Design Science

Natural language processing in-and-for design research

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Abstract

We review the scholarly contributions that utilise natural language processing (NLP) techniques to support the design process. Using a heuristic approach, we gathered 223 articles that are published in 32 journals within the period 1991–present. We present state-of-the-art NLP in-and-for design research by reviewing these articles according to the type of natural language text sources: internal reports, design concepts, discourse transcripts, technical publications, consumer opinions and others. Upon summarising and identifying the gaps in these contributions, we utilise an existing design innovation framework to identify the applications that are currently being supported by NLP. We then propose a few methodological and theoretical directions for future NLP in-and-for design research.

Key words: Natural Language Processing, Design Language, Ontology, Text Processing, Knowledge Base

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1. Introduction

Several natural language schemes such as ontologies (Li and Ramani 2007), controlled natural language descriptions (Chakrabarti *et al.* 2005), documentation templates (Lee *et al.* 2013), argumentation approaches (Eng, Aurisicchio, and Bracewell 2017), artefact representations (Sasajima *et al.* 1996), process models (Gero and Kannengiesser 2012) and function structures (Gericke and Eisenbart 2017) have been adopted in design research to envisage, encode, evaluate and enhance the design process. While these schemes have significantly impacted the development of several knowledge-based applications in design research and practise, it was not until the development of computational (e.g., graphical processing units (GPUs), cloud computing services) and methodological (e.g., NLTK,[1] WordNet[2]) infrastructures that these schemes were popularly utilised to process unstructured natural language text data and extract design knowledge from these. These infrastructures have led to the evolution of what is currently understood and recognised as a family of natural language processing (NLP) techniques.

A typical NLP methodology converts a text into a set of tokens such as meaningful terms, phrases and sentences that are often embedded as vectors for

[1]Natural Language Toolkit, https://www.nltk.org/.
[2]http://wordnetweb.princeton.edu/perl/webwn.

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applying these to standard NLP tasks such as similarity measurement, topic extraction, clustering, classification, entity recognition, relation extraction and sentiment analysis. These tasks primarily rely upon prescriptive language tools (e.g., Stanford Dependency Parser[3]), lexicon (e.g., ANEW[4]) and descriptive language models (e.g., BERT[5]).

The ability of NLP methodologies to process unstructured text opens several opportunities such as topic discovery (Liang *et al.* 2018), ontology extraction (Bouhana *et al.* 2015), document structuring (Morkos, Mathieson, and Summers 2014), search summarisation (Noh, Jo, and Lee 2015), keyword recommendation (Zhang *et al.* 2017) and text generation (Souza, Meireles, and Almeida 2021), which enable design scholars and practitioners to support knowledge reuse (Li *et al.* 2021a), needs elicitation (Lin, Chi, and Hsieh 2012), biomimicry (Shu 2010; Selcuk and Avinc 2021) and emotion-driven design (Dong *et al.* 2021) in the design process. NLP has therefore become an imperative strand of design research, where the scholars have extensively proposed NLP-based tools, frameworks and methodologies that are aimed to assist the participants in the design process, who otherwise often rely upon organisational history and personal knowledge to make important decisions, for example, choosing a lubricant for shaft interface.

In this article, we review scholarly contributions that have applied as well as developed NLP techniques to process unstructured natural language text and thereby support the design process. Several motivations (as follows) have led to the effort of reviewing such contributions.

(i) To identify the methodological advancements that are necessary to bolster the performances of future NLP applications in-and-for design. For instance, the performances of parts-of-speech (POS) tagger and named entity recognition (NER) require significant improvement to process design documents. We have listed various possibilities of such methodological directions in Section 4.2.

(ii) To enhance theoretical understanding of the nature and role of natural language text in the design process. For example, it is still unclear as to which elements of design knowledge are necessary to be present in an artefact description so that it qualifies as adequate. We have asked several open questions along with necessary discussion to highlight such theoretical directions in Section 4.3.

(iii) To summarise a large body of NLP contributions into a single source. A variety of NLP applications to the design process are reported in journals outside the agreed scope of design research. Reviewing and summarising such contributions in this article could therefore be of importance. We have reviewed the contributions according to the type of text source in Section 3.

(iv) To create an NLP guide for developing applications to support the design process. For example, design methods like creating activity diagrams could be significantly benefited by NLP methodologies. We have indicated such cases in Section 4.1 using a design innovation process framework.

[3]http://nlp.stanford.edu:8080/parser/.

[4]Affective Norms for English Words, https://pdodds.w3.uvm.edu/teaching/courses/2009-08UVM-300/docs/others/everything/bradley1999a.pdf.

[5]Bi-directional Encoder Representations from Transformers, https://github.com/google-research/bert.

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In line with the motivations described above, we adopt a heuristic approach (Section 2 and Appendix A) to retrieve 223 articles encompassing 32 academic journals. We review these articles in Section 3 according to the types of text sources and discuss these in Section 4 regarding applications and future directions.

2. Methodology

To retrieve the articles for our review, we use the Web of Science[6] portal, where we heuristically search the titles, abstracts and topics using a tentative set of keywords within design journals. Upon carrying out a frequency-based analysis of the preliminary results, we expand the keyword list as well as the set of design journals. We further expand our search to all journals that include NLP contributions to the design process. We then apply several filters and manually read through the titles, abstracts and full texts of a selected number of articles. In the end, we obtain 223 articles that we review in our work. We detail the search process in Appendix A. We have also uploaded the bibliometric data for all these articles on GitHub.[7]

As shown in Table 1, the final set of papers is distributed across 32 journals. We have strategically chosen these journals such that these are primarily design-oriented and secondarily focused on general computer applications (e.g., Computers in Industry), artificial intelligence (e.g., Expert Systems with Applications) and technology related (e.g., World Patent Information). In addition, we have also included journals that focus on general design aspects such as ergonomics, requirements and safety.

As shown in the year-wise plot (Figure 1), there has been a steady increase in the number of contributions, which could be mainly due to the evolution of computational and methodological infrastructures.[8] While the contributions from the 1990s have been theoretically influential, the peak in the mid-2000s could be attributed to the popularity of biomimicry (Goel and Bhatta 2004), ontologies (Romanowski and Nagi 2004), functional modelling (Bohm, Stone, and Szykman 2005) and functional representation (Chandrasekaran 2005). Besides the year-wise plot, we report the 30 most frequent keywords as a word cloud in Figure 2, where we discard the generic keywords such as ‘design’ and ‘system’.

3. Review

In this section, we review the 223 articles[9] thus selected using the methodology as described in Section 2 and Appendix A. To present the articles that we have reviewed, we considered the following categorisation schemes: 1) the types of natural language text data (e.g., internal reports, technical publications), 2) the types of NLP tasks (e.g., clustering, classification) and 3) the applications in the

[6]https://mjl.clarivate.com/search-results.

[7]https://github.com/siddharthl93/nlp_review/blob/4b9e6b378c8df0bbf61a36e466a50dbb5a0a65d2/nlp_review_papers.csv.

[8]By infrastructures, we mean the following: (a) commercial access to high-end computing systems via services like Amazon, Google Cloud etc., (b) open sources Application Programming Interfaces (APIs) provided by several data sources like YouTube, PatentsView etc., (c) the accessibility to open sources codes and algorithms via online communities like HuggingFace.

[9]Wherever applicable, we also review the supporting and relevant articles alongside the selected 223 articles.

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Table 1. Article count w.r.t. journals

No.	Journal Name	Count
1	*Journal of Mechanical Design*[a]	34
2	*Advanced Engineering Informatics*	24
3	*Artificial Intelligence for Engineering Design Analysis and Manufacturing*[a]	24
4	*Journal of Computing and Information Science in Engineering*[a]	19
5	*Expert Systems with Applications*	16
6	*Computers in Industry*	16
7	*Journal of Engineering Design*[a]	15
8	*Research in Engineering Design*[a]	15
9	*Design Studies*[a]	7
10	*Engineering Applications of Artificial Intelligence*	7
11	*Knowledge-Based Systems*	6
12	*Scientometrics*	5
13	*Requirements Engineering*	3
14	*Design Science*[a]	3
15	*Design Journal*[a]	2
16	*Journal of Computational Design and Engineering*	2
17	*Concurrent Engineering-Research and Applications*	2
18	*Decision Support Systems*	2
19	*Codesign-International Journal of Cocreation in Design and the Arts*[a]	2
20	*International Journal of Design Creativity and Innovation*[a]	2
21	*Applied Ergonomics*	2
22	*International Journal of Interactive Design and Manufacturing*	2
23	*Engineering with Computers*	2
24	*Ergonomics*	2
25	*Word Patent Information*	2
26	*Computer-Aided Design*[a]	1
27	*Applied Artificial Intelligence*	1
28	*International Journal of Design*[a]	1
29	*International Journal of Technology and Design Education*	1
30	*Technovation*	1
31	*Reliability Engineering and System Safety*	1
32	*Artificial Intelligence in Engineering*	1

[a]Indicates the journals that we initially considered as those that fall within the scope of design.

design process (e.g., brainstorming, problem formulation). Among these schemes, we adopt the types of text data because an NLP-based contribution is often associated with one text source data but combines a variety of NLP tasks and could be applied across different phases of the design process.

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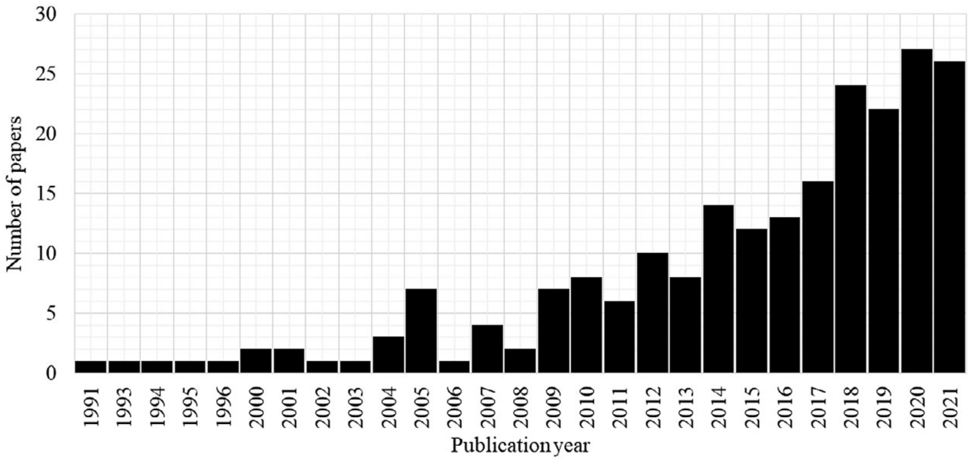

Figure 1. Article count w.r.t. the publication year. The data point at 2021 is applicable only until 19th September 2021.

Figure 2. Top 30 keywords w.r.t. frequency.

As shown in Figure 3, we map the categories of our scheme onto different phases of the design process as given in the model of the UK Design Business Council.[10] Among the types of text data sources as explained below, consumer opinions and technical publications are utilised in the design process, whereas the rest are generated in the design process.

[10]We chose the double diamond model for representing the design process because of its diversity across different streams of design research. If we were to utilise comprehensive, yet specific models, e.g., Pahl and Beitz (2013) that was utilised by Chiarello, Belingheriand Fantoni (2021), it is difficult to choose between embodiment and detailed design phases for categorising articles.

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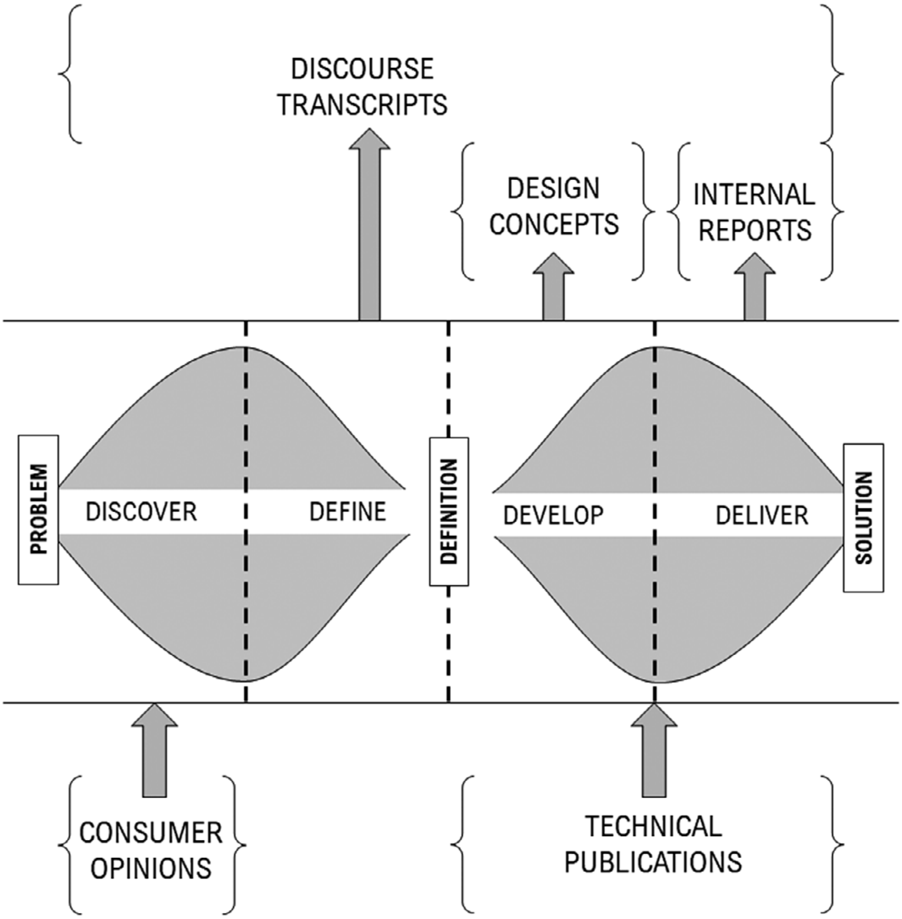

Figure 3. Indication of natural language text data sources related to the design process, following the design process model from the UK Design Business Council.

- The **internal reports** are usually generated in the *deliver* phase of the design process, where the concepts are embodied and detailed into prototypes. These sources of natural language text often include the knowledge of failures, situations, logs, instructions, etc.
- The **design concepts** are generated during the *develop* phase, when the designers search, retrieve, associate and select concepts using various supports. The NLP contributions that we review under this category not only involve processing design concepts but also problem statements, keywords, supporting databases (e.g., AskNature), etc.
- The **discourse transcripts** constitute the recorded communication such as speech transcripts and emails that are obtained from organisational data or think-aloud experiments. These sources need not capture the communication that is pertinent to a particular phase but the design process as a whole.
- The **technical publications** that constitute patents, scientific articles and textbooks are considered external sources that are often utilised in the *develop* and

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deliver phases of the design process. Owing to the quality and quantity of text, these sources are best suited for the application of NLP tasks.
- The **consumer opinions** are external sources that are available in the form of product reviews and social media posts. These sources are predominantly utilised in the *discover* phase of the design process when the designers understand the usage scenarios and extract user needs.
- We categorise the miscellaneous contributions as '**other sources**' that are not indicated in Figure 3.

3.1. Internal reports

Internal reports constitute over 80% of the knowledge in the industry (Ur-Rahman and Harding 2012) and are often present as product specifications, design rationale, design reports, drawing notes and logbooks (Li *et al.* 2014). Although conventional NLP methodologies like building classifiers (Sexton and Fuge 2020) using internal reports are a recent phenomenon in design research, scholars have attempted to process internal reports and discover ontologies (Cavazza and Zweigenbaum 1994), since the early 90s.

Requirement extraction

Scholars initially aimed to extract design requirements as meaningful terms, phrases and segments from internal reports to reuse these in the design process. Such requirements shall also be derived from the past cases of failure in which violated constraints were recorded (Siddharth, Chakrabarti, and Ranganath 2019a). As mentioned below, scholars initially encountered some challenges while extracting design requirements from internal reports.

Kott and Peasant (1995, p. 94) observe that requirements in internal reports are incomplete, ambiguous, include inconsistent rationale and denote a wrong purpose. To mitigate some of these issues, they provide an example (1995, p. 103) as shown below to illustrate how lengthy requirements could be decomposed into short sentences.

> The Loader shall provide the capability of handling HCU6/E pallets, ISO 40-foot containers, and Type V airdrop platforms. Loader shall be able to move forward with speed of at least 5 mph, the goal being 7 mph. An on-board maintenance diagnostic system shall be provided.
>
> The Loader shall be able to perform the Loading function. The Load Type of the Loading function shall be any of: HCU6/E pallets, ISO 40-foot containers, and Type V airdrop platforms. The Loader shall be able to perform function Move Forward. The speed of Move Forward shall be at least 5 mph, the goal being 7 mph. The Loader shall include an On-Board Maintenance Diagnostic System.

Farley (2001, pp. 296, 299) identifies that airtime faults (also called 'snags') include abbreviations (e.g., CHKD – checked, S0V – serviceable), acronyms, spelling errors (e.g., VLVE) and plural terms. While differing in structure and semantics (Kim, Bracewell, and Wallace 2007, p. 155), internal reports also include noisy terms (Menon, Tong, and Sathiyakeerthi 2005, p. 179), 'plastic' terms (e.g., 'progress', 'planning') and implicit phrases (e.g., 'insufficient performance') (Lough *et al.*

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2009, p. 62). Kim, Bracewell, and Wallace (2007, p. 162) suggest that acronyms ('CNC') and abbreviations ('chkd') shall be recognised in text using ontologies. To reduce ambiguity, Madhusudanan, Chakrabarti, and Gurumoorthy (2016, p. 451) suggest that the anaphora ('those') shall be replaced with the corresponding entity in the previous sentence.

When co-ordination ambiguity exists in a sentence, for example, 'slot widths and radii should conform to those of cutters' (Kang *et al.* 2019b, p. 2), it is unclear if the term 'slot' modifies 'widths' or 'radii'. Here, Kang *et al.* (2019b, pp. 6, 7) suggest checking if the corresponding domain ontology includes ('slot', 'hasProperty', 'radii'). To extract meaningful segments that are devoid of ambiguities, Madhusudanan, Chakrabarti, and Gurumoorthy (2016, p. 452) measure coherence between sentences by integrating and extending WordNet-based similarity measures. To extract segments within a sentence, for example, '*sharp corners should be avoided* because they interfere with the metal flow', Kang *et al.* (2019a, p. 294) extract the *italicised* portion using domain concepts (e.g., corner) and attributes (e.g., isSharp). They also discard the unwanted portion using some rules (2019a, p. 295), for exasmple, the subordinate clause that occurs after a marker shall be discarded, except for 'if' or 'unless'.

Ontology construction

To represent design rationale,[11] scholars have proposed a variety of prescriptive-generic ontologies (Ebrahimipour, Rezaie, and Shokravi 2010; Liu *et al.* 2010; Zhang *et al.* 2013; Aurisicchio, Bracewell, and Hooey 2016; Siddharth, Chakrabarti, and Ranganath 2019a) that build upon the fundamental idea of entity-relationship models (Taleb-Bendiab *et al.* 1993). While generic ontologies are capable of capturing rationale from a variety of domains, the performances of these in terms of knowledge retrieval are expected to be low due to the level of abstraction. For example, a list of generic terms that represent 'issue' (Liu *et al.* 2010, p. 4) may not retrieve phrases that inherently or intricately communicate a design issue.

Domain-specific ontologies like QuenchML (Varde, Maniruzzaman, and Sisson 2013) and Kodak Cover (Nanda *et al.* 2007) overcome the limitations of generic ontologies while also being evolvable (Poggenpohl, Chayutsahakij, and Jeamsinkul 2004), machine-readable (Biswas *et al.* 2008; Fenves *et al.* 2008) and semantically interoperable (Ding, Davies, and McMahon 2009). Scholars have therefore attempted to extract domain-specific ontologies from domain text sources.

Among domain-specific ontologies, Kim, Bracewell, and Wallace (2007, p. 160) identify the following categories of relationships from aircraft engine repair notes: background, cause-effect, condition and contrast. Lough *et al.* (2009, p. 33) understand from 117 risk statements that these are indicators of failure modes, performance, design and noise parameters. Using oil platform accident reports, Garcia, Ferraz, and Vivacqua (2009, pp. 430, 431) propose that concept relationships could be generalised as Is-a, Part-Of, Is-an-attribute-of, Causes, Time-Follows, Space-Follows and more. Hsiao *et al.* (2016, p. 147) populate 822 actions contained in 185 risk reports and identify that action could carry the attributes

[11]Design rationale that is mentioned here refers to the previously recorded decisions and underlying reasons that are pertinent to past design issues.

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'purpose' and 'embodiment', which are further categorised as 'Approval', 'Gather_data', 'Coordinate' and 'Request' (Hsiao *et al.* 2016, p. 158).

Scholars have built ontologies by associating technical terms and segments using various similarity measures. Hiekata, Yamato, and Tsujimoto (2010) use an existing ontology to associate word segments (component and malfunction) from 9604 shipyard surveyor reports. Lee *et al.* (2013) mine the task data from shipbuilding transportation logs and cluster these using a variety of distances (e.g., Jaccard, Euclidean). Kang and Tucker (2016) extract functions as topic vectors from 16 module descriptions (Pimmler and Eppinger 1994) of an automotive control system. They propose that the cosine similarity between a pair of topic-vectors (function) quantifies the functional interaction between corresponding modules. Song *et al.* (2017, pp. 265–269) construct a semantic network using iPhone Apps Plus[12] text data that includes 697 service documents indicating 66 feature elements and 95 feature keywords.

Arnarsson *et al.* (2021) use latent dirichlet allocation (LDA) to cluster the Doc2Vec-based embeddings of over 8000 Engineering Change Requests (ECRs) in a commercial vehicle manufacturer. Yang *et al.* (2018) construct an ontology using 114,793 problem-solution records within preassembly reports inside an automotive manufacturer. They use the ontology to process (e.g., identify n-grams), structure and represent new text data in various forms (2018, p. 214) to facilitate the design and managerial decisions. Xu *et al.* (2020) obtain the text data of 1844 problems and 1927 short-term remedies from a vehicle manufacturer. To link the problems and remedies, they transform the text using term frequency – inverse document frequency (TD-IDF) and perform K-means clustering for problems and short-term remedies, while also linking the clusters.

Design knowledge retrieval

While 'knowledge retrieval' could assume a broad meaning across different areas of research and practise, we mention this in reference to the methods that 'retrieve' terms, phrases and segments that include components, issues, constraints and interactions. The outputs of such retrieval methods shall be considered as 'design knowledge' if it is possible to re-represent these as <entity, relationship, entity> triples that form constituents of an artefact that is relevant to the design process.

For example, a segment extracted from a transistor patent (Saeroonter *et al.* 2021, p. 8) – 'an insulating material is deposited on the whole surface of the substrate having the first semiconductor layer' shall be encoded into triples such as <insulating material, is deposited, whole surface>, <whole surface, of, substrate> and < substrate, having, first semi-conducted layer> that form the constituents of the patent that shall be utilised as knowledge aid in the design process. To extract such relevant terms, phrases and segments, the scholars have adopted a couple of directions. First, using an ontology that shares the same domain as target text data so that relevant portions of the text are identified. Second, indexing the unstructured text data using a classification algorithm so that the search is restricted to the relevant portions.

To assist with case-based reasoning, Guo, Peng, and Hu (2013) build a domain ontology using 1000 injection moulding cases that were encountered in a

[12] http://www.iphoneappsplus.com/.

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Shenzhen-based company. They demonstrate using an Information-Content (IC) based similarity measure as to how the ontology aids in knowledge retrieval. For case-based retrieval, Akmal, Shih, and Batres (2014) compare a variety of ontology-based similarity measures (e.g., Tversky's Index, Dice's Co-efficient) against numeric similarity measures (e.g., Wu-Palmer, Lin) to observe that the former deviated less from expert's similarity scores. To retrieve CAD models using text inputs, Jeon *et al.* (2016) demonstrate how ontologies could be used as intermediaries. To assist CAD designers with design rule recommendations, Huet *et al.* (2021) create a knowledge graph around a design rule using relationships such as 'has keyword' (semantic context), 'has material' (engineering context) and 'has employee' (social context).

To relate phenomena and failure modes, Wang *et al.* (2010) extract a light-weight ontology from 400 aviation engine failure analysis reports and utilise the ontology to represent phenomena and failure modes as attribute-value vectors. They (2010, pp. 270, 271) then map the phenomena and failure mode vectors using an artificial neural network. To extract candidate components and responsibilities from the design rationale text, Casamayor, Godoy, and Campo (2012) obtain sentences from IBM supported rationale suite[13] and the UNICEN university repository.[14] Upon classifying the sentences as functional or nonfunctional using a semi-supervised approach, they extract verb phrases as candidate responsibilities and group these using the hierarchical clustering method to identify candidate components.

To understand the coupling between design requirements, Morkos, Mathieson, and Summers (2014, p. 142) construct a bipartite network of terms and 374 requirements obtained from Toho (160) and Pierburg (214) manufacturing projects. They label a portion of these terms as 'useful' or 'not useful' and vectorise these using the network properties (29 features) and string length (1 feature). They train a neural network using the labelled dataset to classify the rest of the terms. Using the set of terms that are classified as 'useful', they reconstruct the bipartite network and retrain the classifier until the length of the list of terms is saturated (Morkos, Mathieson, and Summers 2014, p. 149).

To classify and index airtime faults, Tanguy *et al.* (2016) train a support vector machines (SVM) classifier on 136,861 labelled documents that were obtained from the French Aviation Regulator – DGAC. To classify the causes of automotive issues, Xu, Dang, and Munro (2018) obtain titles and descriptions of 2420 issues from a Chinese automotive manufacturer. They retrieve *cause-related* phrases using a domain ontology and label these with the categories of the Fishbone diagram – Man, Machine, Material, Method and Environment. They use the labelled dataset to train a binary-tree-based SVM classifier.

To identify computer-supported collaborative technologies, Brisco, Whitfield, and Grierson (2020, p. 65) obtain Global Design Project text data from 104 students and classify the sentences into requirements, technologies and technology functionalities using RapidMinerStudio.[15] Lester, Guerrero, and Burge (2020,

[13] http://www-01.ibm.com/software/rational/.
[14] http://isistan.exa.unicen.edu.ar.
[15] https://rapidminer.com/products/studio/.

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pp. 133–135) classify the chrome bug reports[16] into requirements, decisions and alternatives using the Naïve Bayes algorithm to find that features selected using optimisation approaches (e.g., Ant colony) result in higher F-1 measure compared to document characteristics (e.g., TF-IDF).

To index manufacturing rules, Ye and Lu (2020) train a feedforward neural network with two hidden layers (128 and 32 neurons) using the embeddings of manufacturing rules and eight category labels. Song *et al.* (2020) train a Bi-directional LSTM using 350 building regulation sentences to extract predicates and arguments. For example, in a design rule – 'The roof height of the building must be 15 meters or less,' the predicate is 'be less' and the arguments are 'roof height', 'building'and '15 meters.' To automatically extract design requirements, Fantoni *et al.* (2021) process tender documents of Hitachi Railway using a variety of ontologies and classify a sentence as a requirement if it includes certain keywords.

Summary

We summarise the NLP methodologies applied to internal reports in Table 2 according to data, methods, and supporting materials. We indicate the future possibilities of these in bold font. We use the same table format to summarise the literature review for the remaining types of data sources as well. Internal reports mainly include issues and remedies that are pertinent to a specific organisation or a domain. Scholars have used a variety of internal reports to process, extract ontologies, and classify sentences. They have also demonstrated how ontologies are used for effective knowledge retrieval.

We can observe from the data column of Table 2 that internal reports have been utilised from a variety of domains: Aerospace, Shipbuilding and Automotive. Surprisingly, none of the methodologies has utilised data sources from the most popular 'silicon-based streams such as Integrated Circuits, Software Architecture and Data Structures. While discussion platforms like Stack Overflow and Reddit may not be classified as those included within internal reports, they include the knowledge of issues and solutions that are found both in the industry and academia.

Upon training nearly 0.8 million labelled patent documents for a classification task, Jiang *et al.* (2022) observe that the accuracy tends to be higher when the input feature vectors integrate text, image and meta information of the document compared to only-text and only-image feature vectors. Hence, the analysis of mere text in *multimodal* documents like transportation logs (Lee *et al.* 2013) may not reflect the entire design knowledge that is being communicated in these.

As understood from the list of data sources, the *accessibility* to internal reports is highly restricted. Although analyses of internal reports have a high probability of extracting design knowledge, these sources are also characterised by low *information content*, for example, 350 building regulation sentences (Song *et al.* 2020). While this caveat limits the performances of classifiers, the ontologies extracted from these also may not be comprehensive. Hence, it is necessary to aggregate various internal reports from a domain into a single source of natural language text,

[16]Bugs reported on Chrome web browser from the Mining Software Repositories Mining Challenge, http://2011.msrconf.org/msrchallenge.html.

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Table 2. Summary of NLP methodologies and future possibilities (bolded) with internal reports

	Data	Methods	Supporting Materials
Requirement extraction	Airtime faults (snags), manufacturing rules, aircraft assembly documents ***Technical discussion platforms*: Stack Overflow, Reddit**	*Text segmentation*: manual, rule-based approach, semantic similarity (e.g., Lin) *Ambiguity resolution*: ontology-based approach, rule-based approach *Term identification*: ontology-based approach	*Lexicon*: WordNet, **Generic Technical Lexicon** *Ontologies*: Manufacturing
Ontology construction	Aircraft engine repair notes, oil platform accident reports, shipyard surveyor reports, shipbuilding transportation logs, automotive control system descriptions, iphone service documents, vehicle engineering change requests, automotive preassembly reports, vehicle manufacturing problems ***Other streams*: integrated-circuit design, software interface design, algorithm design, virtual spaces**	*Embedding*: Doc2Vec, TF-IDF transformation, **domain-specific language model** *Similarity Measurement*: cosine, semantic similarity measures (e.g., Wu-Palmer) *Clustering*: distance-based (e.g., Jaccard) method, K-means *Topic extraction*: latent dirichlet allocation (LDA) ***Named entity recognition*: domain-specific language model**	*Lexicon*: WordNet, **generic technical lexicon** *Ontologies*: QuenchML, Kodak family, Shipyard, automotive
Design knowledge retrieval	CAD rules, aviation engine failures, rationale suite (IBM), UNICEN repository, Toho project, Pierburg Project, DGAC airtime	*Embedding*: Attribute-value (using ontology), bipartite network properties, Word2Vec, **domain-specific language model**	*Ontologies*: injection moulding, aviation engine, automotive, railway, building

Table 2. Continued

	Data	Methods	Supporting Materials
	faults, automotive manufacturing issues, global design project, chrome bug reports, building regulation sentences, Hitachi railway tender documents	*Similarity Measurement:* information-content based measures, ontology-based measures (e.g., Tversky's Index) *Feature Selection*: TF-IDF, mutual information, information gain, ant colony optimisation, genetic algorithms, **domain-specific language model, sentence embedding models (Doc2Vec)** *Clustering*: hierarchical clustering *Classification*: artificial neural network (ANN), rule-based approach, feedforward neural network, support vector machines (SVM), binary-tree-based SVM, rapid miner, Naïve Bayes, bi-directional LSTM	

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for example, NASA Memorandum on Space Mechanisms – lessons learned (Shapiro *et al.* 1995).

As far as the methods are concerned, although scholars have applied several state-of-the-art methods to perform NLP tasks such as classification and clustering, they are yet to utilise language models like BERT. While such language models are expected to perform poorly on domain documents (Fantoni *et al.* 2021), it would be significantly useful to develop domain-specific language models, for example, BioBERT (Lee *et al.* 2020). These models shall be useful for obtaining embeddings and subsequent tasks such as Named Entity Recognition and Text Classification. Apart from the cost and resource limitations, training these language models also requires high amounts of text data that does not seem currently feasible with internal reports.

Term identification is a fundamental NLP problem that has not been given enough attention by design scholars apart from those that have utilised internal reports. The terms like 'roller bearing' reduce the ambiguity caused by individual words 'roller' and 'bearing'. Since meaningful terms are made of two or more words (Tseng, Lin, and Lin 2007; Fantoni *et al.* 2013), it is critically important to identify these before applying higher-level NLP tasks. Scholars have resorted to ontology-based approaches to identify these terms (Yang *et al.* 2018; Fantoni *et al.* 2021). While ontology-based approaches are recommended over common-sense lexicon (e.g., WordNet), it is necessary to rely on domain-specific language models and generic- design- and technical-oriented lexicon to identify general terms (e.g., rough surface). Although such supports are hard to build, there has been recent progress in the literature that adopts patent databases to develop a generic lexicon (Sarica, Luo, and Wood 2020; Jang, Jeong, and Yoon 2021).

Term disambiguation is another fundamental NLP problem, for example, the terms such as 'cathodic protection anode bed', 'deep anode well' and 'deep ground bed' are often used to refer to 'cathodic protection well' (Xu and Cai 2021, p. 5). Since the ambiguity posed by these terms concerns the underlying meaning, the approach to resolve this issue should concern the measurement of semantic similarities among these terms. Gu *et al.* (2005, p. 108) resolve semantic conflicts between similar sentences, for example, 'I will buy a bike' and 'I will buy a bicycle' using a WordNet-based ontology – FloDL. Such a type of semantic conflict resolution is hardly relevant to industrial applications. While usage of a common-sense lexicon like WordNet is not recommended for such tasks, it is necessary to obtain true embeddings of these terms using domain-specific language models so that cosine similarity reflects 'nearly' actual similarity.

3.2. Design concepts

Often associated with the *develop* phase of the design process (as indicated in Figure 3), design concepts are generated through search, retrieval, association and selection. The NLP methodologies applied to these stages need not use only concept descriptions as primary text sources but also the problems, keywords, source of stimuli, etc.

Concept search

To formulate a comprehensive set of keywords to search for concepts, researchers have sought WordNet for identifying troponyms ('prevent' → 'inhibit') (Cheong

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et al. 2011, p. 3; Linsey, Markman, and Wood 2012, pp. 3, 4), bridge verbs (Chiu and Shu 2007, p. 50), semantically distant verbs (Chiu and Shu 2012, pp. 272, 291) and morphological nouns (Lee, Mcadams, and Morris 2017, p. 5). Chakrabarti *et al.* (2005, pp. 119–121) provide a systematic approach to searching and retrieving biological stimuli based on the SAPPhIRE[17] model. In the Action construct of the SAPPhIRE model, for instance, they propose that the search could be a combination of verb, noun and adjective. Rosa, Cascini, and Baldussu (2015) build upon the approach of Chakrabarti *et al.* (2005) by combining SAPPhIRE and Function-Behaviour-Structure to form a unified ontology for biomimicry.

To effectively search for concepts of biological species, Rosa *et al.* (2011) develop a structured database of these and group these using high-level functions that are represented using <verb, noun, predicate> where the predicate is represented as <preposition, noun>. Vandevenne *et al.* (2015, pp. 21, 22) use the k-nearest neighbours (k-NN) algorithm to index the AskNature[18] database by classifying 1531 unique analogical transfer strategies into the following levels (2015, p. 25): group (e.g., move or stay put, modify), subgroup (e.g., attach, adapt) and function (e.g., temperature, compression). Chen *et al.* (2021) examine 20 AskNature pages to extract meaningful keywords and structure–function knowledge using, respectively, TF-IDF values and selected dependency patterns.

The above-stated contributions aim to enhance the concept search w.r.t. the biological domain. We also review some approaches that sought other domains. To improve the quality of concepts generated by architects (Segers, de Vries, and Achten 2005), De Vries *et al.* (2005) integrate WordNet-based word graphs and a sketching canvas. To assist novice designers to form domain-specific keywords, Lin, Chi, and Hsieh (2012, p. 356) map user needs and domain concepts through the so-called 'OntoPassages' that were extracted using a domain ontology, which was built using 111 documents belonging to the National Center for Research on Earthquake Engineering, Taiwan.

To recommend a suitable design method for a problem description, Fuge, Peters, and Agogino (2014) obtain 886 case study descriptions and method labels from human-centred design (HCD) Connect. They use latent semantic analysis (LSA) to obtain the vectors of the descriptions and train the following classifiers using the labelled dataset: Random Forest, SVM, Logistic Regression and Naïve Bayes. To enhance problem definition, Chen and Krishnamurthy (2020) facilitate human-AI collaboration in completing problem formulation mind maps with the help of ConceptNet and the underlying relationships.

Concept retrieval

The contributions in this section are primarily retrieval systems that are built under the assumption that the problem is well defined, and the search keywords are known beforehand. Chou (2014) and Yan *et al.* (2014) adopt the Su-field problem modelling approach to systematically obtain ideas through TRIZ and manually evaluate these using a fuzzy-linguistic scale. Kim and Lee (2017) integrate various design-by-analogy approaches into an interface called Bionic MIR that allows retrieval of biological systems based on physical, biological and ecological relations.

[17] SAPPhIRE is a model of causality that comprises the following constructs: States, Actions, Parts, Phenomena, Inputs, oRgans and Effects.

[18] https://asknature.org/.

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In a tool named Retriever, for a search keyword (e.g., chair) and a relation (e.g., 'is used for') from ConceptNet[19] categories, Han *et al.* (2018a, pp. 467–469) retrieve three re-representations (e.g., chair, bench, sofa) and corresponding entities (e.g., leading a meeting, growing plants, reading a book) that are connected by the selected relation. In another tool named Combinator, for the same inputs, Han *et al.* (2018b, p. 12/34) retrieve the related entity (noun, verb, adjective) and concatenate it with the search keyword, for example, 'Handbag' → 'Origami Handbag'.

To support the rapid retrieval of concepts, Goucher-Lambert *et al.* (2020) employ LSA on a design corpus to identify a near or far concept from the current concept. They then provide the concept thus identified from the corpus as a stimulus to the designers for generating more concepts. To demonstrate retrieval of concepts using the C-K theory (Hatchuel, Weil, and Le Masson 2013), Li *et al.* (2020) extract a healthcare knowledge graph by mining SVO tripes of the form: $\underbrace{NP_{sub}}_{amod} \xrightarrow{nsubj} \underbrace{VP}_{advmod} \xrightarrow{dobj} \underbrace{NP_{obj}}_{amod}$ from 18,000 Chinese websites. They also populate an FBS-based 'nursing bed' knowledge graph using experts.

Concept association

Once the concepts are generated using the search and retrieval methods, it is necessary to group similar concepts, especially when a large number of concepts are crowdsourced. In this section, we review NLP contributions that associate concepts predominantly using graph-based approaches. Zhang *et al.* (2017, p. 2) group 930 concepts (described as paragraphs) that were obtained from a human-centred design course[20] using Word2Vec and the hierarchical clustering algorithm. Ahmed and Fuge (2018, p. 11,12/30) measure topic level association for 3918 ideas that were submitted to OpenIDEO[21] using a Topic Bison Measure, which indicates if a topic pair co-occurs in an idea as well as the proportions of the pair.

To examine the effectiveness of crowdsourced stimuli, Goucher-Lambert and Cagan (2019) crowdsource concepts as three nouns and three verbs for 12 design problems and categorise these as near, far and medium stimuli based on the frequency and WordNet-based path similarity. He *et al.* (2019) crowdsource text descriptions of thousands of ideas to future transportation systems via Amazon Mechanical Turk. They (2019, pp. 3, 4) form a coword network of these ideas and use MINRES[22] to extract core ideas from the network. Liu *et al.* (2020, p. 6) summarise 1757 scientific articles (solutions to a transmission problem) by building Word2Vec-based semantic networks around the central keywords – {transmission, line, location, measurement, sensor and wave}. Camburn *et al.* (2020a, 2020b) utilise HDBSCAN[23] for clustering crowdsourced concepts and TextRazor[24] for extracting entities and topics from these.

[19] https://conceptnet.io/.
[20] Taught at the University of California, Berkeley.
[21] https://www.openideo.com/.
[22] https://web.stanford.edu/group/SOL/software/minres/.
[23] https://hdbscan.readthedocs.io/en/latest/how_hdbscan_works.html.
[24] https://www.textrazor.com/.

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Concept selection

In this section, we review the contributions that have utilised NLP supports to evaluate and select concepts. These concepts primarily aim to measure one or more success metrics (e.g., novelty). Delin *et al.* (2007, pp. 125–129) use bipolar adjectives obtained from the British National Corpus (BNC) to rate concepts. Strug and Slusarczyk (2009) evaluate floor plan concepts using the frequently occurring patterns in the hypergraph representations of past floor plans. To understand the concept selection phenomenon, Dong *et al.* (2014) model the change of linguistic preferences using the Markov Process and calculate the transition probabilities. To calculate creativity, Gosnell and Miller (2015, pp. 4–6) tie 27 concepts with some adjectives and match these against the terms – 'innovation' and 'feasibility' using DISCO.[25]

Chang and Chen (2015) obtain 108 ideas for future personal computers from DesignBoom[26] and mine the idea-related information using RapidMiner. They apply K-means clustering to group the ideas and Analytic Hierarchy Comparison to evaluate these. Siddharth, Madhusudanan, and Chakrabarti (2019b, pp. 3–5) measure the novelty of a concept by comparing it against all entries in a reference product database across SAPPhIRE constructs and using a WordNet-based similarity. To examine the success of ideas that were submitted to Kickstarter – a crowdfunding platform, Lee and Sohn (2019) shortlist 595 ideas in the Software-Technology category. They apply LDA to extract the most important 50 topics from the text descriptions of these ideas. Using the 50 topics and the funding received by the ideas, they conduct a conjoint analysis to examine the contribution of a topic to the success of an idea (2019, pp. 107, 108).

Summary

As we have summarised in Table 3, the NLP contributions that are pertinent to design concepts assist concept search, retrieval, association and selection. Scholars have utilised a variety of knowledge bases to search and retrieve concepts, while also recommending novel ways to expand search keywords. Since crowdsourcing concepts have recently emerged as an alternative to traditional laboratory-based design studies, scholars have therefore found the need to associate and group the concepts for assessing these. The NLP applications to concept selection are still emerging as there exist many metrics and many ways to compute these.

While scholars have utilised both general and domain-specific text sources for searching concepts, it is also possible to explore more text sources such as Encyclopaedia and How and Stuff Works. One of the most consulted platforms – YouTube seems unexplored. Although being primarily a video-sharing platform, the descriptions, comments and captions on YouTube are still useful text sources for inspiration.

To retrieve suitable search keywords, in addition to NLP-centric approaches like dependency parsing and TF-IDF, it is necessary to construct design knowledge graphs for specific streams such as engineering, architecture and software. Such knowledge graphs are likely to recommend new terms as well as assist with text completion for queries. For example, if we begin to search for 'bearing' and

[25]https://github.com/linguatools/disco/blob/master/src/main/java/de/linguatools/disco/DISCO.java.

[26]https://www.designboom.com/.

Table 3. Summary of NLP methodologies and future possibilities (bolded) with design concepts.

	Data	Methods	Supporting Material
Concept Search	Idea-Inspire, AskNature, National centre for research on earthquake engineering, HCD connect case studies, TRIZ, **encyclopaedia, how stuff works, YouTube**	*Term Retrieval*: lexical relationships, semantic similarity, dependency parsing, TF-IDF values, word graphs, mind maps, **design knowledge graph** *Embedding*: latent semantic analysis (LSA), **BERT, GPT-x** *Classification*: k-Nearest neighbours (k-NN), random forest, SVM, logistic regression, Naïve Bayes, **LSTM variants**	*Lexicon*: WordNet, ConceptNet *Ontology*: SAPPhIRE, FBS, Earthquake
Concept Retrieval	Bionic MIR, healthcare websites, nursing bed knowledge graph, **YouTube, Google patents**	*Term Retrieval*: semantic similarity, subject–verb–object triples, **source domain ontologies, Google API** *Similarity Measurement*: LSA, **BERT, GPT-x**	*Lexicon*: WordNet, ConceptNet *Ontology*: C-K theory, FBS, SAPPhIRE
Concept Association	Human-centred design course, OpenIDEO, crowdsourced transportation concepts, scientific articles (transmission problem)	*Similarity Measurement*: Word2Vec, topic bison measure, path similarity ***Embedding*: BERT, GPT-x, Domain-specific language model** *Clustering*: hierarchical clustering, HDBSCAN *Topic Extraction*: MINRES, TextRazor	*Lexicon*: WordNet
Concept Selection	Floor plan concepts, designboom, kickstarter, **red dot design awards, malcolm baldrige national quality award, award patents, nielsen retail scanner data, standard datasets**	*Similarity Measurement*: hypergraph pattern matching, DISCO, analytic hierarchy comparison, WordNet-based similarity *Term Retrieval*: RapidMiner *Clustering*: K-means *Topic Extraction*: LDA *Others*: Markov Process, conjoint analysis	*Lexicon*: British National Corpus, WordNet, **affective lexicon** *Ontology*: SAPPhIRE, **FBS**

next-word predictions are 'lubricant' and 'load', we could choose 'bearing lubricant' and leverage from next word predictions like 'density', 'film' and 'material'. Common-sense knowledge graphs like Google (and YouTube) make predictions based on many senses of the word 'bearing' and do not return the words as we have indicated in the example.

WordNet and ConceptNet have been the main supporting pillars for concept search as well as retrieval, while generic ontologies such as FBS and SAPPhIRE have been utilised to largely channel the search and retrieval processes. Since creative concepts emerge from the marriage of diverse sets of domains, a common-sense lexicon like WordNet is still a preferable supporting material. Similarly, scholars can also use readily available search methods like Google APIs to retrieve results from sources such as YouTube and patent databases. However, while retrieving concepts from a domain-specific knowledge source, it makes sense to utilise the domain-specific ontologies for query formation.

Alongside ontologies, scholars could benefit from the embeddings of common-sense language models such as BERT and GPT-x[27] to obtain nearby search keywords, compare search results, etc. Since the concept search and retrieval are largely exploratory and preferably involve diverse domains, the usage of common-sense language models shall not limit the desired performance of the NLP applications. While the same applies to concept association as well, the scholars shall also utilise domain-specific language models if the design problem is quite domain-specific.

Concept selection involves one or more metrics such as novelty, value, feasibility, and so forth. Scholars could benefit from an affective lexicon to rate the design concepts and carry out systematic approaches to analyse and present the results. Since the theory behind these metrics is yet to be consolidated, the NLP applications are still in nascent stages. Scholars can only benefit from preliminary NLP tasks such as similarity measurement, frequency analysis and term retrieval to assist them with one or more steps in the concept selection process.

Design theorists could benefit from the NLP methods to examine how successful concepts are selected. For example, Arts, Hou, and Gomez (2021) observe the causality between frequencies of unigrams, bigrams and trigrams and the likelihood of a patent getting an award, for example, Nobel, Lasker, Bower and A.M. Turing. Similarly, scholars could leverage the text descriptions of concepts that have been selected for awards like Red Dot (indicates novelty or surprise)and Malcolm Baldrige National Quality Award (indicates value). Moreover, to understand the actual value of a concept, scholars could also utilise the sales information. For instance, Argente *et al.* (2020) connect the number of product units sold from Nielsen's Retail Scanner data with the 'value' of a patent.

3.3. Discourse transcripts

Design communication is often documented as discourse transcripts in protocol studies, think-aloud experiments and recorded design workshops. Starting with a design issue or a problem, designers communicate subissues, solutions, related artefacts, arguments and justifications. Identifying and analysing the set of

[27] https://beta.openai.com/.

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concepts that arise during such communications allows scholars to reveal a variety of insights about the design process.

A sequence of closely-related concepts within a segment in discourse transcripts represents a period of coherent communication, which could affect the design outcomes in terms of success metrics such as novelty and feasibility (Dong 2007). To identify such concepts, scholars have extracted nouns, phrases, segments and topics, and associated these using vector-based or corpus-based similarity measurement techniques. We review such NLP-based approaches that are currently preferable over traditional linkographs (Botta and Woodbury 2013).

Concept identification

Scholars have adopted different approaches to extract key concepts such as topics, words, ontology-based entities and n-grams. Wasiak *et al.* (2010, p. 58) analyse emails to discover topics such as functions, performance, features, operating environment, materials, manufacturing, cost and ergonomics. From the email exchanges in a traffic wave project, Lan, Liu, and Lu (2018, p. 7) map word-frequency vectors and topic vectors (tasks, timestamps, persons, organisations, locations, input/output, techniques/tools) using Deep Belief Network – DBN (Bengio 2009; Lan, Liu, and Feng Lu 2017).

Goepp *et al.* (2019, p. 165) identify the following speech acts from email exchanges: Information, Explication, Evaluation, Description and Request. These speech acts were associated with a set of verbs, for example, 'Explication' was associated with 'explain' and 'clarify'. To capture significant phrases that denote design changes, using the DTRS7 dataset, Ungureanu and Hartmann (2021) extract n-grams ($0 < n < 8$) based on frequency analysis and examine how short terms progress to a variety of long terms; for example, 'a little' → 'a little bit bigger', 'a little splash of colour' (2021, p. 12).

Design process characterisation

To characterise the design process, scholars have aggregated the concepts thus identified from discourse transcripts into a whole (e.g., a semantic network) and performed analyses as reviewed below.

To characterise coherence in design communication, Dong (2005, pp. 450, 451) obtain vector representations of emails and memos using LSA and measure the standard deviations of these w.r.t. their centroid (mean). A low standard deviation of the set of vector representations is considered to denote a high coherence in communication (Dong, Hill, and Agogino 2004, p. 381). In an alternative approach, Dong (2006, pp. 39, 40) identifies segments by linking noun sequences using lexical relationships obtained from WordNet.

Based on the word occurrences of design alternatives within a time interval, Ji, Yang, and Honda (2012) model the relationship between preferences using the Preference Transition Model and Utterance-Preference Model. Menning *et al.* (2018, pp. 139, 142) use cosine similarity between LSA vectors of consecutive discourse entities to measure coherence. To characterise the uncertainty of the design process, Kan and Gero (2018) measure the text entropy of the transcripts that were obtained from protocol studies.

Georgiev and Georgiev (2018) utilise 49 WordNet-based semantic similarity measures to build a noun-based semantic network of students' and instructors'

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conversations as given in the DTRS10 dataset. They plot the average semantic similarity, information content, polysemy and level of abstraction w.r.t. time for characterising the design communication. Casakin and Georgiev (2021) train regression models to establish a relationship between these network properties and the following metrics of design outcomes: originality, feasibility, usability, creativity and value.

Summary

As we summarise in Table 4, the NLP applications built using discourse transcripts are limited in comparison with other types of text sources due to the least accessibility and information content. While emails do not strictly qualify as 'transcriptions' of design communication, the currently available data sources are mainly DTRS datasets. Scholars could additionally explore panel discussions, protocol studies and client interactions (e.g., architect and customer). The accessibility to such sources is crucial for the development of NLP applications regarding discourse transcripts.

Beyond the likelihood of obtaining one or more of these sources, the probability of extracting meaningful design knowledge from these is quite limited. For instance, the usage of frequent colloquial phrases like 'sort of too big' limits the possibility of applying NLP methods to these (Glock 2009). Moreover, a transcription, unlike any text document, involves a timestamp associated with its parts. Several factors such as lack of context, poor grammar, colloquial language and time variation are beyond what state-of-the-art NLP could handle. Scholars could still conduct preliminary analyses as they have done so far in terms of segment identification and topic discovery. Such analyses could also be benefitted from common-sense language models because verbal communication involves many

Table 4. Summary of NLP methodologies and future possibilities (**bolded**) with discourse transcripts

	Data	Methods	Supporting Material
Concept identification	Emails, DTRS7 dataset, **protocol studies**	*Classification*: deep belief network *Embedding*: TF-IDF, LDA, **BERT, GPT-x** *Segmentation*: N-grams, LDA *Others*: frequency analysis	WordNet, **domain-specific ontologies**
Design process characterisation	Emails, memos, DTRS10 dataset, protocol studies, **panel discussions, client interactions**	*Similarity Measurement*: WordNet-based similarity, lexical relationships, preference transition model, utterance-preference model, cosine similarity *Embedding*: LSA *Others*: network analysis, linear regression, text entropy	WordNet, **domain-specific ontologies**

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common-sense terms. If required, scholars may also utilise domain-specific ontologies to recognise the domain terms in their analyses.

3.4. Technical publications

Technical publications include over 92 million patents and a portion of over 174 million records that comprise textbooks, journal articles and conference proceedings.[28] Due to their coverage, size and accessibility, these sources carry a significant advantage over other sources in terms of knowledge aids for the design process. Moreover, since these sources are peer-reviewed and adhere to grammar and typographical norms, NLP tasks are well-suited to these (Wang, Lu, and Loh 2015).

Patent documents

As mentioned in section 'Design knowledge retrieval', design knowledge that is extracted from the text could be in the form of terms, phrases and segments, that should represent one or more constituents of an artefact that is relevant to the design process. Moreover, if re-represented, such terms, phrases and segments of text must assume the form <entity, relationship, entity> to store these in a machine-readable form. Being a large body of technical inventions, patents offer a *rich source of design knowledge* that is also characterised by high information content, quality and technicality.

To extract design knowledge from patents, scholars have primarily utilised ontologies to channel their extraction approaches. To extract issue-related concepts and relationships (noun–noun, noun–adjectives), using a WordNet-based similarity, Liu *et al.* (2010, pp. 4, 5) compare sentences in 46 patent abstracts against an ontology (list of terms) of issues, disadvantages and challenges. Moehrle and Gerken (2012) use a domain ontology to extract bigrams and trigrams from 522 patents of SUBARU's four-wheel drive. They use the terms thus extracted to measure patent–patent similarity using a variety of measures (2012, p. 817) such as Jaccard, Inclusion, Cosine and DSS-Jaccard.

Liang *et al.* (2012) adopt a sentence graph approach and Issue-Solution-Artefact ontology to extract design rationale from 18,920 Inkjet Printer patents that were assigned to Hewlett–Packard (HP) and Epson. Using a similar dataset of inkjet printer patents, Liang *et al.* (2018) develop the topic-sensitive content extraction (TSCE) model and verify the model by testing the effect of segment length, parameters, sample count and topic count. Fantoni *et al.* (2013) propose a heuristic approach to extract the terms that correspond to functions, behaviours and structures (FBS ontology) from patents. In *function*, for example, they consider the frequent combinations of verb–noun and verb–object.

To discover the structural form assumed by a collection of patents, Fu *et al.* (2013a) perform LSA on 100 randomly selected US patent documents. They consider only verbs (functions) and only nouns (surfaces) to perform two different LSAs and thereby obtain corresponding patent vectors. Using the cosine similarities, they discover the most optimal structural form – hierarchy using which they construct a patent network. They also label the clusters of patents with the closest terms (verbs or nouns).

[28] https://clarivate.libguides.com/webofscienceplatform/coverage.

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Upon training the abstracts of 500,000 patents (CPC-F subsection) using Word2Vec, Hao, Zhao, and Yan (2017) obtain the embeddings of 1700 function terms (e.g., grill, cascade) that are given by Murphy *et al.* (2014). They obtain a patent vector as a circular convolution ($\otimes$) of function terms that are present in the corresponding patent abstract. To support efficient retrieval of patent images, Atherton *et al.* (2018, pp. 247, 248) annotate images in USPTO with geometric features and functional interactions extracted from claims. Song and Fu (2019) obtain three patent-word matrices using 1060 patents and three sets of words corresponding to components, behaviours and materials. They apply a nonnegative matrix factorisation algorithm to these matrices to extract significant topics.

While patents offer design knowledge in specific domains, due to the totality of technology space covered by the patent database, scholars have also attempted to construct WordNet-equivalent lexicon as well as engineering ontologies. Vandevenne *et al.* (2016, p. 86) analyse titles and abstracts in a randomly drawn set of 155,000 patents from the EPO database[29] to discover that nouns are abstract (e.g., system, device) and are meaning enablers (e.g., temperature, pressure) that also point towards the product (e.g., valve, display).

To identify the primary users of technological inventions that are documented as patents, Chiarello *et al.* (2018) extract a generic list of users in terms of job positions, sports, hobbies, animals, patients and others. They identify these generic users in selected patents[30] using a semi-automatic approach and annotate the sentences using these. They then feed the annotated dataset of sentences into SVM and multilayer perceptron for named entity recognition (NER).

Sarica, Luo, and Wood (2020) obtain embeddings of over 4 million unique terms from the titles and abstracts across the US patent database. Using a web-based tool called TechNet,[31] they facilitate a search for these terms (Sarica *et al.* 2021) and utilise the embeddings of these to construct a similarity network (Sarica and Luo 2021). To create an engineering alternative to WordNet, Jang, Jeong, and Yoon (2021) collect 34,823 automotive patents (IPC B60). They examine the dependency patterns in abstracts and claim to extract dependency relations that form the TechWord network. For the words in the network, they create TechSynset by capturing the WordNet synonyms and calculating the cosine similarity between BERT-based embeddings of individual pairs.

Scholars have demonstrated how patents could act as *stimuli for generating concepts* as well as indirect supports for problem-solving through TRIZ-based tools (Cascini and Rissone 2004; Vincent *et al.* 2006; Zanni-Merk, Cavallucci, and Rousselot 2009; Prickett and Aparicio 2012). In the effort to discover patent network structures, Fu *et al.* (2013a) include a design problem in their LSAs to identify a starting point for navigating the patent network. Given a starting point in the network, Fu *et al.* (2013b) consider patents at one and three hops as 'near' and 'far', respectively. They examine the effect of 'near' and 'far' patents on novelty and quality when these patents are given stimuli alongside the design problem.

To support patent retrieval, Murphy *et al.* (2014) adopt a Zipfian statistic approach to extract 1700 function (verbs) terms from 65,000 patent documents

[29]https://www.epo.org/searching-for-patents.html.

[30]The selected patents fall within the A47G33, A61G1-G13 groups that are defined by the International Patent Classification (IPC).

[31]http://www.tech-net.org/.

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and organise these into primary, secondary and tertiary w.r.t. the functional basis (Stone and Wood 2000). They index 2,75,000 patents using these functions that also act as query elements. To map design problems and patents via the Functional Basis, Longfan *et al.* (2020) train a semi-supervised learning algorithm based on Naïve Bayes and E-M algorithm using 1666 patents and the texts labelled with function categories. In another approach, they extract meaningful terms from patents using a frequency-based statistic (2020, p. 8) and cluster the patents according to the terms.

Although several approaches to searching and managing patents exist (Russo and Montecchi 2011; Montecchi, Russo, and Liu 2013; Dirnberger 2016), it is necessary to simplify the patent documents before utilising these as stimuli for generating concepts. To form keyword summaries of patent search results, Noh, Jo, and Lee (2015) conduct an experimental study to find that it is best to extract 130 keywords from abstracts using TF–IDF and Boolean expression strategies.

Sarica et al (2021) propose TechNet (Sarica, Luo, and Wood 2020) as a means to search and expand technical terms, which were extracted from the titles and abstracts in the patent database. To facilitate cross-domain term retrieval, Luo, Sarica, and Wood (2021) organise the output of TechNet into various domains that are associated with a knowledge distance measure. Souza, Meireles, and Almeida (2021) train an LSTM-based sequence-to-sequence (abstract-title → summary) neural network using 7000 patents for generating abstract summaries of patent documents. They group the summaries thus generated using a semantic similarity measure (Al-Natsheh *et al.* 2017) and subsequently identify patent clusters.

Patents not only document technological inventions but are also assigned to specific domains, companies, inventors and countries. Using such meta-data, scholars have developed *technology maps for exploring design opportunities.* Jin, Jeong, and Yoon (2015) extract meaningful terms from patents and use bag-of-words (BOW) approach to create patent vectors that form a technology map. Trappey *et al.* (2014) adopt a similar approach to patents and clinical reports that concern dental implants. Altuntas, Erdogan, and Dereli (2020) use the same dental implant patents and obtain vectors of these using the patent-class matrix. They cluster the patent vectors using the following methods: E-M algorithm, self-organising map and density-based method.

To explore new design opportunities as well as to aid in idea generation, Luo, Yan, and Wood (2017) develop a technology space map using all CPC 3-digit classes and the co-citation proximity measures among these. They implement the map using support called InnoGPS[32] which provides several interactive features that are analogous to Google Maps. The support tool mainly allows the users to position themselves on the technology map, identify the closest domains and navigate the technology space map. Luo *et al.* (2018) conduct an experimental study to demonstrate how the total technology space map is useful for exploring 'white space' design opportunities related to artificial neural networks and spherical rolling robots.

To identify new technology opportunities relating to carbon-fibre heating fabric, Russo, Spreafico, and Precorvi (2020) download 16,743 patents and extract Subject–Action–Object triples where the Subject is 'heating fibre'. Assuming that Action represents a function, they mine dependency patterns to extract

[32]http://www.innogps.com/.

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applications (e.g., ‘applied as’, ‘used for’) and requirements (e.g., ‘enhance…’, ‘un…ability’) pertinent to the heating fibre technology. To explore new technology opportunities using products, Lee et al. (2020) use the patent–product database[33] developed at the Korea Institute of Science and Technology Information (KISTI). They extract Word2Vec embeddings for products and technologies to create an exploration map that allows the identification of technologies closer to products and vice-versa. They also propose 10 indices to assess the performance of technology exploration.

To identify technology opportunities in 3G that could be leveraged in 4G, Zhang and Yu (2020) extract effect phrases from the corresponding patents using a Bi-LSTM with a conditional random field layer. They label the words in the sentences using {Begin, Inside, Other} of an effect phrase and feed the labelled data into the neural network. They combine the effect phrases in a patent using a weighted TF-IDF vector and use topic clustering to group the patents. Depending on the number of patents on each topic, they calculate the technology opportunity score (2020, pp. 560, 561).

Textbooks and handbooks

Several design studies support the notion that exploring concepts from distant domains could lead to novel design solutions. Adhering to this consensus, Shu and colleagues have conducted analyses on a biological textbook (Purves *et al.* 2003) to understand the characteristics that support bio-inspiration. Shu (2010, p. 510) understands that the textbook includes candidates for design-by-analogy, for example, (‘bacteria’, ‘fill’, ‘pores of clothes’) → ‘prevent dirt’. Cheong *et al.* (2011, pp. 4, 5) identify that in the text, domain and common verbs co-occur, for example, ‘*received* and converted or *transduced*’.

To capture causally related biological functions, Cheong and Shu (2014, pp. 1–4) locate and extract pairs of enabler-enabled functions using syntactic rules, for example, ‘Lysozymes *destroy* bacteria to *protect* animals’. Upon searching in the same textbook, Lee, Mcadams, and Morris (2017, pp. 5–7) identify morphological nouns that co-occur with the keywords in a single paragraph. For every noun, they calculate a modified TF-IDF metric (2017, pp. 5, 6) for usage in LSA.

The following articles describe approaches to extracting design knowledge from published handbooks. Hsieh *et al.* (2011) mine the Table of Contents, Definitions and Index from an Earthquake Engineering Handbook to develop a domain ontology. Kestel *et al.* (2019) apply several text mining steps to the published document that describes the standard procedure for simulation of multibolted joints (VDI 2230 Part 2). They extract structured data with specific attributes (e.g., part, contact, load, relation) from the text and utilise these to build ontologies that are integrated with finite element analysis (FEA) tools.

Richter, Ng, and Fallah (2019) obtain the design standards and guidelines for landfilling in different provinces of Canada. They conduct word-frequency analyses using metrics such as Gunning-Fox Index and Lexical Density. Xu and Cai (2021) mine 300 sentences from the underground utility accommodation policies in the departments of transportation such as Indiana and Georgia. They use utility-product and spatial ontologies to process and label the terms in the sentences with

[33] https://repository.kisti.re.kr/handle/10580/14535.

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seven categories (2021, p. 7). They examine the POS and category patterns in these sentences to extract hierarchical knowledge structures.

Scientific articles

Unlike patents and books, the overall motive behind processing scientific articles is unclear, mainly due to a limited number of contributions. We, therefore, review these contributions as follows by explicitly stating the purpose beforehand. To summarise engineering articles by discovering their micro-and macro-structures, Zhan, Liu, and Loh (2011, pp. 5, 6) train Naïve Bayes and SVM classifiers by labelling 1425 sentences from 246 research articles into one of the four categories: background, contribution, methodology, results and conclusions.

To identify the sentences that could aid in bio-inspiration, Glier, McAdams, and Linsey (2014, pp. 5–7) represent sentences from five biology journals using a feature vector of 1869 terms and label these as ‘useful’ and ‘not useful’ for bio-inspiration. They feed the labelled dataset into the following classifiers: SVM, k-NN and Naïve Bayes. To build a bridge between biological and engineering domains and thus aid bio-inspiration, Vandevenne *et al.* (2016, p. 82) map product and organism aspects upon processing 155,000 EPO patents and 8011 papers from the *Journal of Experimental Biology*.

To create a generic engineering ontology, Shi *et al.* (2017, pp. 4–6) develop a large semantic network called B-Link by extracting and combining entities from technical websites and articles, respectively, using Scrapy[34] and Elsevier APIKey.[35] To understand the evolution of typology in design research, education and practise, Won and Park (2021) collect 222 terms[36] from over 300 documents that include design publications, abstracts and discover that these terms have evolved from being object-based to concept-based.

To understand the definitions of contemporary technologies such as Artificial Intelligence and Industry 4.0, Giordano, Chiarello, and Cervelli (2021) identify these terms in the sentences of Elsevier-Scopus abstracts and filter the cases where the neighbour of these terms adhere to a pattern, for example, ‘defined as’, ‘refer to’ (2021, p. 10). They further analyse the frequencies of the constituents of these sentences so filtered. To understand the field of product-service systems (PSS), Rosa *et al.* (2021) develop a concept map by analysing 29 articles relating to the design of PSS.

Summary

We have summarised the NLP contributions that use technical publications in Table 5. Due to high accessibility, information content, quality and technical density, technical publications have been quite popular sources for developing NLP applications. The methodologies have also adopted state-of-the-art NLP methods while also utilising domain ontologies wherever applicable. Therefore, a little could be commented about the potential gaps in these contributions.

Scholars could invest more effort into scientific articles (including conference proceedings) as the literature on patent analyses is extant. In addition, scholars

[34]https://scrapy.org/.

[35]https://www.elsevier.com/solutions/sciencedirect/support/api.

[36]https://www.tandfonline.com/doi/suppl/10.1080/14606925.2021.1906085/suppl_file/rfdj_a_1906085_sm7942.docx.

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Table 5. Summary of NLP methodologies and future possibilities (**bolded**) with technical publications

	Data	Methods	Supporting Material
Patent documents - design knowledge extraction	*Patents*: SUBARU 4-wheel drive, HP inkjet printers, Epson inkjet printers, IPC-A47G33, IPC-A61G1-A61G13, IPC-B60 *Others*: career planner, not-so-boring life, discover a hobby, A-Z-animals, medicine net, centre for disease control and prevention	*Similarity Measurement*: latent semantic analysis, WordNet-based similarity, patent–patent similarity (e.g., Jaccard), dependency parsing, BERT, **domain-specific language model** *Term Retrieval*: topic sensitive content extraction, rule-based mining, dependency parsing, wordnet synonyms ***Relation Extraction*: rule-based approach** *Topic Extraction*: nonnegative matrix factorisation *Named Entity Recognition*: SVM, multilayer perceptron *Others*: bayesian networks	*Lexicon*: WordNet, **TechNet, TechWord** *Ontology*: issues, 4-wheel drive, issue-solution-artefact, FBS
Patent documents - concept generation stimuli	*Patents*: CPC-F	*Embedding*: LSA, Word2Vec, circular convolution, **domain-specific language model** *Similarity Measurement*: bayesian network, semantic similarity *Classification*: Naïve Bayes, expectation–maximisation (E-M) *Text Generation*: LSTM	*Lexicon:* **TechNet, TechWord** *Ontologies*: functional basis
Patent documents - design opportunity identification	*Patents*: dental implants, KISTI patent–product database, 3G, 4G *Others*: clinical reports	*Embedding*: bag of words (BOW), patent-class matrix, Word2Vec, TF-IDF *Clustering*: E-M algorithm, self-organising map, density-based approach *Classification*: Bi-LSTM CRL	*Ontologies*: international patent classification

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Table 5. Continued

	Data	Methods	Supporting Material
Textbooks and handbooks	Biology Textbook, Earthquake Engineering Handbook, VDI 2230 Part 2, Landfilling Guidelines, Underground Utility Accommodation Policies	*Term Retrieval*: rule-based approach, Gunning-Fox index, lexical density, POS patterns, category patterns *Embedding*: TF-IDF, LSA	*Lexicon*: WordNet *Ontologies*: Underground Utilities
Scientific articles	*Articles*: Computer Integrated Manufacturing, Basic and Applied Ecology, Current Biology, Journal of Animal Behaviour, Journal of Animal Ecology, Journal of Zoology, Journal of Experimental Biology, ScienceDirect, Design Publications, Design of Product-Service Systems (PSSs), **Conference Proceedings** *Patents*: European Patent Office	*Classification*: Naïve Bayes, SVM, k-NN ***Term Retrieval*: Rule-based Approach** ***Topic Extraction*: LDA variant** ***Relation Extraction*: Supervised Approach**	

could also report more analyses on full texts of patent documents, as a majority of contributions are limited to titles, abstracts and claims. Scholars could leverage the wealth of knowledge in these sources to create ontologies and knowledge graphs both at the generic and domain-specific levels. As a part of knowledge graph extraction, relation extraction shall adopt a rule-based approach in patent documents as the language is consistent across the entire database. In scientific articles, however, relation extraction requires prior named entity recognition as well as relation label prediction algorithms. Scholars could also immix patent documents and scientific articles in a particular domain to develop a domain-specific graph extraction tool.

3.5. Consumer opinions

Available in plenty as a part of social media text and product reviews, consumer opinions are reflective of actual user experiences (Decker and Trusov 2010), product specifications, requirements and issues (Jin *et al.* 2019). Consumer opinions often include typographical errors (e.g., coooolll), alternative word forms (e.g., LOL), multilingual terms and grammatical errors. It is a challenge to remove symbols, hyperlinks, usernames, tags, artificially generated messages and misspelt words. Lim and Tucker (2016, pp. 1, 2) posit that identifying product features in consumer opinions often involves challenges in term disambiguation (e.g., 'researchers should really screen for this type of error') and keyword recognition ('… just as this court case is about to start, my iPhone battery is dying').

To work around the above-mentioned issues, Tuarob and Tucker (2015a) propose using Carnegie Mellon POS tagger that suits social media text. In addition, He *et al.* (2019, p. 4) recommend using TextRazor[37] for identifying proper nouns like 'Uber' and 'Manhattan'. While processing consumer opinions, Tuarob, Lim, and Tucker (2018, p. 4) prefer not to perform stemming due to its negative effects on the performances of downstream NLP tasks. To improve the grammatical structure, Wang *et al.* (2019a, pp. 456–458) suggest a few transformation rules, for example, sentence 1 (e.g., 'very nice') is prepended with subject and verb to obtain sentence 2 (e.g., 'It is very nice') if the former does not include these. In addition to these approaches to work around the issues with consumer opinions, scholars have incorporated distinct steps before performing sentiment analysis, capturing usage context and modelling user emotions.

Sentiment analysis

Sentiment analysis is an important application of NLP that uses ratings as well as an affective lexicon to determine the polarity and intensity of sentiment in a piece of text. The sentiment scores quantify the product favourability (Tuarob and Tucker 2015a, p. 5) and affective performances (Chang and Lee 2018, pp. 450, 451). Obtaining true sentiment scores is often a challenge, given that 22.75% of a social media text is sarcastic (Tuarob, Lim, and Tucker 2018). In addition, Tuarob and Tucker (2015b) identify that neutral words constitute over 53% and 48.6% of smartphone and automobile-related tweets. Since the sentiment score of a phrase may not often match that of a sentence, Chang and Lee (2018, p. 462) propose to

[37] https://www.textrazor.com/.

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adjust the sentiment score of a local context based on the polarity match with the whole sentence.

Sentiment analysis utilises product features (nouns) and sentiment indicators (adjectives, adverbs and verbs); for example, 'The keyboard is fine but the keys are real slippery' includes product features {keyboard, keys} and sentiment indicators {fine, slippery} (Tang *et al.* 2019, pp. 1, 2). Sentiment analysis requires an affective lexicon like SentiWordnet (Baccianella, Esuli, and Sebastiani 2010), Affective Space 2 (Cambria *et al.* 2015) and SenticNet 6 (Cambria *et al.* 2020). We review in the remainder of this section, the contributions that have conducted sentiment analyses on various design text sources.

Raghupathi *et al.* (2015) compute sentiment scores of Home Theatre reviews from Twitter, Amazon and Flipkart using the SENTRAL algorithm and the dictionary of affect language (DAL). To predict sentiment scores, Zhou, Jiao, and Linsey (2015, p. 4) feed a labelled dataset of Kindle Fire HD 7 reviews into the fuzzy-SVM algorithm along with a lexicon that is populated using ANEW (Bradley and Lang 1999). Jiang, Kwong, and Yung (2017, pp. 2, 4) extract nouns, adverbs, verbs and adjectives from electric iron reviews and utilise SentiWordNet (Baccianella, Esuli, and Sebastiani 2010) to predict sentiment scores.

Zhou *et al.* (2017) compute sentiment scores of specific product features in Kindle Fire HD reviews using ANEW and classification based on a rough set. They augment the sentiment scores with a feature model that was constructed by extracting product features using ARM and combining these using WordNet-based similarity measures (e.g., Resnik, Leacock-Chodorow). Jiang *et al.* (2018, p. 394) assess 1259 reviews of six compact cars using Semantria[38] to obtain sentiment scores. Tuarob, Lim, and Tucker (2018, pp. 6, 8) use TextBlob[39] to compute sentiment scores of tweets related to 27 smartphone models. They account for sarcasm using the analysis of a coword network, where nodes are ranked for likelihood, explicitness and relatedness.

Tang *et al.* (2019) develop the tag sentiment aspect (TSA) Model to extract topics and sentiment indicators simultaneously. They demonstrate the proposed TSA model using DSLR and laptop reviews (Jo and Oh 2011). Sun *et al.* (2019) calculate sentiment scores of 500,000 phone reviews from Zol[40] upon capturing the co-occurrence of product features and sentiment indicators (adjectives, adverbs) within a sliding window. For sentiment analysis, Suryadi and Kim (2019, pp. 3, 4) feed the labelled embeddings of informative laptop and tablet Amazon-based reviews into the long–short term memory (LSTM) model (He *et al.* 2018).

Sun *et al.* (2020) mine 98,700 reviews and product descriptions of Trumpchi GS4 and GS8 vehicles that are manufactured by the GAC group. They use TF-IDF and fastText (Joulin *et al.* 2017) to compute sentiment scores and extract attributes from the text thus mined. Chiarello, Bonaccorsi, and Fantoni (2020) extract 7,165,216 Twitter posts that appeared ahead of the launch of Xbox One X and New Nintendo 2DS XL to examine the effect of sentiment polarity of the social media activity on the success of these products. They label 6500 tweets relevant/irrelevant and build an SVM classifier. Upon classifying the tweets that are outside

[38]https://www.lexalytics.com/support/apps/excel.
[39]https://textblob.readthedocs.io/en/dev/.
[40]https://www.zol.com.cn/.

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the training set, they obtain 66,796 relevant tweets and compute the sentiment scores of these using a specific lexicon (Chiarello, Fantoni, and Bonaccorsi 2017).

Gozuacik, Sakar, and Ozcan (2021) classify Google Glass tweets using a Deep Neural Network for sentiment polarity and opinion usefulness. They include bag-of-words and other embedding techniques for comparing the classification performances. They find using clustering analysis (2021, pp. 9–11) that among the useful opinions, negative ones denote issues and positive/neutral ones denote innovations. To identify sentiment indicators, Han and Moghaddam (2021a) collect 23,564 sneaker reviews and fine-tune BERT for a named entity recognition task with the following labels on each word in a sequence: background, sentiment, attribute and description.

Han and Moghaddam (2021b) extract product attributes of sneakers from catalogues and product descriptions and apply a rule-based approach to compute sentiment scores w.r.t. these attributes. Li *et al.* (2021) identify groups of customers and attribute preferences by clustering the Word2Vec embeddings of 30,000 laptop reviews from JD.[41] They estimate the sentiment score using Microsoft's Deep Structured Semantic Model and utilise these sentiment scores to develop a Kano map between customer groups and attribute preferences.

Extracting usage context

In this section, we review the contributions that capture usage context by examining the product features and their functioning in different environments (Jin, Ji, and Liu 2014; Shu *et al.* 2015; Hou *et al.* 2019). Park and Lee (2011) extract consumer opinions of 135 mobile phone models from a review portal.[42] Upon analysing the opinion data using TextAnalyser 2.0, they mine the frequent product specifications, cluster the consumers and form product-specific networks.

Wang *et al.* (2014) label and group camera reviews from Amazon and NewEgg using the frequent keywords obtained from product descriptions. They extract the aspects from these reviews using Fine-Grained LDA and Unified Fine-Grained LDA. To relate engineering characteristics with consumer opinions, Jin, Ji, and Liu (2015) obtain 770 reviews of HP and Epson printers from Amazon to extract engineering characteristics using *n*-gram language models. To aid House-of-Quality construction, Ko (2015) relate consumer and design requirements using a 2-tuple fuzzy-linguistic approach.

To extract important product features, Jin, Ji, and Gu (2016) select the most representative sentences from 21,952 reviews on CNET using a greedy algorithm and verify these using information comparativeness, information representativeness and information diversity. To classify product reviews, Maalej *et al.* (2016) procure over 1.2 million Smartphone Application reviews from the Apple App-Store and Google Play Store. They label the reviews according to four categories: bug report, feature request, user experience or rating and train the labelled dataset using Naïve Bayes, decision tree and maximum entropy algorithms, while also examining the effect of different approaches such as Bag of Words, Bigrams, Lemmatisation and Stop words.

To extract product usage, Park, Kim, and Baik (2016, p. 4) learn feature ontology by measuring triples like 'fabric + shrink' using Wu and Palmer similarity

[41] https://global.jd.com/.
[42] http://www.mobilephonesurvey.com.

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(Wu and Palmer 1994) and merging with factual (e.g., 'fabric + rayon') and sentiment (e.g., 'shirt + disappoint') ontologies using a Fuzzy Formal Concept Analysis (FFCA) approach. They identify the relationships between triples using explicit causal conjunctions such as 'so', 'due to' and 'because' (2016, p. 6).

To disambiguate product reviews, Singh and Tucker (2017) classify the Amazon review sentences (obtained using import.io) into function, form, behaviour, service and others using the following classifiers: Naïve Bayes, SVM, Decision Tree and IBk classifiers. To identify the type of design knowledge in a product review, Kurtanovic and Maalej (2018) label 32,414 reviews of 52 Amazon Store Apps with the following concepts: Issue, Alternative, Criteria, Decision and Justification. They apply the labelled dataset to the following classification algorithms: Naïve Bayes, SVM, Logistic Regression, Decision Tree, Gaussian Process, Random Forest and Multilayer Perceptron.

To capture bigrams that represent the usage context of wearable technology products, Suryadi and Kim (2018, pp. 6, 7) combine noun-adjective pairs that co-occur in a hierarchical path in the dependency tree. They (2018, p. 8) group the embeddings of the noun–adjective combinations using X-means clustering. In an extended work, Suryadi and Kim (2019, p. 7) identify bigrams that are noun–verb, noun–noun, while verbs end with a -ing (e.g., 'web browsing', 'reading books').

Hou *et al.* (2019, p. 3) structure an affordance description as 'Afford the ability to [action word] [action receiver] [perceived quality] [usage context]'. Based on the structure, they (2019, p. 5) extract perceived opposite qualities (e.g., low, high) from Kindle reviews to train an ordered logit regression model. An affordance i that supposedly has the perceived qualities X_i and Y_i is characterised according to their model by the coefficients α_i and β_i that are used to identify categories of Kano (1984) model: must be, performance, attractive, indifferent, reverse and questionable.

Zhou *et al.* (2020) filter uninformative reviews of Amazon products such as Echo and Alexa, using a fastText classifier and extract topics from these using LDA. To estimate the importance of product attributes, Joung and Kim (2021) collect 33,779 smartphone reviews from Amazon. They identify product attributes using LDA and sentiment scores using IBM Watson. They estimate the importance of product features using k-optimal Deep Neural Networks that were designed using the SHAP[43] method.

Kansei engineering

Kansei engineering aims to support the emotion-driven design and involves the acquisition of emotional responses using bipolar adjectives such as 'hot-cold' and 'unique-conventional' (Gosnell and Miller 2015), extracting descriptive adjectives such as 'fresh' and 'appealing' (Korpershoek *et al.* 2010) and clustering these adjectives (Choi and Jun 2007; Munoz and Tucker 2016). The NLP contributions as we review in the remainder of this section involve developing emotion vocabulary, describing emotions of artefacts, modelling product features and emotions, and developing fuzzy-linguistic membership functions.

Scholars have proposed *design-specific emotion vocabulary* to characterise artefacts. Desmet (2012, pp. 4, 5) proposes nine groups of 25 emotion types and

[43] SHapley Additive Explanations - https://shap.readthedocs.io/en/latest/index.html.

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representative emotion words within these. Chaklader and Parkinson (2017, pp. 2–4) examine 500 reviews of Bose SoundLink headphones to identify 29 cue terms (2017, p. 2) that reflect ergonomic comfort. Kim *et al.* (2019) identify 15 clusters of 4941 reviews of recliners from Amazon and extract the most frequent adjectives from these clusters.

Scholars have applied *existing vocabulary to describe artefacts* in their studies that we review as follows. Karlsson, Aronsson, and Svensson (2003) use several adjectives to describe the interiors of BMW 318, Volvo S60, VW Bora and Audi A6 along the lines of the following factors: pleasantness, complexity, unity, enclosedness, potency, social status, affection and originality. To identify the extent of brand importance in the design process, Rasoulifar, Eckert, and Prudhomme (2014, pp. 144, 145) interview 30 designers about a Tecnifibre tennis bag. From the responses, they extract Kansei, design and brand concepts and organise these into a multiple domain matrix.

To characterise the affective qualities of electronic readers, Wodehouse *et al.* (2018, pp. 489–492) obtain descriptive adjectives of these from a survey on visual attractiveness. They use RAKE[44] to extract keyphrases (e.g., 'prefer physical books') from the patent documents relevant to electronic readers. They form feature vectors of electronic readers using descriptive adjectives and the key phrases to cluster these vectors using ClusterGrammer.[45]

To compare affective performances of similar products, Liao, Tanner, and MacDonald (2020, p. 5/18) ask survey participants to place eight wearable products on the quadrants of two graphs: comfortable versus like clothing and delightful versus like clothing. Upon placing the products, they also ask the participants to select a suitable emotional descriptor (2020, p. 8/18). Hu *et al.* (2020) collect emotional responses of a flash drive regarding its colour, contour and shell material to discover the emotional dimensions via multifactor analysis. Using a case study on Toaster, Guo *et al.* (2021) assess Kansei ratings of groups based on consensus and dominance.

Scholars have attempted to establish a relationship between *emotional descriptors and product features*. Using a dataset of seven interior designs of truck cabs, Zhou *et al.* (2010) adopt K-optimal rule discovery and Ordinary Least-Squares Regression to map design elements and affective descriptors. Upon obtaining participant data on CNC machine tools, Wang (2011) establish a relationship between abstract (e.g., 'Rigid/Flexible') and elementary (e.g., 'Firm/Fragile') Kansei words using Support Vector Regression and Artificial Neural Network.

Vieira *et al.* (2017) measure the actuation force, contact force, stroke and snap ratio for 11 keys in an in-vehicle rubber keypad. They ask participants to rate the performances of these keys using seven Kansei words (e.g., unpleasant/pleasant, smooth/hard, loose/stiff). They observe using regression models that a significant relationship exists between the aforementioned design parameters and the Kansei ratings. To predict the Kansei ratings from the features of a bottle design, Mele and Campana (2018) train a neural network with the following architecture: input layer with 14 design features (e.g., geometry, process, material), two hidden layers and an output layer with eight ratings to corresponding Kansei words (e.g., classic/trendy, masculine/feminine).

[44] https://pypi.org/project/rake-nltk/.
[45] https://clustergrammer.readthedocs.io/.

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Misaka and Aoyama (2018) obtain Kansei ratings of crack patterns on pottery surfaces using 50 adjectives. They use a neural network with one hidden layer to model the relationship between ratings and crack characteristics such as width, fineness and fluctuation. Upon mining 4459 Amazon reviews of 30 road bikes using WebHarvy,[46] Chiu and Lin (2018) construct a functional model and a morphological matrix for six design elements (e.g., saddle, tread surface). They identify the 11 most frequent adjectives and group these into four semantic sets (overall impression, usability, riding experience and weight) and compute the corresponding semantic differentials. They run a linear regression using each semantic differential as a dependent variable and the six design elements as binary categorical variables.

So (2019) conducts a study that involves ranking 115 adjectives to obtain 12 design words and five emotion words. Using the resultant words, he performs factor analysis to discover the following dimensions: tool, novelty, energy, simplicity and emotion. Among these dimensions, he found that emotion was a significant predictor of design preferences via the following models: Linear Regression, Random Forest, Neural Network and Gradient Boosting Machine. For 1474 French Press coffee maker reviews on Amazon, El Dehaibi, Goodman, and MacDonald (2019, pp. 4–6) use crowdsourced efforts to highlight phrases that indicate sustainability and obtain the corresponding degree of emotion. They train a logistic classifier to predict the DoE from highlighted phrases, while also using LDA to extract topics from these.

Wang *et al.* (2019b) propose rules to automatically label reviews with affective attributes (e.g., like–dislike, reliable–unreliable) based on the affective words contained in these. In an alternative approach to automatically labelling reviews, they build a classifier by manually labelling 900 reviews of 20 stuffed toys from Amazon and training the following models: k-NN, Classification and Regression Tree (CART), Multilayer Perceptron, DBN and LSTM. Jiang *et al.* (2019) extract hair dryer reviews from Amazon and estimate the predictability of product attributes (weight, heat, power, speed) upon minimum, maximum and average sentiment scores over four time periods.

Upon mining reviews and product specifications of 19 upper limb rehabilitation devices from Amazon and Alibaba, Shi and Peng (2021) connect these with 10 customer requirements (e.g., flexible wear, no smell) using WordNet-based similarity. For each customer requirement, they measure satisfaction using adjectives and adverbs in the reviews. They also identify the functional implementation through product specifications. Next, they fit a curve to establish a relationship between functional implementation and customer satisfaction.

Chen *et al.* (2021, pp. 84, 85) obtain 60 images of cockpit interior designs from the web and 20 emotional terms (about cockpit) from aircraft experts. They form the similarity matrix among these 20 terms using WordNet and cluster these into four emotional dimensions, which are used to rate each image as per the Likert scale (2021, pp. 90, 91). They train the following neural networks using the images labelled with an emotional degree: Radical Basis Function, Elman and General Regression.

Kansei attributes (Wang *et al.* 2018, pp. 408, 409) and degrees (Wang *et al.* 2018, p. 410) are abstractions of adjectives (affective characteristic) and adverbs

[46]https://www.webharvy.com/.

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(affective degree). Using the affective degrees obtained from surveys or text mining, scholars have attempted to model the *linguistic membership functions* of affective characteristics. Wang *et al.* (2018, p. 411) extract adjective–adverb combinations from McAuley's dataset[47] and map these to corresponding Kansei attributes and degrees. Wang *et al.* (2021) map a variety of fuzzy-linguistic term sets (e.g., {'none', 'very bad', 'bad', 'medium', 'good', 'very perfect', 'perfect'}) to their membership degrees using a trapezoidal asymmetric cloud model. Scholars have adopted similar approaches to model Kansei variables and their corresponding fuzzy membership functions, for example, USB flash drives (Chou 2016) and hand-painted Kutani cups (Chanyachatchawan *et al.* 2017).

Summary

We summarise the NLP contributions that use consumer opinions in Table 6. These sources have been quite popular alongside technical publications, given the extensive accessibility and high information content. However, consumer opinions are quite poor in terms of language quality, which, as discussed previously, poses negative effects on the performance of fundamental NLP tasks. Since prescriptive tools like NLTK do not work well on these sources, NLP scholars have been developing deep learning models to carry out fundamental tasks like POS tagging (Young *et al.* 2018).

Scholars have applied state-of-the-art NLP methods for sentiment analysis and extraction of usage context. Although Kansei engineering only concerns emotional descriptors for artefacts, scholars have significantly advanced this area by relating with product features and developing fuzzy-linguistic models. While scholars could additionally explore the YouTube platform for a newer set of opinions, any advancement in NLP applications to consumer opinions, therefore, depends on the advancement in core NLP research.

The current NLP applications use state-of-the-art methods that can identify negative reviews, filter the less useful ones, extract significant topics and group similar reviews. Companies can hire human resources to conduct *post hoc* analyses and test the products and services under those conditions that the consumers had deemed to malfunction. Developing NLP applications to support such *post hoc* analyses may not carry scholarly merit as much as generating value for the industry.

Scholars could rather utilise detailed product reviews given by experts to extract design knowledge at various levels of abstraction (e.g., Function–Behaviour–Structure). Extracting such knowledge could be of value to discovering design opportunities and generating problem statements. Domain experts who provide such detailed reviews can identify fundamental issues with a concept that is embodied in the product. An expert mentions all specifications, various use cases, do's/don'ts and estimated lifetime. In addition, an expert provides the reviews with necessary context that is often absent in consumer opinions. YouTube provides both expert reviews and consumer opinions on a single platform, which is currently underutilised by scholars.

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[47] http://jmcauley.ucsd.edu/data/amazon/.

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Table 6. Summary of NLP methodologies and future possibilities (**bolded**) with consumer opinions

	Data	Methods	Supporting Materials
Sentiment analysis	*Amazon*: home theatre, kindle fire HD, electric iron, DSLR, laptop, hair dryer, tablet, smartphone, sneaker, upper limb rehabilitation device *Twitter*: home theatre, smartphone, Xbox One X, New Nintendo 2DS XL, Google Glass *Others*: Flipkart – home theatre, compact car, Zol – phone, Trumpchi GS4 & GS8, JD – laptop, Alibaba – upper limb rehabilitation device, **YouTube**	*Text Processing*: Carnegie Mellon POS Tagger, Stanford CoreNLP, ARM *Embedding*: TF-IDF, BOW, Word2Vec, GloVe, BERT *Similarity Measurement*: WordNet-based similarity *Sentiment Prediction*: SENTRAL, Semantria, TextBlob, IBM Watson, deep structured semantic model *Topic Extraction*: tag sentiment aspect (TSA), LDA *Clustering*: K-means *Classification*: Fuzzy-SVM, LSTM, fastText, SVM, Deep Neural Network (DNN), Kano *Named Entity Recognition*: BERT +2 CNN layers *Others*: coword network analysis, curve fitting	*Lexicon:* WordNet *Affective Lexicon*: SentiWordNet, WordNet-Affect, SenticNet4, dictionary of affect language (DAL), ANEW
Extracting usage context	*Amazon*: Camera, HP Printers, Epson Printers, Smartphone, Kindle, Echo, Alexa *Others*: MobilePhoneSurvey – Mobile Phone, NewEgg – Camera, CNET, Apple App Store, Google Play Store, **YouTube**	*Text Processing*: TextAnalyser 2.0, N-gram model *Term Retrieval:* dependency parsing, rule-based approach, **design Knowledge graph** *Embedding*: BOW, Word2Vec, **BERT, GPT-x** *Similarity Measurement*: Wu and Palmer *Clustering*: K-means, X-means *Topic Extraction*: LDA, Fine-Grained LDA, Unified Fine-Grained LDA *Classification*: Naïve Bayes, Decision Tree, Maximum Entropy, SVM, IBk,	*Lexicon*: WordNet ***Ontologies*: domain-specific**

Table 6. Continued

	Data	Methods	Supporting Materials
		logistic regression, gaussian process, random forest, multilayer perceptron, ordered logit regression, Kano, fastText, k-optimal DNNs, SHAP *Sentiment Analysis*: IBM Watson *Others*: fuzzy-linguistic approach	
Kansei engineering	*Amazon*: Bose SoundLink, Recliner, Road Bike, French Press Coffee Maker, Stuffed Toys, Hair Dryer, Upper Limb Rehabilitation Device (also from Alibaba) *Survey Responses*: BMW 318 Interiors, Volvo S60 Interiors, VW Bora Interiors, Audi A6 Interiors, Tecnifibre Tennis Bag, Electronic Reader Patents, Wearable Products, Flash Drive, Toaster, Truck Cab Interiors, CNC Machine Tools, In-Vehicle Rubber Keypad, Bottle Design, Crack Patterns on Pottery Surfaces, Cockpit Interiors, Kutani Cups	*Clustering*: K-means, ClusterGrammer *Classification*: K-optimal rule discovery, ordinary least-squares (OLS) regression, support vector regression, ANN, neural network (two hidden layers), linear regression, random forest, gradient boosting machine, k-NN, classification and regression tree (CART), multilayer perceptron, DBN, LSTM, radical basis function, Elman *Topic Extraction*: LDA, RAKE *Others*: multifactor analysis, Curve Fitting	*Lexicon*: WordNet

3.6. Other sources

Function structures

Built upon traditional function structures (Pahl and Beitz 1988; Hubka and Eder 1990), the functional basis developed by Stone and Wood (2000) constitutes functions (e.g., convert, distribute) and flows (e.g., solid material, mechanical energy). The functional basis led to the development of functional models for several products for over 184 electromechanical products and 6906 artefacts (Bohm, Stone, and Szykman 2005). Due to its tremendous popularity, several scholars have attempted to apply and build upon the modelling technique. We review such contributions that are relevant to NLP.

Sridharan and Campbell (2005, pp. 141, 143) propose several grammar rules to ensure consistency in functional models. For example, to the function 'remove solid', the secondary inflow – 'mechanical energy' and the outflow – 'reaction force' is added, while, the primary outflow is modified to 'two solids' (2005, pp. 145–147). Sangelkar and McAdams (2012) improve on functional models by including user activities obtained from ICF[48] to create action–function diagrams, which they use to compare typical and universal products (e.g., Box Cutter and Fiskars Rotary Cutter).

Sen, Summers, and Mocko (2013) formalise function structures using a prescribed vocabulary for entities and relationships while also proposing several rules for the construction of flows. For example, Rule 14 states (2013, p. 6), 'A Material flow can have one or more upstream flows, all of which must be of type Material'. Agyemang, Linsey, and Turner (2017) propose several pruning rules to reduce uncertainty and improve consistency in modelling function structures. For example, Rule 8 states (2017, p. 504), 'Remove all signal, sense, indicate, process, detect, measure, track and display functions'.

To assist with the construction of function structures, Gangopadhyay (2001) develop the Augment Transition Network – ATN parser that detects the entities and conceptual dependencies upon providing a text input. To automatically construct functional models, Yamamoto *et al.* (2010) extract (noun, part of, noun) triples (e.g., 'wheel of car') using the ESPRESSO algorithm (Pantel and Pennacchiotti 2006) and develop a tree structure, where nouns are replaced by adjacent verbs found in documents.

Wilschut *et al.* (2018, p. 535) extract functions from sentences that comply with a specific grammatical structure, for example, 'Component x provides power p to component y'. Using Wikipedia articles on 'machines', Cheong *et al.* (2017, pp. 4, 5) obtain and classify Subject–Verb–Object (SVO) triples as functions and energy flows if objects and verbs match with secondary terms on a functional basis and their WordNet synonyms. Also, if the combined similarity (Jiang-Conrath and Word2Vec) between the object and 'energy' is greater than 2.9, they classify the object is classified as energy flow.

Miscellaneous

We review some purpose-specific classifiers that were built using miscellaneous sources of natural language text. To classify manufacturing concepts using the manufacturing capabilities, Sabbagh, Ameri, and Yoder (2018) label the concepts

[48] International Classification of Functioning, Disability, and Health, https://tinyurl.com/7ph87kb7.

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(e.g., 'annealing', 'hardening') with capabilities (e.g., 'highspeed machining') using the data provided by 260 suppliers listed in ThomasNet[49] and a manufacturing thesaurus (Ameri *et al.* 2014). They train the labelled dataset using the following classifiers: Naïve Bayes, k-NN, Random Forest and SVM. Sabbagh and Ameri (2020) obtain LSA-based vectors of manufacturing concepts and cluster these using the manufacturing capability data – ThomasNet for 130 suppliers in heavy machining and complex machining.

To map technical competencies and performances, using the methods such as probabilistic latent semantic indexing (PLSI), nonnegative matrix factorisation (NNMF) and latent dirichlet allocation (LDA), Ball and Lewis (2020) extract topics from two corpora: course descriptions and project descriptions of students who were enrolled in the capstone. For each topic and each student, either from course or project, they compute the aggregated score based on his/her grade. They subsequently map course and project vectors using the following methods: linear regression, decision tree, k-NN, support vector regression and ANN.

4. Discussion

In Section 3, we have reviewed and summarised NLP contributions according to the types of text sources. In the summary sections for each type of text source, we have indicated the method-wise and data-wise limitations, while also mentioning specific opportunities. In this section, we discuss how the NLP contributions thus reviewed could be applied in the design process and what are the potential future directions for the scholars who would contribute to NLP in-and-for design.

4.1. Applications

To provide a summary of the design applications that are currently supported by NLP, we utilise the integrated design innovation framework that was developed at the Singapore University of Technology and Design (SUTD). The framework[50] builds upon the double-diamond model of the UK Design Business Council and includes various design modules within each phase. The framework has been utilised to train practitioners from various domains who attend design thinking workshops at the university. Over 20 workshops are held every year – during each workshop (2–3 days), on average, five design innovation facilitators train over 50 practitioners on design thinking. It is important to note that the framework does not span the entirety of the design process, methods and underlying steps. For instance, the framework does not cover immersed spatial thinking (Rieuf *et al.* 2017). We utilise this framework to set a boundary for our discussion and to identify the application gaps that could potentially lead to future research opportunities for design scholars.

We list the modules of the design innovation framework across each phase of the design process, as shown in Table 7. For these modules, we highlight (underlined) the specific steps that are being supported by NLP to indicate the steps that are yet to be supported. We also highlight (bolded), on some occasions, the steps as well as NLP applications that could be considered future opportunities.

[49] https://www.thomasnet.com/.
[50] https://www.dimodules.com/dilearningmodules.

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Table 7. Applications of NLP in the design process. We highlight the currently supported steps (underlined) within the module and future opportunities (**bolded**)

Phase	Module	NLP applications
Discover	*Interviews*: explore usage, identify users, inquire likes/dislikes and use, extract needs and insights *Scenarios*: ideate scenarios (how, who, where), present scenarios, observe user reactions *User-Journey Map*: gather insights, choose persona, identify touchpoints, identify channels, sketch user journey, rate emotional level, extract opportunities, sketch future journey	*Sentiment Analysis*: text classification, network analysis. topic modelling, sentiment indicators, clustering, named entity recognition *Product Feature Modelling*: rule-based approach, kano maps, regression, curve fitting, clustering, text classification, neural networks *User Profiling*: clustering, named entity recognition, affective attributes, affective-design attribute relationship *Usage Scenarios*: topic extraction, language models, house-of-quality, optimisation methods, text classification, ontology extraction, FBS, dependency parsing, regression, Kano map *Design Rationale Extraction*: text classification *Emotion Vocabulary*: clustering *Kansei Engineering*: survey, Kansei-design matrix, clustering, topic extraction, multifactor analysis, Kansei-feature regression, text classification, term similarity, image classification, fuzzy membership function
Define	*Affinity Diagram*: gather needs, group needs *Personas*: gather persona, consolidate behaviour, present persona	
	Activity Diagram: observe user activities, record activities, visualise activity sequence, extract insights	*Action-Function Diagram*: functional basis, rule mining
	Hierarchy of Purpose: **create opportunity statements**, create generalised statements, review statements	*Requirements Elicitation*: documentation guidelines, **text generation, sentence completion**
	System Functions: gather needs, map needs and flows generate functions, create function structures	*Functional Modelling*: grammar rules, action-function linking, function vocabulary, pruning rules, term (function/flow) identification, ontology extraction, text mining, text similarity

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Table 7. Continued

Phase	Module	NLP applications
Develop	*Mind Mapping*: initiate design opportunity, generate categories, generate subcategories, generate solutions, review mind maps, expand mind maps, reorganise mind maps	*Mind Mapping*: term retrieval *Patent Mining*: term-based patent map, class-based technology map, product-based patent map, predicate logic, topic clustering, phrase extraction *Solution Generation*: TRIZ, cosine similarity, patent similarity, function-based patent classification
	6-3-5 (C-Sketch): form a 6-member group, sketch 3 ideas, pass the sketches to a neighbour, **improvise on the sketches**, repeat five times	*Iterative Labelling*: **object recognition, term retrieval, image classification** *Iterative Annotation*: **text generation, sentence completion, knowledge retrieval, ontology-based retrieval (e.g., definitions)** *Iterative Argumentation*: **text classification, text mining, clustering, ontology-based patent mining, knowledge retrieval**
	Design-by-Analogy: identify keywords, search for inspiration, align relational structure, generate concepts, utilise tools, make inferences, iterate	*Key word Identification*: Lexical Relationships, Semantic Similarity, SAPPhIRE, FBS, Text Classification, Domain Ontologies *Relation-based Retrieval*: ontological, lexical, physical, ecological, biological *Solution Generation*: function-based patent classification, text classification *Patent Mining*: FBS-based term retrieval, function-based patent similarity, image annotation, ontology-based topic modelling
	Real-Win-Worth: gather solutions, check reality, check novelty, check value	*Concept Association*: clustering, topic association, network analysis, patent keyword summarisation, patent abstract summarisation *Novelty Assessment*: Kansei attributes, pattern matching, semantic similarity, SAPPhIRE, topic modelling

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Table 7. Continued

Phase	Module	NLP applications
	Multimedia Story Boarding: identify target user, communicate context, **identify key actors, generate flow of events**, present story, **gather feedback**	*User Profiling*: clustering, named entity recognition, **text classification, text mining, term retrieval, ontology-based retrieval** *Usage Scenarios*: **topic extraction, language models, house-of-quality, optimisation methods, text classification, ontology extraction, fbs, dependency parsing, regression, Kano map** *Image Annotation*: **entity recognition, text generation, knowledge retrieval, ontology-based retrieval** *Kansei Engineering*: **survey, Kansei-design matrix, clustering, topic extraction, multifactor analysis, Kansei-feature regression, text classification, term similarity, image classification, fuzzy membership function**
Deliver	*Prototyping Canvas*: choose a solution/concept, fill prototyping canvas, discuss the canvas, build prototype, test prototype, analyse results *Scaled Model*: conduct dimensional analysis, **identify key parameters**, employ scaling, construct scale model, evaluate model	*Requirements Elicitation*: documentation guidelines, network analysis, text classification *Design Rationale Extraction*: text cleaning/segmentation, term/phrase disambiguation, text classification, text mining, clustering, ontology-based patent mining *Ontology Discovery*: text mining, similarity measurement, clustering, topic modelling, patent similarity *Case-based Reasoning*: knowledge retrieval, knowledge graph construction, ontology-based retrieval, case indexing *Failure Analysis*: sequence–sequence mapping, text classification *Parameter Identification*: **survey, kansei-design matrix, kansei-feature regression** *Design Evaluation*: **Kansei attributes, pattern matching, semantic similarity, SAPPhIRE, topic modelling, text classification, success metrics**

We could consider Table 7 as a minimal NLP guide for choosing a module or a step within a module to develop specific NLP-based supports. In future, as more NLP contributions are reported in the literature, we hope to extend this NLP guide using a comprehensive list of design methods like the Design Exchange.[51]

Discover

The design innovation framework suggests, as shown in Table 7, that in the *discover* phase, interviews are conducted with potential users to extract needs and insights. Upon collecting user perceptions on specific usage scenarios, a user journey map is developed. Consumer opinions from e-commerce and social media platforms readily provide user profiles along with their ratings, usage and needs. While the steps in the *discover* modules are largely accomplished using sentiment analysis (Zhou *et al.* 2017; Tuarob, Lim, and Tucker 2018) and usage context extraction (Maalej *et al.* 2016; Park, Kim, and Baik 2016), Kansei engineering methods capture user emotions for the presented usage scenarios (Vieira *et al.* 2017; El Dehaibi, Goodman, and MacDonald 2019).

Kansei engineering also allows establishing a relationship between emotions and product features to predict their importance (Chen *et al.* 2021; Shi and Peng 2021). The design knowledge thus extracted from consumer opinions is often not sufficient to capture the user journey as the opinions lack enough context and detail. Some seeding information like user persona (Li *et al.* 2021), touchpoints and channels (Hou *et al.* 2019) could be extracted to initialise the user journey map, which could only be developed upon mining detailed expert reviews (Jin, Ji, and Gu 2016) and conducting user studies (Misaka and Aoyama 2018).

Define

In the *define* phase, the user needs are identified and grouped while capturing the user personas to develop activity diagrams. The data generated thus far is utilised to concretise design opportunities and create function structures that map needs to product functions. In terms of gathering needs and persona, the NLP supports remain the same as what was discussed in the *discover* phase. To develop activity diagrams, Sangelkar and McAdams (2012) provide partial support by mining association rules from the action-function diagrams.

While there is a need for NLP support in terms of text generation to create opportunity statements, some documentation guidelines have been proposed to structure the requirements such that these are suitable to perform NLP tasks (Moitra *et al.* 2019; Kang *et al.* 2019a). The scholars have extensively invested in NLP approaches to map needs to functions (Murphy *et al.* 2014; Vandevenne *et al.* 2015), generate functions (Fantoni *et al.* 2013; Wilschut *et al.* 2018) and develop function structures (Gangopadhyay 2001; Yamamoto *et al.* 2010; Gericke and Eisenbart 2017) as we have reviewed in this article.

Develop

The *develop* phase capitalises on the concretised needs, problem statements and function structures from the *define* phase to generate solutions using various approaches such as mind-map, 6-3-5 sketching and design-by-analogy. Supports

[51] https://www.thedesignexchange.org/design_methods.

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have been developed regarding the mind maps to generate nodes (Chen and Krishnamurthy 2020) and organise these into categories (Camburn *et al.* 2020a). In the absence of user needs, scholars have proposed various approaches to initiate design opportunities from technology maps (Trappey *et al.* 2014; Luo, Yan, and Wood 2017) and biomimicry strategies (Vandevenne *et al.* 2016; Cao *et al.* 2021). The approaches to design opportunity identification could also lend themselves to widening strategies such as keyword expansion (Linsey, Markman, and Wood 2012; Sarica *et al.* 2021) and concept exploration (Han *et al.* 2018b; Goucher-Lambert *et al.* 2020).

While 6-3-5 sketch is often overlooked by scholars in terms of NLP, it is possible to label the sketches using object recognition and image classification algorithms. While the label for such algorithms often tends to be abstract (e.g., man, animal), it is possible to retrieve specific and label-related terms using ontologies and context information (Akmal, Shih, and Batres 2014). The sketches are often annotated with titles, definitions and the flow of events. To reduce annotation time and make plausible annotations, it is possible to use text generation approaches, especially sentence completion algorithms. In digital sketching interfaces, definitions of components (retrieved from knowledge bases) may pop up on hover.

Scholars have extensively contributed to the research in design-by-analogy in terms of identifying search keywords (Cheong *et al.* 2011; Lee, Mcadams, and Morris 2017), generating solutions (Verhaegen *et al.* 2011; Goel *et al.* 2012; Fu *et al.* 2013b), especially via relation-based retrieval algorithms (Kim and Lee 2017; Han *et al.* 2018a). These supports, however, inform less whether the analogies are suitable. The analogical inferences are therefore yet to be supported.

The design innovation framework shown in Table 7 suggests that the solutions thus generated should be gathered and checked for reality, novelty and value. The NLP contributions have been effective in associating and discovering categories among several crowdsourced solutions (Liu *et al.* 2020; Zhang *et al.* 2017). While several other performance indicators such as flexibility and manufacturability are also important metrics to be considered while selecting concepts, computing value is difficult while developing a concept, as value requires sufficient usage context. Current NLP contributions are capable of supporting interim tasks in novelty assessment that is carried out in many ways (Ranjan, Siddharth, and Chakrabarti 2018).

Deliver

To *deliver* the solutions, the framework suggests creating a multimedia storyboard that communicates the role of solutions in specific scenarios. Scholars have proposed approaches to identify generic users and usage context from consumer opinions that could stimulate ideas for storyboarding. Object-detection algorithms coupled with knowledge graphs (Wan *et al.* 2021) could be useful for labelling and describing scenes like storyboards. Kansei engineering methods could be adopted to capture emotional feedback on the storyboards. Besides multimedia storyboarding, NLP techniques could provide direct as well as indirect support for prototyping and developing scaled models.

To build, test and analyse prototypes, the current NLP supports help understand requirements including dependencies (Morkos, Mathieson, and Summers

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2014), elicit requirements (Kott and Peasant 1995), capture design rationale (Liu *et al.* 2010; Deken *et al.* 2012), analyse failures (Ebrahimipour, Rezaie, and Shokravi 2010; Wang *et al.* 2010) and facilitate case-based reasoning (Guo, Peng, and Hu 2013; Akmal, Shih, and Batres 2014). While these existing supports are applicable for testing scaled models as well, building a scaled model requires dimensional analysis that maps the key design parameters (e.g., viscosity) onto the performance parameters (e.g., energy consumption).

As an alternative to dimensional analysis, scholars have adopted deep learning approaches to associate design and performance parameters. For example, upon combining three datasets,[52] Robinson *et al.* (2017) map building features such as area, number of floors, heating degree days and building activity onto the annual energy consumption using several models such as gradient boost, multilayer perceptron, KNN and SVR (2017, p. 894). While performance parameters like energy consumption are largely derived from industry standards, the influential design parameters could be chosen and evaluated based on Kansei methods (Vieira *et al.* 2017; Misaka and Aoyama 2018).

4.2. Methodological directions

Based on our review, we propose eight methodological directions for future NLP applications to support the design process.

First, we prioritise the extraction of knowledge graphs from text, which will be utilised in the design process as a knowledge base. Second, we recommend the development and utilisation of domain-specific language models to perform tasks such as classification, NER and question-answering. In the third and fourth directions, we propose the development of one or more text generation and neural machine translation models. Next, we propose the adoption of NER methods and collaborative tagging approaches to facilitate the tasks such as classification and relation extraction. Further, we propose that scholars develop standard datasets using design text as a common evaluation platform for future NLP applications. Finally, we propose to develop success metrics for evaluating the efficacy of NLP supports.

We have listed these directions along with examples in Table 8. We provide specific examples for the first six directions using a publicly available text.[53] For the remainder of this section, we explain these directions in individual subsections.

Design knowledge graph

A knowledge graph comprises facts of the form – $\{\langle h, r, t \rangle\}$ and serves as an infrastructure for the development of various NLP applications. A design knowledge graph includes facts like <‘stapler’, ‘comprises’, ‘leaf spring’>, < ‘hammer’, ‘push’, ‘staple’ > that could be utilised or generated in the design process. A design knowledge graph carries informative as well as reasoning advantages over

[52]Commercial Buildings Energy Consumption Survey - https://www.eia.gov/consumption/commercial/.

New York City Local Law 84 (LL84) - https://www1.nyc.gov/html/gbee/html/plan/ll84_about.shtml.

New York City Primary Land Use Tax Lot Output (PLUTO) - https://www1.nyc.gov/site/planning/data-maps/open-data/dwn-pluto-mappluto.page.

[53]https://ceramicpro.com/what-does-a-nano-ceramic-coating-do/.

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Table 8. Methodological directions with examples

Methodological direction	Example input	Example output
Design knowledge graph	'A nano-ceramic coating, a scientifically formulated solution meant to penetrate microscopic imperfections, fill those gaps in the top range of the nanoscale and provide a layer of protection that's nearly as strong as solid quartz. 9H ceramic coating work by bonding with the existing surface to form a protective nano-ceramic shield on the surface.'	<nano-ceramic coating, penetrate, microscopic imperfections> <nano-ceramic coating, provide, protection layer> <nano-ceramic coating, form, nano-ceramic shield> <nano-ceramic coating, bond, existing, surface> <existing surface, bond, nano-ceramic shield>
Domain-specific language model	'Nanoceramic coating', 'solution', 'ceramic'	Embeddings
Text generation	'Nano-ceramic coating'	'Nano-ceramic coating provides protection layer' 'Nano-ceramic coating forms nano-ceramic shield' …
Neural machine translation model	'Nano-ceramic coating provides protection layer' 'Nano-ceramic coating forms nano-ceramic shield'	<nano ceramic coating, *hasFunction*, provide protection layer> <nano ceramic coating, *hasBehaviour*, form nano ceramic shield>
Named-entity recognition	'A *nano-ceramic coating*, a scientifically formulated solution meant to penetrate microscopic imperfections, fill those gaps in the top range of the nanoscale and provide a layer of protection that's nearly as strong as *solid quartz*'	'Nano-ceramic coating' – coating material, coating solution 'Solid quartz' – coating material, coating solution
Collaborative tagging	'A nano-ceramic coating, a scientifically formulated solution *meant to* penetrate microscopic imperfections, fill those gaps in the top range of the nanoscale and *provide* a layer of protection that's nearly as strong as solid quartz. 9H ceramic coating *work* by *bonding* with the existing surface to *form* a protective nano-ceramic shield on the surface.'	'A nano ceramic coating…' – Function '9H ceramic coating…' – Behaviour
Standard datasets	**NLP Tasks**: Text Classification, Text Similarity… **NLP Applications**: Functional Representation, Design Rationale Extraction…	Standard Datasets
Success metrics	Text Comprehension, Keyword Diversity, Problem Understanding…	Success Metrics

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networks (Han *et al.* 2021) that provide pairwise statistical (Sarica, Luo, and Wood 2020), semantic (Casakin and Georgiev 2021) and syntactic (Jang, Jeong, and Yoon 2021) relationships among a large collection of design terms (lexicon).

To process and recognise entities in text sources like internal reports, design concepts and consumer opinions (Li *et al.* 2021b), it is necessary to build design knowledge graphs that could replace the common-sense lexicon (e.g., WordNet). Domain-specific ontologies (e.g., QuenchML) capture design knowledge using relationships (r) such as 'hasProperty', 'partOf' and 'hasWeight' that are technically preferable in comparison with that of common-sense ontologies like ConceptNet, that is, the relationships such as 'atLocation' and 'usedFor' captured by these. However, domain-specific ontologies capture abstractions (e.g., <Component, hasWeight, xx>) rather than facts (e.g., <clamp, weighs, 65 grams>) that are extracted from natural language text and captured using knowledge graphs.

We have shown an example in Table 8 for the facts that could be extracted from a sample text. As discussed in Section 3.4.4, technical publications that include patents and scientific articles are preferable sources for extracting facts and developing design knowledge graphs due to their high accessibility, information content and quality. Scholars have indicated the possibility of extracting triples from the patent text (Soo *et al.* 2006; Cascini and Zini 2008; Korobkin *et al.* 2015). Siddharth *et al.* (2021), for example, apply some rules to extract facts from patent claims by exploiting the syntactic and lexical properties. While patents could offer rule-based extraction methods due to consistent language, scientific articles require a mix of rule-based, ontology-based and supervised approaches.

Domain-specific language model

Early models of language given by traditional grammar have often proposed a restricted set of rules for forming sentences (Chomsky 2014, pp. 5, 6), which limits the opportunity to produce a vast number of sentences. The modern view of a language model involves training large corpora to capture the likelihood of a given sequence of words (or tokens), for example, 'metallic bond is strong' in the same order. Originally developed as N-gram models, these models have evolved into deep learning-based models or transformers such as BERT and GPT-x. These models advance the theory of acquisition model of a language (Chomsky 2014, p. 38) via statistical embeddings of generative grammar, which is otherwise represented as parts of speech and structural dependencies.

These models capture the embeddings of tokens and sequences through masked language modelling where a large number of sequence–sequence pairs are provided as training data. The input–output pair must belong to the same sequence but nearly 15% of the input tokens are expected to be masked. The embeddings that result from these models could be directly used to train classifiers, sequence-to-sequence tasks like Q & A and NER tasks. Several variants of BERT have been introduced at the corpora level, for example, BioBERT (Lee *et al.* 2020) and at the architecture level, for example, k-BERT (Liu *et al.* 2019). The variant k-BERT, for instance, stitches facts from a domain knowledge graph onto the tokens for training the model.

Using domain-knowledge embedded language models like k-BERT provides embeddings of terms that are meaningful. As opposed to common techniques such as BOW, LSA and Word2Vec, embeddings from domain-specific language models

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should return 'nearly true' cosine similarity between a pair of artefacts (described using text) that have domain-association, similar physical properties and perform similar functions. Moreover, such domain-specific embeddings could aid in efficient concept retrieval in the respective domain. For example, a radiology-specific language model should identify the terms closest to 'Magnetic Resonance Imaging' than a common-sense language model.

Text generation

Originally referred to as natural language generation (NLG) systems, for example, the DOCSY model (Andersen and Munch 1991), applications that generate text reduce cost, ensure consistency and maintain the standard of documentation (Reiter, Mellish, and Levine 1995, pp. 261–265). Such applications are relevant to the design process where requirements must be elicited, opportunity statements must be generated and solutions must be described. In Table 8, we indicate an example where a seeding term 'nano-ceramic coating' results in plausible sentences using text generation algorithms.

To support ontology-based verification of requirements, Moitra *et al.* (2019, p. 347) propose that a requirement shall be expressed as follows: REQUIREMENT R (name); SYSTEM shall set x of X to x_1 (conclusion); when $y \in Y$ (condition). Likewise, scholars have proposed templates for describing design concepts as well (Siddharth and Chakrabarti 2018; He *et al.* 2019; Luo, Sarica, and Wood 2021). While such a template-based approach works with a limited scope, it is necessary to implement text generation algorithms that are built out of RNNs, LSTM and Transformers.

Zhu and Luo (2021) fine-tune GPT-2 for mapping the problems (including categories) to solutions using problem-solution data obtained from RedDot.[54] They also explore the capabilities of GPT-3 that support analogy-by-design in terms of generating text descriptions upon providing source-target domain labels as inputs. For a given technology domain, using KeyBERT,[55] Zhu and Luo (2022) extract topics (terms and keyphrases) from patent titles and create a dataset of topic-title pairs. They fine-tune GPT-2 for mapping topics to titles so that solutions (as hypothetical titles) could be generated using search keywords (topics of interest).

Neural machine translation

Neural machine translation (NMT) models are trained to map sequence-to-sequence using an encoder–decoder framework (Tan *et al.* 2020). These models are often associated with Transformers owing to the similarity in structure and behaviour of the neural networks that were built to accomplish the mapping task. NMT models have been specifically built to perform cross-language translation tasks and these are useful to increase semantic interoperability in design environments. For example, the rules 'Smith Ltd shares machines with NZ-based companies' and 'Smith Ltd allows NZ-based companies to use its machines' mean the same but are written in different forms (Ye and Lu 2020).

[54] https://www.red-dot.org/.
[55] https://github.com/MaartenGr/KeyBERT.

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In Table 8, we have shown an example of semantic forms that could be mapped from design text through neural machine translation. To standardise manufacturing rules, Ye and Lu (2020) map a manufacturing rule into a semantic rule using a neural machine translation model (Luong, Pham, and Manning 2015) that comprises an encoder and a decoder with 256 gated-recurrent units (GRUs) present in each (Ye and Lu 2020). Chen *et al.* (2020) propose semantic rule templates to formalise requirements so that these are easily verified using ontologies. NMT models coupled with semantic rule templates are necessary to translate ambiguous natural language sentences into a machine-readable form.

Named entity recognition

NER is a sequence-to-sequence task like POS tagging where entities and their respective tags are identified, for example, 'General Electric' as an organisation and 'San Francisco' as a location. From a design perspective, the term 'fan' shall be recognised as a product and the terms 'ceiling fan', 'exhaust fan'and 'CPU cooling fan' shall be recognised with specific categories. While plenty of NER models and associated datasets exist for common-sense entity recognition (Yu, Bohnet, and Poesio 2020), design-based datasets and models are yet to evolve. NER is also the first step towards the extraction of knowledge graphs, as described in Section 4.2.1.

In Table 8, we have shown that in a given design text, entities like 'nano-ceramic coating' and 'solid quartz' must be identified using tags like *coating material* and *coating solution*. Before the identification of entity tags, it is necessary to recognise terms that comprise one or more words (n-grams). Scholars have often utilised POS tags, dependencies and ontologies to recognise n-grams. Due to poor performance, such approaches must be replaced with deep learning models, as demonstrated by Chiarello *et al.* (2018) in their NER application.

Collaborative tagging system

Collaborative tagging (or folksonomy) is useful for the classification of a large set of documents as well as sentences in these. This bottom-up approach has been recently popular instead of a traditional top-down approach where the classification scheme is defined by the experts, for example, International Patent Classification. The current classifications in vast knowledge sources like Patent Databases, Web of Science and Encyclopaedia are less useful for developing NLP applications to support the design process. For instance, the classification codes that are assigned to a patent could inform the type of invention but not its purpose, behaviour and components.

We have indicated an example in Table 8 for the design-specific tags that could be assigned to individual sentences in a text document. The tags shall be recommended based on external knowledge as well as the previous tags (Hsieh *et al.* 2009). These tags could also be expanded using classifiers (Sexton and Fuge 2020). While several advantages to collaborative tagging exist, scholars are yet to introduce or develop many interfaces that help to assign tags to documents that are universally accessible. COIN platform is an example of such a collaborative tagging system (Panchal and Messer 2011). The use of such interfaces in design education, workshops and laboratory settings allows a variety of tags to be assigned to an open-source document that could be reused for developing retrieval algorithms.

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Standard datasets

None of the NLP contributions that we have reviewed in this article leverage a design-specific gold standard dataset for evaluation. If an embedding technique is used for measuring the similarity between text descriptions of two artefacts, what is the trueness of that similarity? Similarly, if an application combines several tasks like NER and classification, to extract FBS from text, what is the efficacy of the application? For such cases, scholars are currently creating their datasets from scratch, which reduces the possibility of comparing different applications within design research.

A gold standard dataset is necessary for NLP applications that aim to measure artefact level metrics such as novelty, feasibility and so forth. These metrics shall be measured in different ways, but it is recommended that scholars provide a gold standard for different ways to benefit the development of NLP applications. For example, given a text description of an artefact, a dataset may include the novelty scores measured using distance-based and frequency-based approaches while also indicating the reference product databases utilised for the measurement.

Success metrics

A variety of NLP applications have been and will be developed to support various design tasks. To ensure the efficacy of these applications, success metrics are necessary. The metrics like accuracy for classification only tell us that the classifier performs well on the test data. However, the utility of such a classifier is often assessed based on the artefact level metrics such as novelty, quantity and variety. While such metrics are crucial, it would be useful to also measure the 'goodness' of envisioned scenarios, activity diagrams, mind maps, opportunity statements, search keywords and requirement formulation.

The expert designers spend a majority of the time proposing and evaluating solution alternatives (Cross 2004, p. 430), while novices spend more time understanding the problem. Even if novices generate quick solutions, experts have a better ability to recognise good solutions. Novices could therefore significantly benefit from NLP support in terms of keyword recommendation, opportunity statements, identifying novel solutions and so forth. Since novices need to develop expertise throughout the design process, success metrics at each step could be beneficial for their learning as well as for understanding the efficacy of NLP supports.

4.3. Theoretical directions

While the proposed methodological directions could impact the development of NLP applications in the near future, our review also led us to raise a few questions regarding constructs that embody the design-centric natural language text and the roles of these constructs in the design process. Addressing these questions could be of importance in the extended future to facilitate the development of cognitive assistants that make independent decisions in the design process based on long-term memory and extensive reasoning capabilities. We discuss these questions in the remainder of this section.

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Characteristics and constructs

In our review, we have indicated the text characteristics of various types of natural language text sources that are utilised or generated in the design process. These characteristics are only relevant to the NLP methodologies applied to the text sources. The literature does not communicate the characteristics of natural language that allow us to distinguish a piece of text that is relevant to the process. Let us consider the following sentences for example.

(i) 'The pan is heated while the steak gets seasoned,'
(ii) 'During the recrystallization stage, the material is heated above its recrystallization temperature, but below its melting temperature.'

The first sentence mentions a cooking tip and the second one is part of the annealing process.[56] The underlying factors of distinguishability between these two sentences are unclear. If we assume that the distinction could be attributed to the usage of technical ('recrystallization', 'temperature', 'material') and common-sense ('pan' and 'steak') terms, it is also possible that these terms could be used interchangeably in other text sources. Hence, we raise the first open question as follows.

> *What are the unique characteristics of natural language text that are relevant to the design process?*

While the efforts to identify the design-specific characteristics in natural language may lead to a bifurcation of technical and common-sense natural language text, it is necessary to acknowledge that design knowledge is present in various flavours within the common-sense text as well. We provide an example using the reviews of a Scotch-Brite kitchen wiper on Amazon.[57]

- Affordance – 'I am using this not in kitchen but as a car wash assessary to clean all windows…'
- Recommendation – 'You can definitely buy this product…'
- Satisfaction – 'The quality of this one is ok'
- Feature description – '…the green color rubber part is very small and thin'
- Characterisation – 'I am not sure about this durability'
- Aesthetics – 'Too small and badly designed'
- Technical description – '…the actual size of the blade is mere 6.2 inches, which is too small for cleaning a large surface area… the blade is bent at an angle of almost 30–40° to the handle…'

From our review, we are unable to obtain sufficient explanation for the assignment and evolvement of the knowledge categories that we have tied to the sentences in the above example. Scholars have conducted large-scale analyses on consumer opinions while informing a little on what these sources communicate in the context of design. The constructs of design knowledge that embody the natural language text are often captured by ontologies and language models. These systems, however, are not capable of providing a cogent explanation of the phenomenon behind the judgement of design knowledge in a given text. It is therefore important to understand the following.

[56] https://www.metalsupermarkets.com/what-is-annealing/.
[57] t.ly/1ifJ.

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What are the unique constructs that embody design knowledge into natural language text?

There has been extant literature on ontologies that have aimed to address the question above. These ontologies are built by domain experts (top-down) as well as extracted from text sources (bottom-up). The outcomes of these approaches have often been distinguishable (Panchal and Messer 2011). In addition, there exists a significant difference in the level of abstraction between elementary (Lee *et al.* 2013; Varde, Maniruzzaman, and Sisson 2013) and abstract ontologies (Chandrasekaran and Josephson 2000; Kitamura *et al.* 2002).

Despite the recent attempts to extract abstract ontologies from text, for example, SAPPhIRE (Keshwani and Chakrabarti 2017) and FBS (Fantoni *et al.* 2013), it is easier to recognise elementary ontologies, as indicated by various knowledge retrieval systems developed using these. The elementary ontologies, however, do not cover a large scope of design like abstract ontologies. To address the above-mentioned question, it is, therefore, necessary to obtain investigate the following.

How to bridge elementary and abstract ontologies to support the design process?

Comprehension

The following questions relate to the performances of the natural language text concerning comprehension in the design process. Let us consider a natural language explanation for the firing cycle of a Glock handgun.[58]

> … when the trigger is pulled, this pulls the firing pin backward … a connector pin that guides the connector in a downward motion… this motion frees up the firing pin, allowing it to strike the primer…

While the above-stated text captures components and the causality of events, it is hard to visualise the orientations and positions of components such as ‘trigger’, ‘firing pin’ and ‘connector pin’ without (annotated-) images. In addition, the text is only pertinent to the firing cycle and does not include other subsystems of the handgun like the safety mechanism. It is difficult to interpret and reproduce the knowledge of system architecture (the hierarchy of a handgun in this example) purely using natural language text. Hence, a multimodal explanation is often necessary, especially in the design process (Siddharth and Chakrabarti 2018). The affordance in comprehension through textual mode shall therefore be investigated as follows.

What is the expected level of comprehension offered by natural language text in the design process?

Addressing the above-stated question could set a boundary for the performance of NLP applications. Large-scale analyses on crowdsourced natural language text (e.g., consumer opinions) often seem to highlight the lack of information quality, while providing less importance to the amount of design knowledge offered within a particular window of text. Since consumer opinions must

[58] https://ghostinc.com/ghost-inc-blog/how-does-a-glock-work/.

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adhere to word limits on platforms such as Amazon and Twitter, usage scenarios are often captured through images and videos. It would be worth investigating how text could be elaborated such that it provides a level of comprehension similar to that of a multimodal explanation. We, therefore, ask the following question.

> How to elaborate natural language text to obtain the desired level of comprehension in the design process?

Creativity

Cognitive scientists define an insight or 'Aha' moment as the instance of sudden realisation that is often associated with a stimulus. In terms of semantic memory, insight occurs when there is a new connection between entities that lead to a sequence of new connections (Schilling 2005). Such insights are necessary for solving problems, especially during the design process. A particular case of insight occurs in the design process when there is a relational alignment between two pairs of entities (Jamrozik and Gentner 2020).

Let us consider an example. Wall-climbing robots adopt various adhesive mechanisms to establish contact with the climbing surface. These mechanisms are less effective when robots are heavy and the surfaces are hard, flat and smooth. Let us consider a stimulus for this design problem. Mudskippers climb slippery surfaces of rocks by generating a vacuum at the limb interface. The interaction – 'generate vacuum' at the rock interface fits well in the wall interface. Such an alignment of relation creates an insight that leads to 'making sense of new interactions like releasing vacuum and decreasing pressure.

Scholars have proposed representation schemes like FBS and SAPPhIRE to model 'far' domain examples such that relations are explicitly shown. A majority of far-domain examples, however, are only available as natural language text that often does not explicitly state these relations. It is difficult to surf through several documents to encounter such relations and experience insights. To address this issue, scholars have proposed to summarise several documents by extracting the representative terms (Luo, Sarica, and Wood 2021). These terms alone are insufficient for gathering insights due to the lack of context. It is, therefore, necessary to investigate the following question.

> How to represent natural language text such that design insights are maximised?

Souza, Meireles, and Almeida (2021) generate short summaries of patent documents through an LSTM-based sequence-to-sequence mapping. Such statistical approaches are less guided by design theories that inform the constructs of design knowledge that should be present in such summaries. While a succinct representation of natural language text is necessary for gathering insights, it is also important to form the right queries to search for documents that could potentially include stimuli for solving design problems.

The mental representation of a design problem is translated to opportunity statements that are simplified into search keywords that form queries. It is a common phenomenon that the search results often guide the development of more keywords. If the initial set of keywords is not representative of the problem

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statement, the user has the chance to be misled by the results. In such situations, an expert could provide reliable guidance on how the problem statement is translated into search keywords by identifying the gaps and discrepancies in the problem formulation.

Let us consider an example of pumping water out of the basement. A direct search for terms like ‘pumping water‘ and ‘basement water’ might lead to several unwanted results. An expert, on the other hand, might question the type of basement, the cause of water in the basement, the type of water and the basement surroundings. These intricate details help elaborate the problem statement, from which the expert could extract important cues and translate these into keywords that are appropriate as well as technical (if necessary). It is therefore worth examining how problems should be narrated such that it is possible to translate these into meaningful opportunity statements and in turn appropriate search keywords.

From our review, we understand that keyword expansion approaches are largely driven by the search results alone (Lin, Chi, and Hsieh 2012; Lee, Mcadams, and Morris 2017) rather than by the missing details of the problem statement. The current NLP applications are therefore less capable of playing the expert’s role in examining the problem statement. To address this caveat, it is necessary that scholars provide a theoretical explanation to the following question.

> How to narrate a design problem such that it is better translated to appropriate search keywords?

We expect that in the future, NLP applications recommend keywords that are guided by the problem statement and provide results using succinct natural language text such that more insights are experienced in the design process. Given that insights often lead to solutions to design problems in the form of design concept alternatives, it is necessary to choose among these alternatives for implementation and testing purposes. Several design metrics such as feasibility, novelty and utility are being used to choose the alternatives.

Given that human judgement on alternatives often involves extensive effort and bias, scholars have proposed some NLP applications to compute the design metrics using natural language text data (Gosnell and Miller 2015; Siddharth, Madhusudanan, and Chakrabarti 2019b). Herein, both the alternatives and reference material (e.g., Kansei attributes) comprise natural language text. Since the usage of terms in the text descriptions of concept alternatives significantly impacts the judgement of design metrics it is important to address the following question.

> What is the role of natural language in the judgement of design metrics?

4.4. Summary

From our review of 223 articles related to NLP in-and-for design research, we identified the supported applications in the design process using a framework as discussed in Section 4.1. We have also indicated the steps and modules within the framework that are currently not supported by NLP. While we expect that such gaps are addressed by scholars in the near future, we hope that an NLP guide is developed using a more comprehensive design framework. We expect that such a

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Table 9. Summary of methodological and theoretical directions

	Methodological directions
1.	Design knowledge graph – text cleaning, term identification, relation extraction, functional representation, question answering, graph-based reasoning and graph embedding
2.	Domain-specific language model – text classification, named entity recognition, sentence completion, sentiment analysis, term extraction and similarity measurement
3.	Text generation – sentence completion, requirements elicitation, statement generation and technical documentation
4.	Neural machine translation – sentence disambiguation, storage compression and language standardisation
5.	Named entity recognition – term identification, ontology construction, term disambiguation, document indexing, knowledge graph extraction and functional representation
6.	Collaborative tagging – text classification, document indexing, ontology construction and sentiment detection
7.	Standard datasets – text classification, creativity assessment and functional representation
8.	Success metrics – text comprehension, problem diversification, problem detailing, solution assessment and keyword expansion
	Theoretical directions
1.	What are the unique characteristics of natural language text that are relevant to the design process? (Characteristics)
2.	What are the unique constructs that embody design knowledge into natural language text? (Constructs)
3.	How to bridge elementary and abstract ontologies to support the design process? (Constructs)
4.	What is the expected level of comprehension offered by natural language text in the design process? (Comprehension)
5.	How to elaborate natural language text to obtain the desired level of comprehension in the design process? (Comprehension)
6.	How to represent natural language text such that design insights are maximised? (Creativity)
7.	How to narrate a design problem such that it is better translated to appropriate search keywords? (Creativity)
8.	What is the role of natural language in the judgement of design metrics? (Creativity)

guide informs the following for an individual module: type of text sources used/generated, example case studies, relevant state-of-the-art NLP methods and rubrics to evaluate NLP methods. After summarising the applications, we presented the directions (listed in Table 9) for the advancement of NLP in-and-for design.

The methodological directions are necessary to enhance the performances and conduct a robust evaluation of NLP applications in-and-for design. In Table 9, we have also indicated the downstream tasks and applications that could entail the

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methodological directions. While design knowledge bases, text generation and named entity recognition could be developed using state-of-the-art NLP approaches, language models and neural machine translation require further improvement in core NLP. For the remaining methodological directions, scholars may consider operationalising the existing design theories into metrics and datasets so that NLP applications could be developed without theoretical challenges.

The theoretical directions call for an understanding of the characteristics and constructs of natural language text that influence the affordance of comprehension and creativity in the design process. As the volume of natural language text data grows multifold with time, it is necessary to distinguish the text that is applicable to the design process. The characteristics and constructs that constitute design language should also indicate the missing elements of design knowledge that influence the abilities to form search keywords, comprehend design text, generate insights and judge the solutions.

The proposed directions primarily call for an understanding of the structure and role of the design language that should help bolster the performances of natural language text in learning, design and computational environments. For example, in a computational environment, a piece of text (e.g., a movie review) may return an accurate sentiment score. In another example, a well-written chapter on kinematics may be useful in a learning environment. These two examples, however, may be less useful in a design environment. Similarly, a design text (e.g., technical requirement) may perform poorly in learning and computational environments. In order not to be misled by the performance in a single environment, it is important to distinguish natural language text by identifying the characteristics and constructs that constitute design language.

5. Conclusions

The purpose of this review article was to encapsulate a large body of NLP contributions that are relevant to the design process so as to identify unsupported design applications, potential methodological advancements and gaps in design theory. We gathered 223 articles published in 32 journals for our review. We organised, explained and examined these articles according to the type of text sources: internal reports, design concepts, discourse transcripts, technical publications and consumer opinions. We then discussed our findings in terms of design applications and future directions. The overall conclusions from the review and the entailing discussions are as follows:

(i) A comprehensive NLP guide is necessary for the identification of specific design modules and developing NLP supports according to the type of text sources utilised/generated in these.
(ii) While several methodological directions could be pursued using state-of-the-art NLP tools, the development of standard datasets and success metrics require the operationalisation of existing design theories.
(iii) It is necessary to identify the unique characteristics and constructs that help distinguish design-centric natural language text as well as influence the performances in terms of comprehension and creativity in the design process.

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APPENDIX A

We use the Web of Science[59] advanced search tool to retrieve the articles for review. We input all queries in the following format,

$$((\mathrm{TS} = \mathrm{kw1}^{*}\,\mathrm{OR}\,\mathrm{kw2}^{*}\,\mathrm{OR}\,\mathrm{kw3}^{*}\ldots)\,\mathrm{OR}$$
$$(\mathrm{TI} = \mathrm{kw1}^{*}\,\mathrm{OR}\,\mathrm{kw2}^{*}\,\mathrm{OR}\,\mathrm{kw3}^{*}\ldots)\,\mathrm{OR}$$
$$(\mathrm{AB} = \mathrm{kw1}^{*}\,\mathrm{OR}\,\mathrm{kw2}^{*}\,\mathrm{OR}\,\mathrm{kw3}^{*}\ldots))\,\mathrm{AND}$$
$$(\mathrm{SO} = \mathrm{dj1}\,\mathrm{OR}\,\mathrm{dj2}\ldots)$$

where TS = Topic/keyword, TI = Title, AB = Abstract, SO = Journal, kw $\in$ {keyword list} and dj $\in$ {journal list}. We executed the queries on 19th September 2021 and the outcomes of each query are shown in Table A1.

We explain the queries as shown in Table A1 for the remainder of this section. In the first query, we consider eight 'well-known' design journals[60] using the following keywords: 'semantic', 'text', 'language', 'pars', 'ontolog', 'abstract', 'word', 'phras' and 'sentence'. We retrieve 890 articles and obtain the frequent terms from topics (> 1), titles (> 4)and abstracts (> 4) to identify more keywords – 'vocabular', 'sentiment', 'gramma', 'lexic', 'linguistic', 'syntactic' and 'term'. We include these additional keywords in the second query to retrieve 1744 articles. To include more journals that fall within the scope of design research, we consult the literature that provides a broad view of design research (Gemser and de Bont 2016; Mansfield 2016) as well as reviews (Coskun, Zimmerman, and Erbug 2015). Based on the literature, we include five additional journals[61] in the third query to retrieve 2328 articles.

Since NLP applications that benefit design research could also be published outside the design journals, in the fourth query we remove the journal filter and retrieve 6,930,765 results. Since these results also include conference proceedings and book chapters, in the fifth query, we select only journal articles to retrieve 4,908,353 articles. To filter these, in the seventh query, we include an additional keyword 'design' and particular subject categories[62] to retrieve 78,919 articles. For these articles, we manually selected the journals using the following criteria: article count $\geq$ 10, nondistant domain (e.g., not 'Journal of Biological Chemistry'), nonspecific topic (e.g., not 'Applied Surface Science'), general design-related (e.g., Computers in Industry), technology-related (e.g., Scientometrics). These filters result in 6523 articles.

[59] https://mjl.clarivate.com/search-results.

[60] We included the following design journals: *Artificial Intelligence for Engineering Design Analysis and Manufacturing*, *Research in Engineering Design*, *Journal of Engineering Design*, *Design Studies*, *Design Science*, *Journal of Mechanical Design*, *Journal of Computing and Information Science in Engineering*, *International Journal of Design.*

[61] We include the following journals in addition to the previously populated list of design journals: *Design Journal*, *Design Quarterly*, *Design Issues*, *International Journal of Design Creativity and Innovation*, *Journal of Computer-Aided Design.*

[62] The selected categories include the following: Engineering Manufacturing, Engineering Multidisciplinary, Engineering Mechanical, Computer Science Interdisciplinary Applications, Computer Science Software Engineering, Art, Computer Science Artificial Intelligence, Engineering Industrial, Social Sciences Interdisciplinary, Architecture.

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Table A1. Precisions of different queries

#	Query step	Results	Relevant	Precision %
Keywords				
1	Design journals	890	95	10.674
2	*Expanded keywords*, Design journals	1744	102	5.849
3	Expanded keywords, *Expanded Design journals*[a]	2328	117	5.026
4	Expanded keywords, *Web of Science*	6930765	223	0.003
5	Expanded keywords, Web of Science, *article type*	4908353	223	0.005
6	*Expanded keywords including 'design'*, Web of Science, article type	593765	206	0.035
7	Expanded keywords including 'design', Web of Science, article type, *selected categories*	78919	206	0.261
8	Expanded keywords including 'design', *selected journals, journals with count > = 10*, article type and selected categories[a]	6523	206	3.158

[a]Denotes the step where we manually read the titles, abstracts and full texts to obtain the final set of articles.

We merge the results of the third and final queries as the first three queries did not include the 'design' keyword filter. We examine the titles and abstracts[63] of the merged results to obtain 277 articles. Upon reading the full texts of 277 articles, we obtain the final set – 223 articles that we have made accessible on Github.[64] Using the final set of articles, we also report the precisions of each query as shown in Table A1.

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[63]An example of discarded result had the following text within the abstract: '… material properties that are computed in terms of the microstructural texture descriptors.' (Acar 2020).

[64]https://github.com/siddharthl93/nlp_review/blob/4b9e6b378c8df0bbf61a36e466a50dbb5a0a65d2/nlp_review_papers.csv.

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