, S. L., 1993, “Engineering Design, Conceptual Design, and Design Theory: A Report,” Design Methodology and Relationships with Science, Springer, pp. 103–120.

[89] Chiarello, F., Belingheri, P., and Fantoni, G., 2021, “Data Science for Engineering Design: State of the Art and Future Directions,” Computers in Industry, 129, p. 10347.

[90] Luo, J., Sarica, S., and Wood, K. L., 2019, “Computer-Aided Design Ideation Using InnoGPS,” ASME 2019 IDETC/CIE, p. V02AT03A011.

[91] McComb, C., Cagan, J., and Kotovsky, K., 2017, “Mining Process Heuristics from Designer Action Data via Hidden Markov Models,” Journal of Mechanical Design, 139(11).

[92] Chandrasekaran, B., 1990, “Design Problem Solving: A Task Analysis,” AI Mag, 11(4), p. 59.

[93] Luo, J., 2015, “The United Innovation Process: Integrating Science, Design, and Entrepreneurship as Sub-Processes,” Design Science, 1.

[94] Jiang, S., Hu, J., Wood, K. L., and Luo, J., 2022, “Data-Driven Design-By-Analogy: State-of-the-Art and Future Directions,” ASME Journal of Mechanical Design, 144(2), p. 020801.

[95] Qian, L., Gero, J. S., and others, 1996, “Function-Behavior-Structure Paths and Their Role in Analogy-Based Design,” Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 10(4), pp. 289–312.

[96] McCaffrey, A., 2016, Analogy Finder (United States Patent, Patent No. US9501469).

[97] Chakrabarti, A., Sarkar, P., Leelavathamma, B., and Nataraju, B. S., 2005, “A Functional Representation for Aiding Biomimetic and Artificial Inspiration of New Ideas,” Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 19(2), pp. 113–132.

[98] Sarica, S., and Luo, J., 2021, “Design Knowledge Representation with Technology Semantic Network,” Proceedings of the Design Society: International Conference on Engineering Design (ICED), Gothenburg, Sweden, Aug. 16-20.

[99] Han, J., Forbes, H., Shi, F., Hao, J., and Schaefer, D., 2020, “A Data-Driven Approach for Creative Concept Generation and Evaluation,” Proceedings of the Design Society: DESIGN Conference, Online, pp. 167–176.

[100] Han, J., Sarica, S., Shi, F., and Luo, J., 2022, “Semantic Networks for Engineering Design: State of the Art and Future Directions,” Journal of Mechanical Design, Transactions of the ASME, 144(2), pp. 1–11.

[101] Choi, S., Lee, H., Park, E., and Choi, S., 2022, “Deep Learning for Patent Landscaping Using Transformer and Graph Embedding,” Technological Forecasting and Social Change, 175, p. 121413.

[102] Risch, J., Alder, N., Hewel, C., and Krestel, R., 2021, “PatentMatch: A Dataset for Matching Patent Claims & Prior Art,” Proceedings of the 44th International ACM SIGIR Conference, the 2nd Workshop on Patent Text Mining and Semantic Technologies (PatentSemTech).

[103] Risch, J., Garda, S., and Krestel, R., 2020, “Hierarchical Document Classification as a Sequence Generation Task,” Proceedings of the ACM/IEEE Joint Conference on Digital Libraries in 2020, pp. 147–155.
[104] Lyu, L., and Han, T., 2019, “A Comparative Study of Chinese Patent Literature Automatic Classification Based on Deep Learning,” *2019 ACM/IEEE Joint Conference on Digital Libraries (JCDL)*, pp. 345–346.

[105] Shalaby, M., Stutzki, J., Schubert, M., and Günemann, S., 2018, “An LSTM Approach to Patent Classification Based on Fixed Hierarchy Vectors,” *Proceedings of the 2018 SIAM International Conference on Data Mining*, pp. 495–503.

[106] Qi, J., Lei, L., Zheng, K., and Wang, X., 2020, “Patent Analytic Citation-Based vsm: Challenges and Applications,” IEEE Access, 8, pp. 17464–17476.

[107] Lin, H., Wang, H., Du, D., Wu, H., Chang, B., and Chen, E., 2018, “Patent Quality Valuation with Deep Learning Models,” *International Conference on Database Systems for Advanced Applications*, pp. 474–490.

[108] Bhattarai, M., Oyen, D., Castorena, J., Yang, L., and Wohlberg, B., 2020, “Diagram Image Retrieval Using Sketch-Based Deep Learning and Transfer Learning,” *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pp. 174–175.

[109] Chen, L., Xu, S., Zhu, L., Zhang, J., Lei, X., and Yang, G., 2020, “A Deep Learning Based Method for Extracting Semantic Information from Patent Documents,” *Scientometrics*, 125(1), pp. 289–312.

[110] Zuo, H., Yin, Y., and Childs, P., 2022, “Patent-KG: Patent Knowledge Graph Extraction for Engineering Design,” *Proceedings of the Design Society*, 2, pp. 821–830.

[111] Zhang, Z., Cui, P., and Zhu, W., 2020, “Deep Learning on Graphs: A Survey,” IEEE Transactions on Knowledge and Data Engineering.

[112] Gao, J., Li, P., Chen, Z., and Zhang, J., 2020, “A Survey on Deep Learning for Multimodal Data Fusion,” Neural Computation, 32(5), pp. 829–864.

[113] Rezende, D. J., Mohamed, S., and Wierstra, D., 2014, “Stochastic Backpropagation and Approximate Inference in Deep Generative Models,” *Proceedings of the 31st International Conference on Machine Learning (ICML)*, Beijing, China, June 21-26, pp. 1278–1286.

[114] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y., 2014, “Generative Adversarial Nets,” *Proceedings of the 27th Conference on Neural Information Processing Systems (NIPS)*, pp. 2672–2680.

[115] Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., and others, 2020, “Language Models Are Few-Shot Learners,” *The Proceedings of 33th Conference on Neural Information Processing Systems (NeurIPS)*, Virtual, Online, Dec. 7-12, pp. 1877–1901.

[116] Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K., 2019, “BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding,” *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, Minneapolis, MN, USA, June 2-7, pp. 4171–4186.

[117] Regenwetter, L., Nobari, A. H., and Ahmed, F., 2021, “Deep Generative Models in Engineering Design: A Review,” arXiv preprint arXiv:2110.10863.
Zhu, Q., and Luo, J., 2022, “Generative Design Ideation: A Natural Language Generation Approach,” Design Computing and Cognition, Glasgow, UK.

Arrieta, A. B., Díaz-Rodríguezb, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-López, S., Molina, D., Benjamins, R., and Others, 2020, “Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI,” Information Fusion, 58, pp. 82–115.

Liu, Q., and Wong, K. P., 2011, “Intellectual Capital and Financing Decisions: Evidence from the US Patent Data,” Management Science, 57(10), pp. 1861–1878.

Hegde, D., and Luo, H., 2018, “Patent Publication and the Market for Ideas,” Management Science, 64(2), pp. 652–672.

Wu, L., Hitt, L., and Lou, B., 2020, “Data Analytics, Innovation, and Firm Productivity,” Management Science, 66(5), pp. 2017–2039.

Bakker, J., 2017, “The Log-Linear Relation between Patent Citations and Patent Value,” Scientometrics, 110(2), pp. 879–892.

Bass, S., and Kurgan, L., 2010, “Discovery of Factors Influencing Patent Value Based on Machine Learning in Patents in the Field of Nanotechnology,” Scientometrics, 82(2), pp. 217–241.

Du, W., Wang, Y., Xu, W., and Ma, J., 2021, “A Personalized Recommendation System for High-Quality Patent Trading by Leveraging Hybrid Patent Analysis,” Scientometrics, 126(12), pp. 9369–9391.

Chan, T. H., Mihm, J., and Sosa, M. E., 2018, “On Styles in Product Design: An Analysis of US Design Patents,” Management Science, 64(3), pp. 1230–1249.

Huenteletr, J., Ossenbrink, J., Schmidt, T. S., and Hoffmann, V. H., 2016, “How a Product’s Design Hierarchy Shapes the Evolution of Technological Knowledge—Evidence from Patent-Citation Networks in Wind Power,” Research Policy, 45(6), pp. 1195–1217.

Lee, J.-S., and Hsiang, J., 2020, “Patent Claim Generation by Fine-Tuning OpenAI GPT-2,” World Patent Information, 62, p. 101983.

Parraguez, P., Maier, A., and others, 2017, “Data-Driven Engineering Design Research: Opportunities Using Open Data,” Proceedings of the 21st International Conference on Engineering Design (ICED 17), pp. 41–50.

Lee, K., and Lee, J., 2021, “National Innovation Systems, Economic Complexity, and Economic Growth: Country Panel Analysis Using the US Patent Data,” Innovation, Catch-up and Sustainable Development, Springer, pp. 113–151.

Aristodemou, L., and Tietze, F., 2018, “The State-of-the-Art on Intellectual Property Analytics (IPA): A Literature Review on Artificial Intelligence, Machine Learning and Deep Learning Methods for Analysing Intellectual Property (IP) Data,” World Patent Information, 55, pp. 37–51.

Shalaby, W., and Zadrozný, W., 2019, “Patent Retrieval: A Literature Review,” Knowledge and Information Systems, 61(2), pp. 631–660.

Krestel, R., Chikkamath, R., Hewel, C., and Risch, J., 2021, “A Survey on Deep Learning for Patent Analysis,” World Patent Information, 65, p. 102035.

Fleming, N., 2018, “How Artificial Intelligence Is Changing Drug Discovery,” Nature, 557(7706), p. S55.

Teng, F., Sun, Y., Chen, F., Qin, A., and Zhang, Q., 2021, “Technology Opportunity Discovery of Proton Exchange Membrane Fuel Cells Based on
Generative Topographic Mapping,” Technological Forecasting and Social Change, 169, p. 120859.