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Patent Data for Engineering Design: A Review

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Abstract

Patent data have been utilized for engineering design research for long because it contains massive amount of design information. Recent advances in artificial intelligence and data science present unprecedented opportunities to mine, analyse and make sense of patent data to develop design theory and methodology. Herein, we survey the patent-for-design literature by their contributions to design theories, methods, tools, and strategies, as well as different forms of patent data and various methods. Our review sheds light on promising future research directions for the field.

Keywords: engineering design, data-driven design, artificial intelligence (AI), big data analysis, data mining

1. Introduction

Mining patent data to develop design theory and methodology has a long history, and can be dated back to the 1950s: Altshuller and his team developed the theory of inventive problem solving (TRIZ) by manually examining thousands of patent documents (Altshuller and Shapiro, 1956). Recently, advancements in artificial intelligence (AI) and data science present a growing opportunity to mine big patent databases in design research and practice. In contrast to human-curated design repositories (Fuge et al., 2014, Bohm et al., 2008), patent databases present two advantages for data-driven design. First, patent databases are natural large-scale repositories that accumulate over time as inventors file patent applications for their inventions. For example, United States Patent and Trademark Office (USPTO) database contains over 7.7 million granted patents from 1963 to 2020. Second, patents contain massive design information on technologies, systems, or processes from all domains in both textual and visual forms, innovation activity footprints of inventors and organizations in the bibliometrics, and their relations to prior or future designs through the citations. Moreover, every patent is assigned to class(es) by patent examiners, making patent data ready for supervised machine learning applications.
In recent years, several design research groups actively explored cutting-edge data science techniques to mine the patent database for diverse applications, such as design representation, design space exploration, design prior art searching, stimuli recommendation, idea generation and evaluation, etc (Jiang *et al.*, 2021; Liu *et al.*, 2020; Luo *et al.*, 2021; Sarica *et al.*, 2021; Siddharth *et al.*, 2022; Song *et al.*, 2020; Song and Fu, 2019). These patent-for-design studies relied on a broad collection of methods, ranging from classic statistical analysis to latest network analysis, natural language processing (NLP), machine learning and data visualizations. To the best of our knowledge, there is no systematic review of the patent-for-design research despite its rapid growth. Therefore, to elucidate research trends and reveal promising future opportunities, we conducted this review.

2. Literature Retrieval Methodology

To retrieve prior patent-for-design publications, we employed the following search process to ensure comprehensiveness and relevance (Retrieval Date: Oct 23, 2021). Figure 1 presents the distributions of these papers by A) publication years, B) journals and C) keyword co-occurrence. To create the keyword co-occurrence figure, we conducted lemmatization to reduce inflectional forms of similar keywords, and then removed all the keywords that only appear once in the literature.

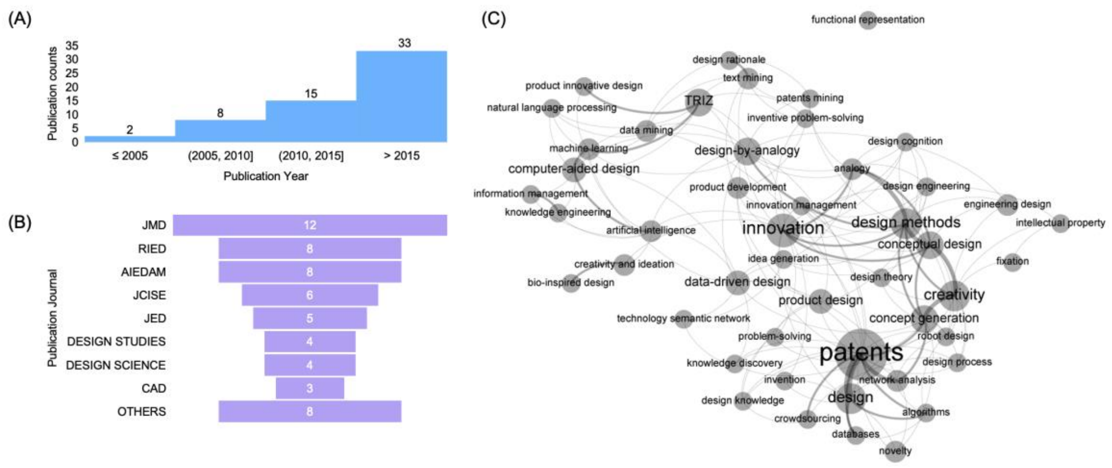

Figure 1. Distribution of the patent-for-design literature

In the first round, we ran a query in Web of Science, focusing on the following engineering design journals: (1) ASME JMD (Journal of Mechanical Design); (2) ASME JCISE (Journal of Computing and Information Science in Engineering); (3) RIED (Research in Engineering Design); (4) JED (Journal of Engineering Design); (5) Design Studies; (6) Design Science; (7) AI-EDAM (Artificial Intelligence for Engineering Design, Analysis and Manufacturing); (8) CAD (Computer-Aided Design). The following query was used: *(TI="patent" OR AB="patent") AND (SO=X) AND (PY=1950-2021)*, where *X* represents one of the eight journals. The search returned 46 papers. We manually checked these papers and identified 32 papers that fit the scope of this review. The inclusion criteria are: (1) Patent data are used as research data in the body text; (2) The paper contributes to engineering design theory or methodology development. These 32 papers form the initial paper list.

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

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

Finally, in the fourth round, we further checked the forward and backward citations of the papers in the core list via a snowballing process, and found another 3 relevant papers to add to the list. In sum, we curated a patent-for-design literature list of 58 papers to review.

3. Applications of Patent Data in Engineering Design Research

As we review the patent-for-design literature, it becomes clear that patent data have been utilized to advance (1) Design Theory; (2) Design Methodology; (3) Design Tool; (4) Design Strategy. Thus, our literature analysis is organised by these four categories. We examined contribution of each study and assigned them into one or multiple categories, as summarized in Figure 2.

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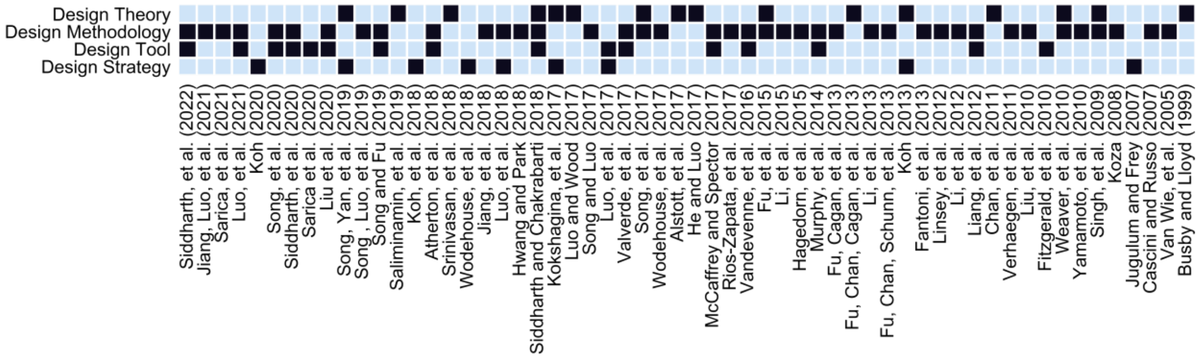

Figure 2. The distribution of patent-for-design literature by application domains

3.1. Design Theory Research

Design theory research develops new understanding of the design process and design rules. Busby et al. (1999) conducted an experiment on what factors influenced solution search activities and used patent database as the searching pool. Weaver et al., (2010) and Singh et al. (2009) developed transformation design principles by examining patents, products and biological cases. Many Design-by-Analogy (DbA) studies utilized patent databases as sources of design stimuli for drawing analogies (Jiang *et al.*, 2022). They examined how the analogical distance (Chan *et al.*, 2011; Fu, Chan, Cagan, *et al.*, 2013; Fu *et al.*, 2015; Song *et al.*, 2017; Srinivasan *et al.*, 2018), commonness (Chan et al., 2011), and the modality of examples (Chan et al., 2011) influence DbA-based ideation outcomes. Similarly, Saliminamin et al. (2019) used patents as idea triggers to explore the effect of precedents and design strategies on idea generation. Moreover, a few recent design theory studies mined bibliometric, citation and classification information of patent documents to reveal the fundamental patterns in designers' exploratory behaviours (Alstott et al., 2017), the causality between design novelty and potential impact (He and Luo, 2017) and the growing complexity of the design and invention process (Luo and Wood, 2017).

3.2. Design Methodology Research

As seen in Figure 2, most patent-for-design literature aimed at developing new design methodologies. The earliest work 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. More recent studies used NLP to identify innovative solutions from patent database to design problems to facilitate the use of TRIZ (Cascini and Russo, 2007; Li et al., 2013, 2015). Another strand developed design methodologies that leverage design knowledge in patents for design representation and reasoning. For instance, Van Wie et al. (2005) represented engineering products based on the Function-Behaviour-Structure (FBS) ontology (Qian et al., 1996) by analysing patent documents. Yamamoto et al. (2010) extracted the Subject-Verb-Object tuples from patent texts for function dividing in conceptual design. Fantoni et al. (2013) proposed an approach to extract function–behaviour–state information from patents. Liu et al. (2010) and Liang et al. (2012) proposed a text mining algorithm to discover design rationales from patent documents. Valverde et al., (2017) create a discovery matrix in which physical phenomena and technologies are matched via patents to inspire engineers. Hwang and Park (2018) developed the design heuristics sets for X (DHSfXs) from products and patents, aiming to facilitate concept design for specific goals. Atherton et al. (2018) proposed a functional representation method using annotation of geometry interaction derived from patent claims, which assists designers to understand prior designs better.

Since patent databases are natural repositories of design precedents, methods of retrieving patents as inspirational stimuli to augment design ideation are of the central interest of the conceptual design researchers. For instance, Verhaegen et al. (2011) retrieved candidate patents as product precedents for analogical design by distilling product features. Rios-Zapata et al. (2017) presented a creative design method that fuses combination and mutation models to support patent prior art search and analysis in early design stages. Song et al. (2017) proposed a method for patent stimuli searching based on community detection within a patent class network. Song and Luo (2017) described an approach to retrieve patent precedents for data-driven design by integrating searches through keywords, citation and

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co-inventor networks. Jiang et al. (2018) presented a framework that can assist designers in comparing prior arts and obtaining inspirations from them. Their framework is built on a functional knowledge graph with human-created ontologies. Liu et al. (2020) proposed a method to extract functional terms from a patent database and processed the terms using clustering algorithms for design ideation. Luo et al. (2021) utilized 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.

Specifically, a group of studies focused on patent data retrieval to support DbA. Linsey et al. (2012) 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, Cagan, et al. (2013) and Fu, Chan, Schunn, et al. (2013) utilized the combination of a Bayesian model and latent semantic analysis (LSA) to map a set of patent documents in a network structure to guide patent search for analogical inspirations. Murphy et al. (2014) proposed a functional vector method based on bag-of-words to encode patent documents into high-dimensional vectors to support analogy search.

In particular, the latest advances of data science and artificial intelligence enable the development of automated or semi-automated design methods that process massive patent data. Koza (2008) developed a genetic programming algorithm to solve design problems automatically and utilized patent database to examine the novelty of newly generated solutions. Wodehouse et al. (2017) presented a clustering method to analyse design opportunities using crowd intelligence. Song, Luo, et al. (2019) proposed a data-driven product platform design method based on the core-periphery structure detection within functional word co-occurrence networks that are created from patent texts. Jiang, Luo, et al. (2021) proposed a convolutional neural network-based representation method for design images from patent documents, aiming to facilitate visual DbA. Sarica et al. (2021) presented an idea generation methodology based on a large technology semantic network of over 4 million technical terms based on a word embedding model trained on the patent database (Sarica et al., 2020).

3.3. Design Tool Development

A few recent studies have leveraged patent data to develop data-driven design tools, facilitating and automating relevant design methodologies. Fitzgerald et al. (2010) developed a design-for-environment (**DfE**) tool to manage and facilitate the analysis and reuse of successful products for conceptual design. Their tool is a rule-based system built on TRIZ and DbA. Vandevenne et al. (2016) developed a tool named scalable search for systematic biologically inspired design (**SEABIRD**), which enables the scalable search for biological stimuli for designers. SEABIRD utilizes rule-based text mining techniques to extract and map product aspects of technical systems in patent documents and organism aspects of biological systems in academic papers for identifying candidate analogies. Mccaffrey (2016) developed **Analogy Finder**, a DbA support system to identify adaptable semantic analogies from the patent database. Later, McCaffrey and Spector (2018) devised a visual and verbal problem-solving representation to support human–machine collaboration in innovative design. Luo et al. (2017) developed **InnoGPS** a cloud-based tool that employs 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 and his team proposed a series of data-driven design applications, including design opportunity identification (Luo et al., 2017, 2018) and analogical conceptual design (Luo et al., 2019, 2021). Siddharth and Chakrabarti (2018) developed the **Idea-Inspire 4.0** with the validation on patents. Idea-Inspire represents both engineering concepts and biological ideas using SAPPhIRE model ontology (Chakrabarti et al., 2005) for biologically inspired design. Based on Idea-Inspire tool and SAPPhIRE model, they further developed an automated novelty evaluation method for engineering design solutions (Siddharth et al., 2020). Song and Fu (2019) utilized a topic modelling algorithm to structure a repository of mechanical design patents with three facets: behaviour, material, and component, and developed a visual interaction tool for seeking design inspiration, named **VISION** (Song et al., 2020). Sarica et al. (2020) applied word embedding techniques on patent data and constructed a large-scale technology semantic network of over 4 million terms called **TechNet**, which is accessible via API and a public web portal. TechNet has been used for design representation (Sarica and Luo, 2021), prior art retrieval (Sarica et al., 2019), idea generation

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(Sarica et al., 2021), and concept evaluation (Han et al., 2020). Siddharth et al. (2022) created a large and scalable engineering knowledge graph based on the entire USPTO database, which can be used to support inference, reasoning, and knowledge exploration in engineering design applications.

3.4. Design Strategy Research

Patent databases also enable researchers to distil design strategies in both manual and automated ways. For example, Jugulum and Frey (2007) studied a large number of inventions and summarized general strategies employed in those inventions as a taxonomy of concept designs for improved robustness. Koh et al. studied the proper ways and the repercussions of reviewing patent documents during the early design stage (Koh, 2013, 2020; Koh and De Lessio, 2018). Kokshagina et al. (2017) proposed the 'design-for-patentability' strategy to guide the innovation of engineering designers.
Several researchers have studied how to mine patent data to identify potential design opportunities and long-term strategic planning for innovation. For example, Luo and his colleagues proposed a series of patent-data driven methods to enable high-level design opportunity identification, strategic planning, analysis of the structure and expansion trajectories of domains, using the total technology space map based on the patent classification system (Luo et al., 2017, 2018; Song, Yan, et al., 2019).

4. Analysis of Methods and Algorithms

The patent-for-design literature has employed a wide variety of research methods, ranging from qualitative analyses and reasoning to the latest network analysis and data science techniques. Figure 3 visualizes the co-uses of methods and different parts of patent data in prior studies. One may adopt multiple methods on multiple data sources. We counted each item, ensuring that each method was matched to the corresponding part of patent data. Different line colours denote different parts of patent data, and the width of a line indicates the number of corresponding studies.

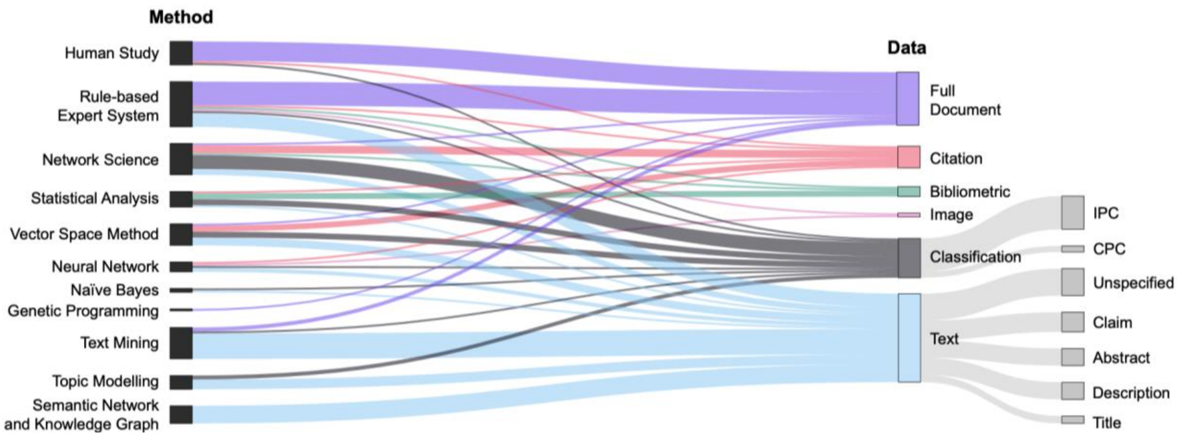

Figure 3. Methods in relation to different parts of patent data

Human subject experiments were the primary method to develop theories. In these human studies, full patent documents were often directly provided to designers as design aids such as prior art solutions or design stimuli for engineering design. Besides, a group of qualitative studies adopted knowledge-based rules or strategies to boost computer-aided engineering design and developed rule-based expert systems, which require designers to collaborate with algorithms to tackle specific problems.
A wide range of data science techniques have been used in the patent-for-design literature. For instance, complex network analysis has been adopted to mine relational information from citations or proximities of semantic content among patents (Fu, Cagan, Kotovsky, *et al.*, 2013; Luo *et al.*, 2017, 2018; Song *et al.*, 2017; Song, Luo, *et al.*, 2019; Song, Yan, *et al.*, 2019; Song *et al.*, 2020; Song and Fu, 2019). Using network-based metrics, such as centrality, entropy, and coherence, prior studies have developed new scientific understanding of design artefacts and processes (He and Luo, 2017; Song, Yan, et al., 2019) and proposed patent data-driven design methodologies and strategies (Luo et al., 2021). Some design

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tools, i.e., InnoGPS and VISION, use network visualizations to guide designers in exploring the design or technology spaces, constructed on patent data or patent classification labels.

NLP techniques are growingly used to retrieve design knowledge from patent texts. A few studies adopted standard text pre-processing pipelines, including lemmatization, stemming and stop-words removal techniques to clean the raw design text for further processing. In addition, design knowledge is extracted in certain forms of templates from given patent text utilizing syntactic dependencies to support the automation of TRIZ (Yamamoto et al., 2010) and construction of knowledge graphs (Fantoni et al., 2013; Siddharth et al., 2022). Besides, topic modelling algorithms such as non-negative matrix factorization (Song et al., 2020; Song and Fu, 2019) and latent semantic analysis (Fu, Cagan, Kotovsky, *et al.*, 2013; Fu, Chan, Cagan, *et al.*, 2013; Fu Chan, Schunn, et al., 2013) have been applied on patent texts to represent design repositories in a more structured form.

Semantic networks and knowledge graphs have been used to support design research. Several early studies leveraged pre-trained common-sense semantic networks (Linsey et al., 2012) or manually curated ontology-based knowledge graphs (Atherton et al., 2018; Hagedorn et al., 2015; Jiang et al., 2018) to support design innovation and problem solving. Until recently, the patent database is mined to construct large-scale cross-domain engineering semantic networks and knowledge graphs (Sarica et al., 2020; Siddharth et al., 2022), serving as a knowledge infrastructure to support data-driven engineering design research and practice.

Artificial neural networks and deep learning, because of their abilities to learn complex patterns from big data, have been employed in the patent-for-design literature. For instance, Li et al. (2012) trained a neural network to classify patents by novelty levels of invention as defined in TRIZ. Recently, researchers have developed design methodologies based on convolutional neural network (CNN) (Jiang *et al.*, 2021) and language models (Sarica et al., 2020) trained on the dataset of patent images and patent texts, respectively. Other machine learning models such as Naïve Bayes and advanced statistical analysis methods 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 with the use of diverse data science techniques, as seen in Figure 3.

5. Discussion on future research opportunities

5.1. Discussion on Data

Patent databases are natural benchmark datasets for supervised machine learning applications, because every patent is rigorously labelled by patent offices about its technological domain class(es). The classification information and citation-based metrics of patents can serve as the golden standard that enables the training, test and comparison of the performance of different algorithms. In Figure 3, we have shown how different parts of patent documents can be used in different computing methods for design research. In addition, patent texts constitute a heavy load of design information which can be used for creating datasets for NLP-related tasks such as entity recognition and hierarchical analysis of inventions. However, these datasets would require heavy labelling and annotation, which are still human-intensive tasks requiring considerable expertise, time and resources. Besides, we can see that bibliometrics, images, citations and classification information of patents are not commonly mined in Figure 3, compared to textual information. It is recommended that researchers leverage multimodal patent information instead of a single modality to develop more systemic understandings of design artefacts and processes or more powerful design methods and tools. Besides, most current literature focused on patents from USPTO and EPO as the data source (primarily because they are written in English). We believe patents from other countries, such as Japan and China, are also useful to support engineering design research.

5.2. Discussion on Algorithms

Because of the large volume, patent databases are suitable for implementing modern deep learning techniques on specific tasks that usually require big data for the model training. The dramatic development of deep learning provides us many opportunities to combine up-to-date advances into

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engineering design research. First, recent progress on graph neural networks enables us to extract relational information among patents and derive high-dimensional representation for downstream tasks (Zhang et al., 2022), such as design repository reshaping and design stimuli identification. Various machine creation studies in the computer science field, including text and image generation based on deep generative models (e.g., VAE (Rezende et al., 2014) and GAN (Goodfellow et al., 2014)) or large pre-trained language models (e.g., GPT-3 (Brown et al., 2020) and BERT (Devlin et al., 2019)), can also be utilized to develop idea or design generation methodologies. Thus, researchers can develop generative models (Regenwetter et al., 2021) specifically for design synthesis by learning engineering design-related knowledge from big patent data.

Besides, the studies and innovations in natural language understanding also have a great potential to create meaningful representations of inventions. Hence, comprehensive knowledge bases of the cumulative technology space can be created using accurate semantic relations and meanings (Chen *et al.*, 2020) which may offer not only the structural and flow relations explicitly stated in patent texts but inherent causal relations, hence working mechanisms, within inventions. Such methods can be extremely useful and stimulating in early design phases with the help of efficient and effective data storage and knowledge management strategies. Last but not the least, given that patent documents normally contain multimodal information on design, we can take advantage of multimodal deep learning techniques to develop more intelligent design applications (Gao *et al.*, 2020), including multimodal knowledge graph construction, cross-modal idea generation, and cross-modal design retrieval.

5.3. Discussion on Applications

Figure 2 shows that patent data are mostly used to develop design methods and tools, while applications in design science and strategy research at higher levels are limited. The large-scale patent databases that contain detailed multimodal content and rich bibliometrics, citation 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 behaviours and interactions of design agents across diverse technological domains and the conditions for the emergence of the breakthrough design innovation. However, at present, only a few studies have adopted data-driven approaches to build theories in the design science field. We believe such data-driven endeavours using patent data could substantially deepen and further our fundamental understanding of design team science, designer behaviours and rationales, design impact dynamics, and so on.

As for design strategies, existing patent-for-design studies have shown the potential of mining patent databases to explore white space and identify feasible directions for R&D activities of designers, design teams, and large companies (Luo et al., 2017). Some patent analysis and management firms, such as Patsnap and Incopat, have already utilized AI-powered and machine learning technologies to inform innovation activities. We recommend researchers to experiment various explainable AI methods on patent documents and unlock more potential of data-driven design innovation (Luo, 2022).

6. Conclusion

Patent databases are ideal knowledge resources for researchers to develop design theories, strategies, methods, and tools because of the richness of design information contained in patent documents. The last decade has witnessed the growing trend of using data science techniques to mine and analyse the patent database to support engineering design research and applications. This paper contributes to the patent-for-design literature by elucidating the status quo of this field and identifying future research opportunities. We hope our review and propositions can serve as a guide for design researchers and practitioners in discovering the more value of patent databases for advancing design research and developing patent data-driven design methods and tools.

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