Utilizing Text Analysis in Systematic Review Design: Perceptual and Cognitive Barriers to Adoption of Robotic and Automated Systems in Construction

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ABSTRACT

Construction, the last major analog and craft manufacturing industry, is showing early signs of industrialization through the emergence of new robotic and automated systems that can perform construction tasks in situ. While much is understood about the technical and economic challenges to be overcome for widespread adoption of robotics, less is known about the human barriers to adoption, and much less is summarized. Considering the amount of human cooperation required by existing robotic applications, a comprehensive review of barriers that are cognitive or perceptual in nature using a systematic literature assessment methodology is warranted. However, such a review is not straightforward to design. While matters of cognition and perception as pertinent to construction and automation may be queried directly from the literature, there is no certainty that a review based on directly querying abstract phenomena (i.e., perception) could be comprehensive. Thus, systematically reviewing this topic calls for a robust methodology for the design of database queries. In this paper, we perform text analysis with the quanteda package for R in order to (1) understand the language composition of an initial review corpus, and (2) with that understanding design further queries to capture additional articles otherwise not possible through standard query design. Findings indicate that performing text analysis on a systematic review design can produce valuable insight into a review corpus and inform queries that capture additional unique literature relevant to the review.

KEYWORDS: Systematic review, text analysis, construction, automation

INTRODUCTION

The construction industry is on the verge of a new frontier, with major progress being made in robotics (Bock, 2015), information systems (Zhang et al., 2013), data capture (Teizer et al., 2010), and artificial intelligence (Darko et al., 2020). However, despite growing interest in industrialization, the industry has remained slow in adopting semi-autonomous and autonomous robotic systems that operate *in situ (*i.e. on-site and among human workers) (Khoshnevis, 2004). Beyond the primary barrier of economics that construction firms face in adopting robotic systems there exist formidable secondary barriers. These include barriers that are cognitive and perceptual in nature, such as perceptual factors pertaining to the safety of robotic systems working alongside humans, and the corresponding cognitive component of hazard recognition systems (Jeelani et al.,

2021). This paper details the design phase of a systematic literature review of the cognitive and perceptual factors in applications of robotic systems and their potential effects on the willingness of stakeholders to adopt such systems. A better understanding of how these factors pose a barrier to the adoption of robotics in construction could inform decision makers on how to facilitate further adoption of robotic systems in the construction workplace as well as advance the general understanding of the human-robot frontier. The rationale behind reviewing this topic presupposes that technical and economic barriers to industrialization (i.e. the adoption of robotic or automated systems) of the construction industry are better understood and documented than barriers found at the interface of human and machine (i.e. matters of cognition and perception). To our knowledge there have been no systematic reviews published to date on this review topic. That is not surprising given the challenge of designing a systematic review around topics that are abstract (perception in particular is an abstract cultural phenomenon), rather than concrete and positivist topics that traditional systematic literature reviews tend to target. Considering that querying an abstract topic such as perception directly (by including the word perception in the query) provides no guarantee that the literal representations of perception may be fully captured in the returns of the query (as the correct set of documents that represent the body of knowledge on the topic), an additional step in the design of this systematic review is warranted. Therefore, we utilize text analysis in the form of natural language processing (NLP) performed with the quanteda package for R (Benoit et al., 2018) to analyze the corpus of an initial review design in the effort of (1) understanding the semantic structure of the language found within that corpus, and (2) to use that understanding in designing additional database queries. This was done to ensure that our eventual systematic review is as comprehensive and as representative of the understanding of cognition and perception (as they relate to automation in construction) as possible.

BACKGROUND

Systematic reviews originated from the biomedical field but have been gaining traction in other research domains due to the reliability and reproducibility of their results (Haddaway et al. 2015). By systematizing the search methods used to query documentation the researcher may avoid the pitfalls of selection bias and the requirement for expert knowledge in their field needed for a traditional or narrative literature review to be perceived as legitimate by interested parties (Pahlevan-Sharif et al. 2019). Systematic reviews allow anyone with access to the databases used for the review to perform the same query and return an identical set of documents that may then be referenced against the results and synthesis of the review, therefore enhancing reproducibility in literature reviews.

INITIAL SYSTEMATIC REVIEW DESIGN

The initial core query, formatted for the database *Web of Science* is provided below.

Field tag = (construction AND (automat OR robot*) AND (perce* OR cogn*))*

The query is designed to address the review topic directly and with keywords from the topic itself. The full query iterates over this core query to include contents of titles, keywords, and abstracts, in addition to further refinements and exclusion criteria designated in the PRISMA statement (Moher et al. 2009). These are listed below in addition to other review parameters.

- **Publication date:** 2000-Present
- **Language:** English
- **Publication status:** Articles
- **Screening:** Single researcher, three phase (title, abstract, full text)
- **Eligibility:** Reference to cognitive or perceptual factor pertaining to automation within the domain of construction (not architecture, engineering, and construction generally)
- **Objective**: To understand what barriers lie beyond those which are technical or economic in nature to the adoption of robotic and/or automated systems in the construction workplace (i.e. cognitive or perceptual)

Articles published prior to the year 2000 are excluded on the premise that literature from before this date is not only outdated, but that the conditions under investigation (the deployment of robotic or automated systems *in-situ*) have undergone enough change to warrant excluding prior dates of publication. Languages under query are limited to English only, although limitations of this parameter are acknowledged (Nuñez and Amano, 2021). Initial screening was performed by a single researcher in three phases. Of 598 returns from the query 304 documents passed initial title screening and 85 passed abstract screening. Articles were excluded only upon positive confirmation of being out of scope of the review (i.e. there was evidence for exclusion, not inclusion). These articles were then converted to text files and preprocessed for analysis in R through the removal of all text not included as the contents of a subheading, including the removal of text included in tables and figures.

ANALYZING REVIEW DESIGN WITH NATURAL LANGUAGE PROCESSING

Several open source software packages exist to aid in text analysis and natural language processing tasks. For investigating the semantic structure of our initial review corpus we used the quanteda package for R developed by Benoit et al. (2018). quanteda offers extensive functionality for the handling and analysis of text documents in the form of corpus objects, as well as interoperability with other text analysis packages in R for functionality not currently supported, such as with Latent Dirichlet analysis (LDA) topic modeling.

Correspondence analysis

Correspondence analysis is a technique similar to principal component analysis but is designed for use with categorical variables within a bivariate contingency table (Nenadic & Greenacre, 2007). In the context of text analysis correspondence analysis is used to scale documents on one or two dimensions in a way that groups similar articles together. The correspondence analysis of the abstracts of the initial 85 article corpus, represented graphically in Figure 1, shows a tight cluster of most of the 85 articles around the origin, with three outlying articles widely deviating from the cluster on one (Ye, Ni and Lin 2013) or both (Jeong et al. 2014; Chen et al. 2020) dimensions. By verifying that these outlying documents are closely related to the review topic and qualify for inclusion in the corpus, we are able to better understand our initial corpus as a semantically closely associated set of documents. This analysis also served to aid screening of the corpus by flagging these outliers for further scrutiny prior to the full-text screening phase.

Relative frequency analysis

Based on the results of the correspondence analysis shown in Figure 1, we may then analyze individual outlying documents for relative frequency of features in comparison to the corpus

(Manning & Schutze, 1999). This is performed in order to understand what particular features about a document stand out in relation to the corpus. Based on the terms shown in Figure 2, which are found at much greater frequency within Chen et al. (2020) than within the entire corpus, it is reasonable to expect that multi-criteria decision making (MCDM) for bid selection is a topic that deviates from the 'topics' of the corpus. Similarly, as shown in Figure 3 the terms found within Ye, Ni, and Lin (2013) which appear in much greater frequency than within the corpus lend to the assumption that the corpus generally represents vertical construction (buildings) as opposed to the underground tunneling topic discussed by Ye and colleagues.

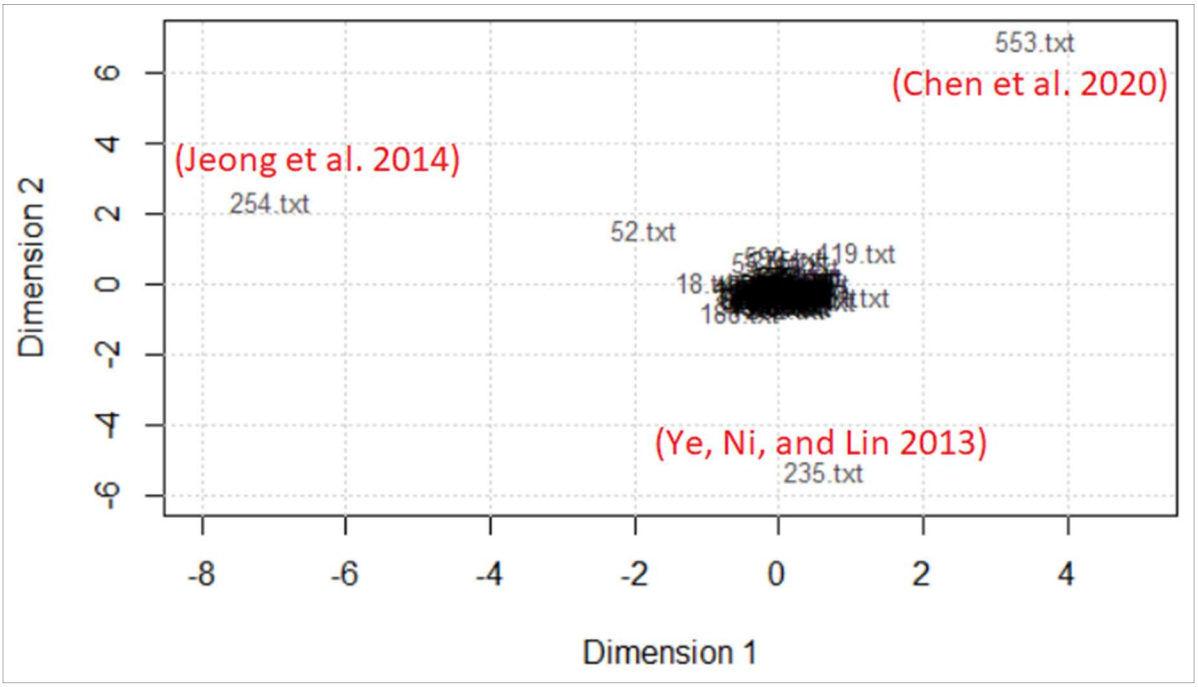

Figure 1. Two-dimensional correspondence analysis of corpus

Semantic relatedness

Another natural language processing technique that can be performed using the initial corpus and is independent of the correspondence analysis and relative frequency analysis already discussed is that of semantic relatedness. Corpus-based measures, as opposed to knowledge-based measures, of semantic relatedness quantify the co-occurrence of terms in a body of text (Chen et al. 2018). Figure 4 summarizes terms most closely related to keywords 'automation,' 'cognition,' 'robot,' and 'perception.' respectively. In addition to informing further queries, semantic relatedness reveals more information of interest on the subject matter itself than the previously discussed methods. For example, within the corpus it is observed that 'excavation' is the term most closely related to automation. The measurement of this relation between terms could serve as a piece of evidence that, for example, earthwork is seen as the most rapidly automating scope of work in the construction industry. As another example, the relationship between 'humans' and robot as the most frequent terms occurring together of those summarized in Figure 4 highlights the importance of the human element to robotics in construction, though an argument could be made that this relationship is presupposed by the query terms.

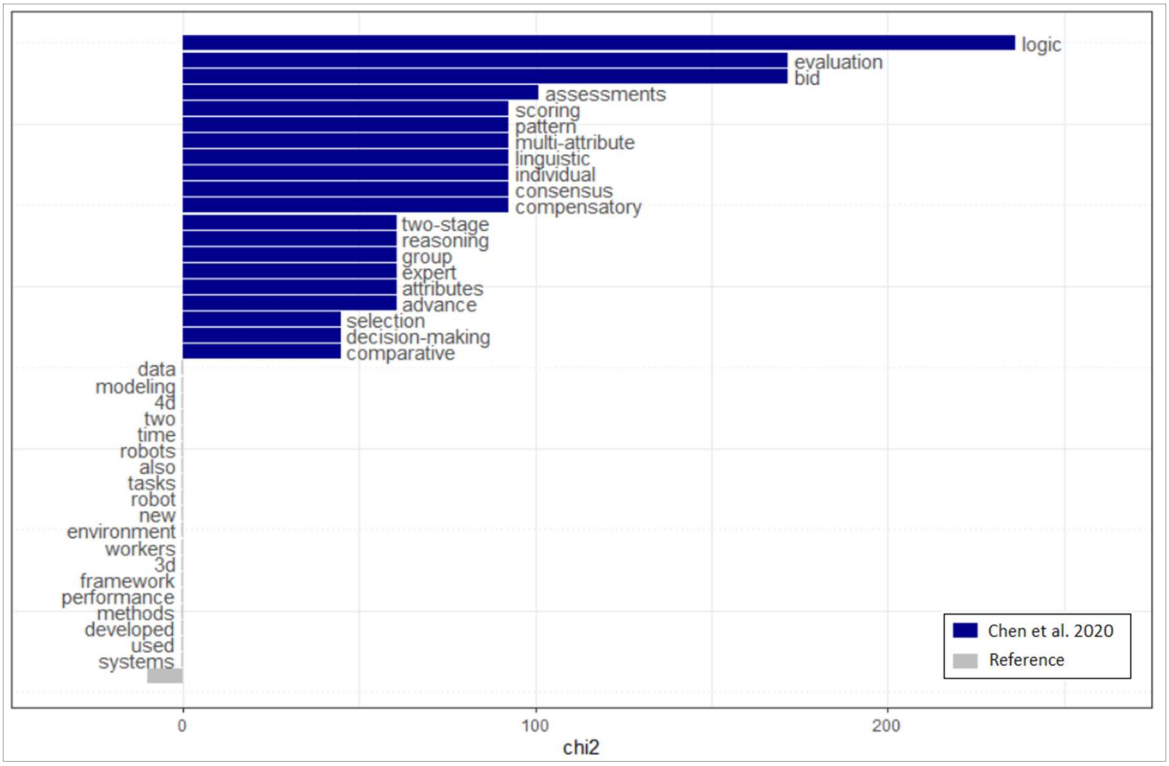

Figure 2. Feature frequency between the reference (corpus) and outlier Chen et al. (2020)

Topic modeling

Topic modeling is a method of unsupervised classification used to identify 'topics,' or underlying semantic structures within a corpus or set of documents (Blei, 2012). Latent Dirichlet Allocation (LDA) is an approach to topic modeling that utilizes a generative probabilistic technique for modeling features of a dataset (i.e. words) over a set of classes (or topics) which are in turn modeled over a set of classification probabilities (Blei et al., 2003). The resulting topics and probable features represent structure existing within the dataset or document corpus. The results of LDA topic modeling of the review corpus, which produced a total of four logically coherent topics, are shown in Figure 5. Topic 1 consists of a set of terms related to the creation of 3D models of a room or space using point clouds (LiDAR or other remote sensing products). These models are often needed to allow robots to be aware of their surroundings, as construction sites are dynamic environments. Topic 2 consists of terms about robots and humans, which also focuses on control and sensing. Safety is one of the biggest issues with working around robots, with the concern being that human workers can be struck by a robotic arm or vehicle. Many types of sensors and systems have been proposed to control the interaction between robots with humans. Topic 3 is a set of terms related to automation of software, rather than robots. Design, construction, and building operation often encounter trade-offs between cost and performance. Algorithms may be developed that consider both historical and live data to automate the operation of the building, or to design a flexible control system. Thus, algorithmic automation of either system operation or design represents a primary 'topic' of the corpus. Topic 4 consists of a set of terms related to the broader information management process on construction projects. Information (e.g., product details, service information, geometry, scheduling, etc.) is commonly incorporated now within a Building Information Model (BIM). As a repository or central source of project information, this data is critical for the understanding of robotic applications.

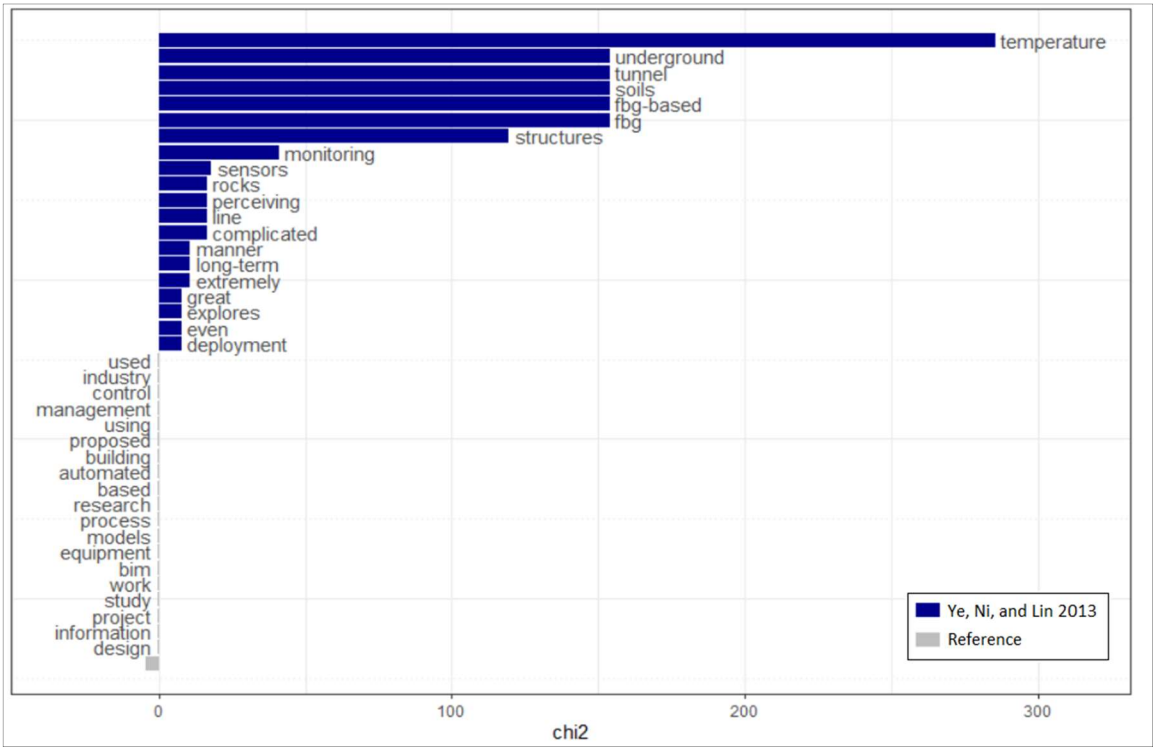

Figure 3. Feature frequency between the reference (corpus) and outlier Ye, Ni, and Lin (2013)

Further queries

Additional queries may be constructed through keyword relatedness. An example is provided below.

Field Tag = (construction AND (auto OR robot*) AND (human* OR labor*) AND (collaborat* OR cooperat*))*

This new query is contrasted with the original query, provided below:

Field tag = (construction AND (automat OR robot*) AND (perce* OR cogn*))*

The query relaxes the constraint on terms stemming from 'perception' and 'cognition' and emphasizes the relationship between human and machine. This new query produces 109 total (non-screened) results after the application of refinements on the *Web of Science,* a substantial difference from the 598 of the initial query. This difference is not surprising given the query contains an additional inclusive statement, but it is important to point out that this query was only made possible through analysis of the text and is thus in itself a demonstration of the utility of text analysis in designing systematic review queries. Duplicates between queries are to be expected when a query is informed by the text analysis of the other, yet only 6 duplicates from the initial corpus were produced by this new query. Many additional papers that contain unique information on the review topic were obtained through this additional query, which is informed by the text analysis of the initial corpus.

Automation (automat*)			
Feature	Rank order	chi2	p
excavation	1	31.087	0.000000
acquisition	2	19.202	0.000012
equipment	3	15.369	0.000088
focused	5	14.546	0.000137
checking	7	12.383	0.000433
user	8	12.383	0.000433
progress	9	10.578	0.001144
recognition	10	10.118	0.001469
rules	11	10.118	0.001469
planner	12	8.364	0.003828
reports	13	8.364	0.003828
erroneous	14	8.116	0.004387
benefit	19	6.399	0.011419
crucial	20	6.399	0.011419
labor	23	6.399	0.011419

Cognition (cognit*)			
Feature	Rank order	chi2	p
logic	1	49.890	0.000000
science	2	45.753	0.000000
compensatory	3	33.529	0.000000
habits	4	33.529	0.000000
mapping	5	33.529	0.000000
pattern	6	33.529	0.000000
operators	9	26.357	0.000000
aimed	10	21.376	0.000004
attributes	11	21.376	0.000004
reasoning	15	21.376	0.000004
fuzzy	18	15.316	0.000091
hazard	25	7.580	0.005903
spatial	26	7.580	0.005903
abilities	27	7.124	0.007604
brainwaves	35	7.124	0.007604

Robot (robot*)			
Feature	Rank order	chi2	p
humans	1	61.894	0.000000
autonomous	2	44.804	0.000000
perform	3	44.804	0.000000
pose	4	35.699	0.000000
alongside	5	30.662	0.000000
teleoperation	6	26.662	0.000000
collaborative	7	26.401	0.000000
excavator	9	22.278	0.000002
cooperation	10	20.623	0.000006
kinematic	11	20.623	0.000006
trust	13	20.623	0.000006
working	14	18.890	0.000014
tasks	15	18.275	0.000019
workspace	16	18.207	0.000020
agents	17	14.267	0.000159

Perception (percept*)			
Feature	Rank order	chi2	p
accurate	1	19.922	0.000008
errors	2	16.804	0.000041
environments	3	14.104	0.000173
nature	4	12.809	0.000345
strain	5	12.809	0.000345
subjective	6	12.809	0.000345
variables	7	12.809	0.000345
visualization	8	12.809	0.000345
weight	9	12.809	0.000345
absolute	11	9.791	0.001753
avoidance	12	9.791	0.001753
stakeholder	22	9.791	0.001753
manipulation	23	9.333	0.002251
robot	24	7.527	0.006078
changes	25	6.199	0.012785

Figure 4. Selected keyword relatedness to review query terms

Topic 1	Topic 2	Topic 3	Topic 4
model	robot	design	construction
point	task	data	project
construction	system	cost	information
data	sensor	classification	model
object	control	number	technology
3d	work	building	bim
equipment	human	performance	data
joint	object	different	design
system	worker	results	process
image	construction	algorithm	management

Figure 5. LDA topic model of initial review corpus

CONCLUSIONS

This work demonstrates that (1) text analysis (specifically, NLP) can be a valuable tool for the design of systematic review queries in the construction domain as well as more generally, and (2) that products of NLP can inform the researcher on meta-level trends in the literature, or more specifically in the construction literature in the case of this work. The application of text analysis and natural language processing techniques not only serve as diagnostic for review design but can also inform review authors on patterns of speech within the review corpus, leading to additional insights into the body of knowledge on a review topic. Further, text analysis can assist researchers undertaking systematic reviews through automating the detection of documents that deviate substantially from patterns in the corpora. By performing text analysis we were able to ensure that our systematic review queries produced a corpus that represents a maximal amount of pertinent documents from the construction literature, a feat that would otherwise require an extensive amount of labor and expert knowledge of a highly specific topic. From the confidence that can now be placed in our review corpus, our further work is to proceed with the systematic review on the cognitive and perceptual barriers to the adoption of automation and robotics in construction.

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