

# Less Is More? In Patents, Design Transformations that Add Occur More Often Than Those that Subtract



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**Abstract** This article examines how design transformations are described in one specific but important context: patents. Using text analytics, we examined term frequency and term frequency-inverse document frequency from 33,100 full patents from 2017 sourced from the US Patent and Trade Office. Using a corpus-based approach, we developed lexicons to capture two general types of design transformation: addition and subtraction. In patent data we collected and analyzed, addition design transformations were more common than subtraction design transformations (2.7:1). The ratio of addition to subtraction was higher than ratios in non-design texts (1:2.5). While patents represent one area of design, and the patent texts we analyzed were not necessarily written by designers themselves, something about the process that produces patents leads to far greater use of addition than subtraction. We discuss possible reasons for and implications of these findings.

## 1 Patents: An Opportunity to Understand Design

Design occurs in a variety of disciplines. Many of these disciplines converge at the need for intellectual property. Patents give legal rights to inventors to own their ideas—excluding others from making, using, or selling an invention [1]. A patent must meet patentability requirements including: novelty, usefulness, and non-obviousness [2]. Novelty evaluates the uniqueness of the design, while usefulness requires a need for intellectual protection. Non-obviousness remains a debated term among legal scholars, but indicates that design cannot be the combination of two previously patented designs. Patents provide archival documentation to understand how the design and legal community evaluate novelty, usefulness, and non-obviousness in ideas. Bearing this in mind, patent records provide one opportunity to identify and understand design transformations.

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Patents document some aspects of design and patent mining can be used to study these designs [3]. Keyword-based approaches seek to discover technology trends [4, 5], and patent-based analogy search tools assist with innovation concept generation [6, 7]. Other research has sought to approximate a patent's measure of novelty, conventionality, and value of invention using patent reference and citation data [8]. Through similar analysis of archival patent documents, the research described in this paper examines trends in design transformations.

### ***1.1 Transformations: How Designers Go from Present to Goal-Satisfied States***

Those who design evaluate a present state, apply a series of transformations and achieve new, goal-satisfying state [9]. Design transformation help designers to avoid design fixation [10], realize the minimum transformation costs for optimum designs [11], and facilitate new functionality [12]. Our conceptualization of design transformation expands on these prior definitions by acknowledging design transformation can be represented in ideas, products, and processes. These transformations can be categorized into more general classes of actions such as addition, scaling, and substitution [13]. Designers use a series of more specific transformations to attain goal states.

Many scholars advocate for designers to pursue a diversity of approaches and transformations to attain the widest set of possible designs [14, 15], and [16]. From a diverse set of possible designs, designers can realize designs that are innovative, and at times overlooked.

Two general types of design transformation are addition and subtraction. Design transformation of addition enact improvements by increase a unit of measure, where design transformation of subtraction enact improvements by decreasing a unit of measure, whether idea, process, or product. This set of categories does not comprise all design transformation categories, but helps to characterize two distinct and fundamental sets.

Designers have been described as “engaging in a conversation” with the situations they transform [17]. These “conversations” can take written form, enacting design [18]. In other words, written forms of language used in design reflect the design itself. By thinking of language in design as ‘doing’ design, the descriptions can indicate functional and conceptual cognitive actions and design transformations [19, 20]. Text analytics can be used to identify design transformations within written design. Language provides a coherent frame to enact design; embedding information of the designed work because language, in part, communicates and frames the design work into a conceptual structure. Functional and conceptual cognitive actions that are ‘done’ in design texts, including patent claims, offer a rich perspective to show design transformations.

In this paper, we collected design texts from the United States Patent and Trade Office, developed lexicons that describe design transformations of addition and subtraction, and applied text analytics. We found that design texts contain higher frequencies of addition relative to non-design texts.

## 2 Data

### 2.1 *Aggregating Design Texts: United State Patent and Trade Office*

We use patents as a proxy of invention and artifact of design. Research has used patents to understand novelty, conventionality, and the value of an invention [8], measure a technology's development and dispersion [21], and develop tools mining patent texts that steer designers during the design process [22]. Patents contain rich information that, using text analysis, can characterize the design transformations that describe the design, with statistical power.

Specifically, our analysis analyzes utility patents from 662 classifications and multiple countries. We collected the data from the US Patent and Trade Office. The US Patent and Trade Office cooperate internationally to make patents from multiple countries electronically available. The Cooperative Patent Classification (CPC) allows for random sampling from each classification. We chose to sample by CPC to allow representation from all design disciplines. Patent data collected included structured and unstructured data. Structured data included Inventor Name (s), Company Name, Patent Date Filed, Patent Date Issued, City Filed, Country Filed, Cooperative Patent Classification. Unstructured data included Patent Title, Patent Abstract, Patent Claims, and Patent Description.

We designed scripts using 'pypatent' [23] to pull 50 random samples from each Cooperative Patent Classification (n = 662) for the year 2017 (n = 33,100 patents) including structured and unstructured data. The purpose for this sampling methods allows in depth analysis for patent titles, claims, descriptions etc. For instance, patent claims contain important terminology for intellectual protection and indicate the scope of design transformations. Prior work focuses on patent claims as the most important part in patent analysis because they comprise the legally defensible design texts [24].

Unstructured patent data contains the design text that reveals design transformations. Patent claims, titles, abstracts, and descriptions provide different aspects of the patent. Patent claims define, in technical terms, the extent of the protection conferred by a patent [25]. A patent's claims provide legal, intellectual protection during prosecution and litigation alike. The title of the design should be brief but technically accurate and descriptive, containing less than 500 characters while excluding non-descriptive language (e.g. "improved" or "new") [26]. Patent abstracts provide a summary of the disclosure, indicate the technical field in which

the design pertains and identifies a clear understanding of the technical problem, the essence of the solution of that problem through the design, and the principal use(s) of the design [27]. Lastly, a patent description can detail the scope of the design, and expand on the abstract and claims [26]. Yet, patent descriptions often vary in quality and length because the descriptions do not provide legal protections. Analyzing the various sections of the patent texts affords a scoping insight to each patent's design. Patent claims and titles provide insight into the design transformations because of the stringent requirements to be technically accurate and descriptive, while also claiming the scope of the design.

## 2.2 *Preparing Patent Data: Structured and Unstructured Data*

Text-mining patents require dual-measure approaches to understand both structured and unstructured data [1, 28]. Unstructured data contains information and text about each patent's intent, novelty, non-obviousness, and purpose. To understand subtraction and addition in patents, we cleaned the texts following text mining procedures. We converted all text to lowercase, removed punctuation, and tokenized each patent's unstructured data [4, 29]. We merged all data into a searchable data frame. We also collected non-design texts from *New York Times* articles from 2017 to act as a point of comparison for word usage and term frequency in design texts relative to non-design, colloquial texts.

## 3 Method

We aim to develop an approach for quantifying subtractive and additive transformations in design texts. We use lexicon-building as a descriptive and efficient method to navigate unstructured data and reveal design transformations used to achieve novel designs. In doing so, we seek to maximize the efficiency of the method and the sensitivity to measure design transformations.

By maximizing these criteria, transformations can be sufficiently identified across the large corpus of patent data. We acknowledge this method is not entirely sufficient to determine each *instance* of transformation, but the method is pragmatic in characterizing categories of transformations like addition and subtraction.

### 3.1 *Building Lexicons to Qualify Design Transformations*

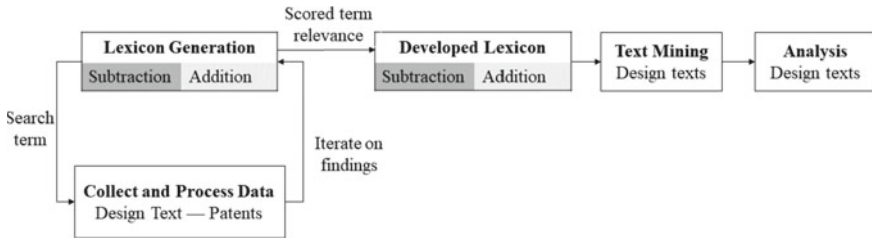
We developed a lexicon to indicate subtractive or additive transformations. Lexicon building is a common method to understand texts for exploratory and predictive concepts [30, 31]. Individual coding for patents would be labor intensive and therefore reduced to a small sampling of disciplines. Our method works as a word-based, generation lexicon to prioritize depth of the specific transformation before breadth [32, 33]. In other words, we want the lexicon to efficiently retrieve fewer, more relevant patents, as opposed to many, less relevant patents. We seek to navigate and analyze large sets of unstructured data. Depth of understanding allows us to accurately identify designs that use subtractive or additive transformations from a large set of unstructured design data.

We built a semantic lexicon for design transformation categories: subtraction and addition [34]. We followed an established best-practice for lexicon building methods [31, 32] by generating a list of words describing each design transformation and prioritizing central components (or terms) when compared to peripheral components (or terms) that describe design transformations. Given a handful of seed words for a design transformation category and a representative text corpus, one can build a semantic lexicon for a category. Using prior design research, we identified two lists of seed words that indicate subtraction and addition as the design transformation [14, 35], and [36]. Our method focuses on English design texts because the USPTO requires English-written patents.

The seed words comprised the unrefined lexicons. We searched for each seed word in the unrefined lexicon within the patent corpus. We determined the fit or unfit for the seed word describing the design transformation category. We selected the best fits for the lexicon as they appear in the patent corpus. We assigned weights based on the relevance of the term within the corpus as it relates to the design transformation. We omitted terms from the lexicon because they did not reveal the design transformation. After several iterations, the design transformation lexicons contain relevant and weighted terms to describe the design of the patent.

As shown in Fig. 1, we refined the initial list by following previously developed corpus-based approaches to building lexicons for sentiment analysis [37], which require searching each term, evaluating the results, and determining if the results fit the initial intent of describing transformations of the designs. We applied the developed design transformation lexicon to the design and non-design corpora to count for term occurrences, term frequency, and term frequency-inverse document frequency (TFIDF).

We use TFIDF to measure how important a word is in the design text. TFIDFs are calculated for addition and subtraction lexicons to measure each transformation separately. The TFIDF value increases proportionally to the number of times a word appears in a document, and offset by the number of documents in the corpus that contain that word. In so doing, TFDIF adjusts to the possibility that some words will occur more frequently than other words. The TFIDF value for the transformation lexicons is shown in equation below.



**Fig. 1** Methodology for developing design transformation lexicons

$$\text{TFIDF} = f_{t,d} \cdot \log(N/n_t)$$

The lexical term,  $t$ , found within each document,  $d$ , of the corpus,  $D$ , generated the term frequency denoted by  $f_{t,d}$ .  $N$  represents the total number of documents, and  $n_t$  represents the number of documents where the term,  $t$ , appears. The developed lexicons only contain terms found within the corpus, ensuring  $\text{tf}(t,d) \neq 0$ . TFIDF provides insight for the importance of a term, while term frequency shows the terms pervasiveness, and term occurrence shows the popularity of the term. Together, we triangulate to unveil the design transformations described in the patent corpus.

Our method optimizes for the efficiency and sensitivity of addition and subtraction as design transformations categories. Our method sufficiently meets these parameters and characterizes design transformations within the design corpus.

## 4 Results

We collected our primary data, patents, using the ‘PyPatent’ python package for a total of 33,100 full patents filed in 2017. Finally, we collected *New York Times* articles to act as a non-design, colloquial comparison to the patent sample. The patent sample represented inventors from over 100 countries and 662 patent classifications.

### 4.1 *Developed Additive and Subtractive Lexicons*

We developed a semantic, transformation lexicon that assists in identifying transformations found within patents. The lexicon contained regular expressions (regex) that allowed for quick, searchable, and in some cases excludable results. We generated seed words based on relevance from existing design ontologies, design texts, and existing dictionaries. The gathered seed words comprise the unrefined lexicon. Finding language that performs addition came fairly easily from this search

method. Yet, we found difficulty in finding language that performs subtraction, and therefore gathered more seed words so not to overlook any context. We show the seed words that comprise of the unrefined lexicon for design transformations of addition and subtraction in Table 1. Words that are grayed out represent seed words that did not describe the design transformation in the context of patents per the coders’ review. Seed words that are not grayed out make up the refined lexicon and describe the specific design transformations within patents shown in Table 1.

We used a negative case analysis to try and maintain neutrality in lexicon refinement. As shown in Table 1, seed words that did reflect the design transformation were removed from consideration for the refined lexicon. We removed seed words if they did not reflect the subtraction transformation or weakly represented the transformation. For this reason, we omitted the following seed words from the subtraction refined lexicon: *decrease, deduct, economical, eliminate, exclude, inexpensive, and take away*. The seed word, *isolate*, revealed discipline specific meaning relating to chemistry. We removed seed words if they did not reflect the addition transformation, or weakly represented the transformation. For this reason, we omitted the following seed words from the addition refined lexicon: *enhance,*

**Table 1** Transformation lexicons

Subtraction	Addition
Decrease	Augment
Deduct	Add
Detach	Attach
Detract	Bolster
Economical/inexpensive	Coating
Eliminate	Connect
Exclude	Enhance
Free	Gain
Hybrid	High
Integrate	Increase
Isolate	Join
Less	Magnify
Limit	More
Low	Multi
No	Reinforce
Reduce	Robust
Remove	With
Simplify	
Subtract	
Take away	
Withdraw	
Withhold	
Without	

*high, increase, magnify, more, robust.* The seed word, *gain*, reveals discipline specific meaning relating to electricity. The remaining seed words that fit the definition of subtraction or addition comprised the each refined design transformation lexicon, respectively.

Assigned weights maximized sensitivity of the refined lexicon. Weighting each term in lexicons creates relevance when applying the lexicons to the patent corpus. We assigned weights to each term in the lexicons based on their strength of describing the design transformation of addition or subtraction. We examined how precisely each term described the design transformation. We tried to maintain neutrality by discussing relevancy for each term to each other, and relate the term occurrences with the design transformation definition. For example, within the refined subtraction lexicon, *detach*, sometimes described subtraction and in other cases, describe the act of something that can be subtracted, used for a purpose, and then put back into the reference frame (e.g. a detachable shower head). Similarly, *connect*, was down-weighted because it describes design transformations of additions and describes merging two pieces together (e.g. a connector used for HDMI to USB). Lexicons rely on weights to attribute meaning to some words more than others. A weighted, refined lexicon allows for sensitivity and depth when evaluating design transformations in patent texts.

Within the lexicon, we modified some terms to exclude language that did not describe the design transformation. The term *less* omitted designs that described *wireless* or *brushless* motors, as these largely describe the state of technology used, not the design developed.

#### ***4.2 Design Transformations Describing Addition Occur More Frequently Than Those Describing Subtraction***

We calculated the term occurrence, term frequencies, and TFIDF for subtraction and addition lexicons for the unstructured data. In the patent corpus, we calculated these for the entire corpus, and each section: title, claims, abstract, and descriptions. The same text measures were calculated in the *New York Times* (non-design) corpus. Table 2, shown below, shows the results from applying the design transformation lexicons to each corpus.

In Table 2, the observe term frequency per thousand words is shown for the Patent's Claims, Patent Titles, and *New York Times* corpora. Terms found in the subtraction design transformation lexicon show similar frequency between design and non-design texts. While terms found in the addition design transformation lexicon show a higher term frequency in design contexts relative to non-design contexts. In design contexts, design using transformations of addition occurs at least twice as much as subtraction, as shown in the *ratio* row of Table 2. Interestingly, the two highest values for TFIDF (2.5 and 1.7), a measure of term importance,



**Table 2** Results from developed design transformation lexicons on texts Table legend appears above table

	Patent title	Patent abstract	Patent claim	New York times
Subtract. Mean Term Frequency*	2.3	2.4	2.3	2.2
Add. Mean Term Frequency*	8.0	5.9	5.1	0.94
Ratio <sup>+</sup>	3.5	2.4	2.2	0.42
Subtract—Mean TFIDF	0.073	0.47	1.7	1.3
Add—Mean TFIDF	0.16	0.79	2.5	0.85

\*denotes # for every 1000 terms in each corpus  
 +ratio calculated by (Add Mean Term Frequency)/(Subtract Mean Term Frequency)

occurred in the patent’s claim section, the section that provides the scope for infringement of patent claims. This is interesting because descriptions of design transformations may be relevant in providing scope for intellectual property rights.

## 5 Discussion

In the patents analyzed, design transformations describing addition occur more frequently than those describing subtraction. This more frequent description of addition was not present in the *New York Times* text, where the subtraction mean term frequency was 2.2, while the addition mean term frequency was 0.94. These findings suggest that those who write patents may describe addition transformations far more than non-design writers. Instances of subtraction remained at similar frequencies in both design and non-design texts.

These results are unexpected. We anticipated designers might use similar frequencies of addition and subtraction transformations within patents. The requirement to be novel has been discussed in design literature frequently [8]. Many scholars promote a diversity of approaches and transformations to attain the widest set of possible designs [14, 15], and [16]. We expected that novelty of design would be most rewarded by a diversity of transformations described within patents. Further, addition transformations occurred 3× more often than non-design texts, suggesting an emphasis of addition transformations within design texts like patents.

Designers could be applying design transformation of addition more than subtraction. Addition might be a more accessible design transformation than subtraction. Designers seek to use design transformations to move from a reference state to a desired state. Designers may be influenced to add rather than subtract. Expert designers have long describe *getting to the essence* as a difficult and lifelong skill. The counterintuitive advice of Antoine de Saint-Exupery shows the ease of adding and the difficulty in subtracting, “A designer knows he has achieved perfection not when there is nothing left to add, but when there is nothing left to take away.”

Patents as a design context provided insight into design transformations, but also may indicate other influences in the design and patent process. In other words, just because a design transformation is described in a patent, doesn't mean it is how a designer went about designing or even how they might think about the changes from a prior state. Those seeking designs to be intellectually protected with a patent come from a variety of disciplines, countries, and contexts. Yet, obtaining a patent requires financial investment, and a personal belief in protecting the design. For this reason, we understand our sample limits to those with financial abilities and beliefs in the need for intellectual property of their design. It also could be that those with designs using subtraction do not apply for patents, while those with designs using addition apply for patents. The patent approval process may also reward language that proves its value and non-obviousness. Hindsight bias and other cognitive biases might influence a patent reviewer's view on non-obviousness; a reviewer may see that subtracting something is obvious and can't be patented.

Lastly, a designer and a lawyer often write the patent application together. In this instance, designers may adapt their language with the guidance of a patent lawyer that favors patentability requirements, which may inadvertently favor designs that describe addition. During this process, the patent may overemphasize addition. These factors, while speculative, could be happening in tandem and call for further investigation.

Our method contributes to the design computing literature. We provide evidence that a corpus-based approach can build lexicons to describe and therefore uncover and analyze design transformations. Identifying complementary design transformations requires an in-depth analysis of previous design ontologies and design transformation literatures. A similar lexicon-building approach may optimize for efficiency and sensitivity toward design transformations and can be applied to other design texts such as design instructions, specifications, and books. The method may also be applied to other types of transformations in design, such as substitution or scaling. Generally, the method outlined here is one way to gain depth of understanding from large sets of unstructured, textual data, which are commonly found within design.

## 6 Conclusion

This study contributes to the design literature, in particular, the literature on semantics and design [37, 38]. The study reveals an asymmetric use of addition in comparison with subtraction for design transformations within patent texts. Patents can serve as a large design texts data set, and also informs the design literature about how design may be described for intellectual property. The study informs future directions and research for understanding design transformations. More research needs to be done at various scales to understand the nature of these findings. In more observable design situations, researchers could use the framing of design transformations to study how designers transform the current reference state

to a desired one. Using multiple methods, the design literature can understand preferences and potentially design biases.

The article presents a new approach for measuring design transformations within design texts. Developing lexicons that measure design transformations within design texts provides a novel approach to understanding functional and conceptual aspects of the design transformations. Compared to a conventional, manual review of patents, our approach provides efficiency and sensitivity for understanding the design transformations. While our process focuses on addition and subtraction, there are opportunities to expand into other design transformation categories such as replacement. The method may be applied to new design texts such as design reports. Developing lexicons for other contexts will provide insights into the functional and conceptual aspects of the design transformations.

Instances of addition occurred more frequently than subtraction in patents, indicating a potential trend within the design community. Limiting design transformations may limit the diversity of potential designs. The large-scale data using refined lexicons indicates an over emphasis on design transformations describing addition when compared to subtraction. Even more, the frequency of language enacting addition occurs significantly more often than in non-design language. The extreme difference in usage for addition relative to both subtraction and non-design language points to a potential trend within the design community: a tendency to add. More research will need to be done to understand the extent of design transformations involving addition through other design contexts and methods. If designers and the design community overemphasize addition, they will miss out on other design transformations, such as subtraction.

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## References

1. Tseng Y-H, Lin C-J, Lin Y-I (2007) Text mining techniques for patent analysis. *Inf Process Manag* 43:1216–1247. <https://doi.org/10.1016/j.ipm.2006.11.011>
2. Oxford Academic (2019) Global Collaborative Patents. *The Economic Journal* | Oxford Academic. <https://academic.oup.com/ej/article/128/612/F235/5089453>. Accessed 29 Nov 2019
3. Zhang L, Li L, Li T (2015) Patent mining: a survey. *ACM SIGKDD Explor Newsl* 16:1–19. <https://doi.org/10.1145/2783702.2783704>
4. Yoon B, Park Y (2004) A text-mining-based patent network: analytical tool for high-technology trend. *J High Technol Manag Res* 15:37–50. <https://doi.org/10.1016/j.hitech.2003.09.003>
5. Lee S, Yoon B, Park Y (2009) An approach to discovering new technology opportunities: keyword-based patent map approach. *Technovation* 29:481–497. <https://doi.org/10.1016/j.technovation.2008.10.006>
6. Murphy JT (2011) Patent-based analogy search tool for innovative concept generation. Thesis

7. Trappey AJC, Trappey CV, Wu C-Y, Lin C-W (2012) A patent quality analysis for innovative technology and product development. *Adv Eng Inform* 26:26–34. <https://doi.org/10.1016/j.aei.2011.06.005>
8. He Y, Luo J (2017) Novelty, conventionality, and value of invention. In: John S G (ed) *Design Computing and Cognition 2016*. Springer, Cham, pp 23–38
9. Simon HA (1973) The structure of Ill structured problems. *Artif Intell* 21
10. Goldschmidt G (2011) Avoiding design fixation: transformation and abstraction in mapping from source to target. *J Creat Behav* 45:92–100. <https://doi.org/10.1002/j.2162-6057.2011.tb01088.x>
11. Dong A (2017) Functional lock-in and the problem of design transformation. *Res Eng Des* 28:203–221. <https://doi.org/10.1007/s00163-016-0234-3>
12. Singh V, Skiles SM, Krager JE et al (2009) Innovations in design through transformation: a fundamental study of transformation principles. *J Mech Des* 131. <https://doi.org/10.1115/1.3125205>
13. Holyoak KJ (1984) Mental models in problem solving. In: *Tutorials in learning and memory: essays in honor of gordon bower*, pp 193–218
14. Daly SR, Christian JL, Yilmaz S et al (2012) Assessing design heuristics for idea generation in an introductory engineering course. *Int J Eng Educ* 28:463–473
15. Dym CL, Agogino AM, Eris O et al (2005) Engineering design thinking, teaching, and learning. *J Eng Educ* 94:103–120. <https://doi.org/10.1002/j.2168-9830.2005.tb00832.x>
16. Cross N (2001) Design cognition: results from protocol and other empirical studies of design activity. In: *Design knowing and learning: cognition in design education*. Elsevier, pp 79–103
17. Schön DA (1992) Designing as reflective conversation with the materials of a design situation. *Knowl-Based Syst* 5:3–14. [https://doi.org/10.1016/0950-7051\(92\)90020-G](https://doi.org/10.1016/0950-7051(92)90020-G)
18. Dong A (2007) The enactment of design through language. *Des Stud* 28:5–21. <https://doi.org/10.1016/j.destud.2006.07.001>
19. Suwa M, Purcell T, Gero J (1998) Macroscopic analysis of design processes based on a scheme for coding designers' cognitive actions. *Des Stud* 19:455–483. [https://doi.org/10.1016/S0142-694X\(98\)00016-7](https://doi.org/10.1016/S0142-694X(98)00016-7)
20. Poggenpohl S, Chayutahakij P, Jeamsinkul C (2004) Language definition and its role in developing a design discourse. *Des Stud* 25:579–605. <https://doi.org/10.1016/j.destud.2004.02.002>
21. Fu B-R, Hsu S-W, Liu C-H, Liu Y-C (2014) Statistical analysis of patent data relating to the organic Rankine cycle. *Renew Sustain Energy Rev* 39:986–994. <https://doi.org/10.1016/j.rser.2014.07.070>
22. Sorce S, Malizia A, Gentile V et al (2019) Evaluation of a visual tool for early patent infringement detection during design. In: *7th international symposium on end-user development (IS-EUD 2019)*
23. Eads D (2018) pypatent: Search and retrieve USPTO patent data
24. Shinmori A, Okumura M, Marukawa Y, Iwayama M (2003) Patent claim processing for readability. In: *Proceedings of the ACL workshop on Patent corpus processing*, vol 20, pp 56–65. <https://doi.org/10.3115/1119303.1119310>
25. Bekkers R, Bongard R, Nuvolari A (2011) An empirical study on the determinants of essential patent claims in compatibility standards. *Res Policy* 40:1001–1015. <https://doi.org/10.1016/j.respol.2011.05.004>
26. United States Patent and Trade Office (2020) Title of Invention. In: *United State Patent and Trade Office*. <https://www.uspto.gov/web/offices/pac/mpep/s606.html>. Accessed 17 Jan 2020
27. United States Patent and Trade Office (2020) The Abstract: PCT Rule 8. In: *United State Patent and Trade Office*. <https://www.uspto.gov/web/offices/pac/mpep/s1826.html>. Accessed 17 Jan 2020
28. Kasemsap K (2017) Text mining: current trends and applications. In: *Web Data Mining and the Development of Knowledge-Based Decision Support Systems*, pp 338–358. <https://doi.org/10.4018/978-1-5225-1877-8.ch017>

29. Niemann H, Moehrle MG, Frischkorn J (2017) Use of a new patent text-mining and visualization method for identifying patenting patterns over time: concept, method and test application. *Technol Forecast Soc Chang* 115:210–220. <https://doi.org/10.1016/j.techfore.2016.10.004>
30. Iordanskaja L, Kittredge R, Polguère A (1991) Lexical selection and paraphrase in a meaning-text generation model. In: Paris CL, Swartout WR, Mann WC (eds) *Natural language generation in artificial intelligence and computational linguistics*. Springer, Boston, pp 293–312
31. Mel'čuk I, Polguère A (2018) Theory and practice of lexicographic definition. *J Cogn Sci* 19:417–470. <https://doi.org/10.17791/jcs.2018.19.4.417>
32. Cumming S (1986) The lexicon in text generation. In: *Proceedings of the workshop on Strategic computing natural language - HLT 1986*. Association for Computational Linguistics, Marina del Rey, California, p 242
33. Rice DR, Zorn C (undefined/ed) Corpus-based dictionaries for sentiment analysis of specialized vocabularies. *Political Sci Res Methods* 1–16. <https://doi.org/10.1017/psrm.2019.10>
34. Riloff E, Shepherd J (1997) A Corpus-Based Approach for Building Semantic Lexicons. [arXiv:cmp-lg/9706013](https://arxiv.org/abs/cmp-lg/9706013)
35. Witherell P, Krishnamurty S, Grosse IR (2007) Ontologies for supporting engineering design optimization. *J Comput Inf Sci Eng* 7:141–150. <https://doi.org/10.1115/1.2720882>
36. Pilehchian B, Staub-French S, Nepal MP (2015) A conceptual approach to track design changes within a multi-disciplinary building information modeling environment. *Can J Civ Eng* 42:139–152. <https://doi.org/10.1139/cjce-2014-0078>
37. Riloff E, Shepherd J (1997) A Corpus-Based Approach for Building Semantic Lexicons 8
38. Khalaj J, Pedgley O (2019) A semantic discontinuity detection (SDD) method for comparing designers' product expressions with users' product impressions. *Design Stud* 62:36–67. <https://doi.org/10.1016/j.destud.2019.02.002>