Facilitating the Discovery of Relevant Studies on Risk Analysis for Three-Dimensional Printing Based on an Integrated Framework

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Abstract –In an accurate and timely manner, capturing the risk signals for a specific emerging technology from academic publications is important to facilitate risk governance and to reduce the potential negative impact on socioeconomic systems. In the past decade, three-dimensional printing (3D printing) has become a promising emerging technology. To identify the relevant research on risk analysis for 3D printing, term clumping on "risk analysis" is explored using a quantitative method, and an integrated framework for risk identification is proposed with regard to 3D printing. This method involves a variation of TF*IDF and several new metrics for a Boolean query of the literature. The empirical results for the risk analysis studies of 3D printing show that, to date, very little attention has been paid to the relevant topics. However, although the risk signals of 3D printing are still weak and dispersed in many different categories, the potential threats to human health, cyber-security, and the environment are revealed in some facets. This enables initiation of strategies for anticipatory governance, involving science and technology policies and regulations.

Key words: emerging technology; risk analysis; 3D printing; TF*IDF

1. Introduction

In terms of emerging technologies (e.g., autonomous vehicles, the Internet of Things, and three-dimensional printing [3D printing]), new opportunities and promising prospects in marketing and entrepreneurship are the focus of research and public attention. Innovations, technological revolutions, and dramatic changes in society are often related to the development of emerging technologies. However, although technological evolution can produce excitement and have a positive impact on society and the economic system, some emerging technologies also bring new risks and threats to the environment, to health, and to safety (Taleb 2010; Kipper and

Rampolla 2012; Sandler 2014).

While examining several historical cases about the development of emerging technologies, complementary or alternative means were not considered until the risk had developed into a real danger, or even a disaster. For instance, although early research articles noted the detrimental impact of leaded gasoline on human health, the ban on leaded gasoline was only gradually implemented from the 1980s (in Japan) to the 2000s (in China and India), and leaded gasoline had been used for over 70 years (Zheng et al. 2004; Nichani et al. 2006; Huang et al. 2012). Leaded gasoline was an emerging and exciting technology in the 1920s when it was invented and commercialized in the US. Therefore, as electric vehicles, an emerging or disruptive technology replacing traditional fuel-driven vehicles, are developed, we must be aware of and emphasize their potential negative impacts on our future. For example, electric vehicles can reduce the emission of greenhouse gases and the particles of PM2.5 and decrease noise pollution; however, battery recycling, the sudden burden on, and pollution of, power plants, and the rapid growth in the operational complexity of the power system in urban areas could cause serious social and economic risks and problems (Keefe et al. 2008; Cabrera-Castillo et al. 2016; Yang et al. 2016).

In the past ten years, studies on 3D printing have dramatically increased, and the growth in publications related to 3D printing in WOS (Web of Science) based on a relatively simple search[1] is depicted in Figure 1.

[1] TS= ("3D Print*" or "Additive Manufactur*" OR "Three Dimension* Print*" OR "3D Bioprint*" OR "4D print*") Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC Timespan=1990-2016. A more complete or complicated strategy of search will be discussed in the following content.

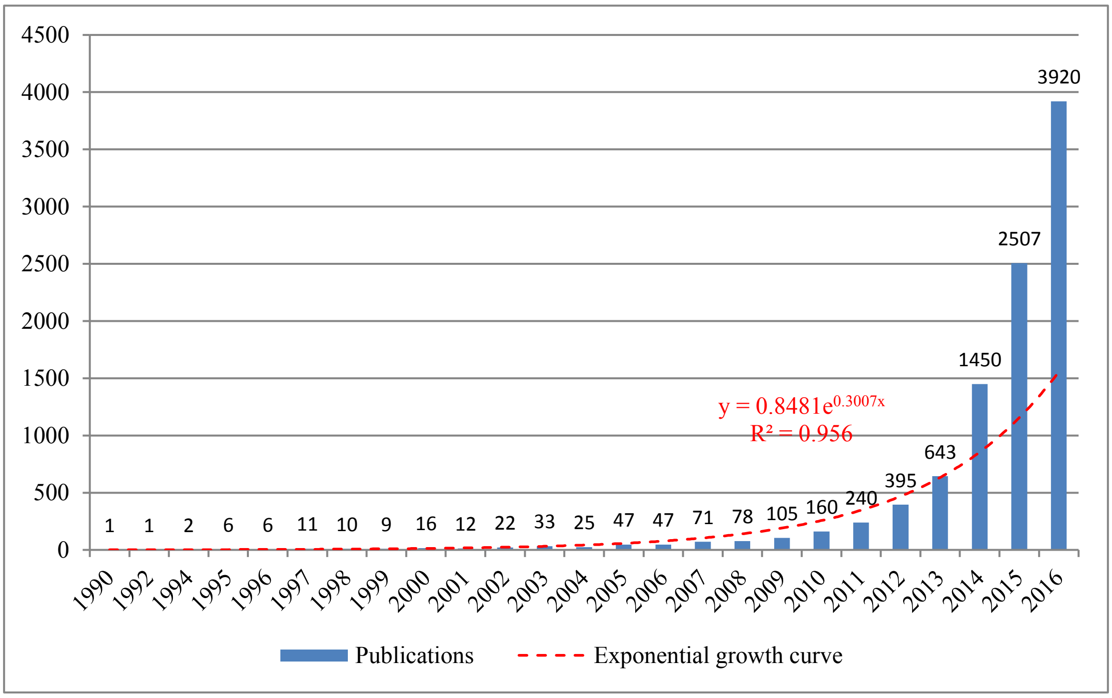

Figure 1. The growth in publications related to 3D printing in WOS between 1990 and 2016

Basically, neither *3D printing* nor *Additive Manufacturing* is a novel concept in some engineering areas (Espalin et al. 2014); however, the rapid growth has occurred in the past five years – more than an exponential growth curve since 2013. Massive, center-oriented, and standard manufacturing patterns must confront the challenges from small volumes and extreme customized requirements (Espalin et al. 2014). Meanwhile, with the growth in small/home factories, distributed production lines, flexible delivery systems, creativity industries, and innovated incubators, 3D printing could become office or even home equipment in following years (Niaki and Nonino 2017).

Meanwhile, with the irreversible commercialization of 3D printing technology, very little attention has been paid to the possible negative impact of 3D printing technology on socioeconomic systems and the environment. Stephens et al. (2013) argue that desktop 3D printers could significantly increase the emissions of ultrafine particles and possibly harmful aerosols. Further, in a recent control experiment on the emissions of a 3D printer, lung deposition calculations indicated a threefold higher polylactic acid (PLA) particle deposition in alveoli compared to ABS (acrylonitrile butadiene styrene) (Yi et al. 2016). In addition to the emissions issues of 3D printing, the 3D-printed parts could pose threats of toxicity to human health (Oskui et al. 2015).

Therefore, more holistically mastering the facets of risk to the environment, society, and humans is significant for public policy-making and the other relevant issues in anticipatory governance. To further explore the relevant issues, this article is organized as follows: (a) related work; (b) methodology and analytical framework; (c) empirical study of the risk analysis of 3D printing technology; and (d) limitations and discussions.

2. Related Work

Basically, risk analysis for a specific emerging technology is typically interdisciplinary research, which involves different categories such as multi-engineering, multidisciplinary social sciences, and so on (Kunreuther 2002). In contrast, for nanotechnology, as a notable and developed emerging technology, its risk analysis could be more abundantly studied in past decades, even derived from some specific branches (e.g., nanotoxicology [Oberdörster et al. 2007; Podila and Brown 2013; Shatkin and Ong 2016]), and these relevant studies provided important implications for policy-making. Similarly, studies on the risks of 3D printing technologies to socioeconomic systems, the environment, and ecosystems, and relevant issues in cyber security, human health, and intellectual property within the context of 3D printing, also have critical significance in anticipatory governance.

Although the concept of emerging technology can be traced to the mid-1980s, the uniform definition for emerging technology is still controversial, and there is a lack of consensus in some fundamental elements. Recently, five distinguishing characteristics of an emerging technology have been proposed: (a) radical novelty, (b) relatively fast growth, (c) coherence, (d) prominent impact, and (e) uncertainty and ambiguity (Rotolo et al. 2015). In particular, the evaluation of uncertainty and ambiguity with respect to emerging technologies remains a largely unexplored area (Rotolo et al. 2015).

Regarding risk analysis, the nature of risk is the primary issue. Although risk could have many definitions in different scientific areas, Kaplan's (1997) concept of risk and risk analysis could be a typical view, based on which *risk* is a triplet of scenarios, likelihoods, and consequences, and *risk analysis* concerns finding the complete set of such triplets (Kaplan 1997). In situations of deep uncertainty, each element in Kaplan's triplet of risk is difficult to determine. To mitigate the gap between traditional statistical methods and practical risk management, some constructive methods have been explored in the past five years; for example, robust and adaptive risk analysis has been proposed (Kunreuther 2002; Pate-Cornell 2012). However, these more constructive methods of risk analysis are only facilitated to improve the measuring of alternative acts and probable consequences, whose completeness hypothesis about risk scenarios is the same as that of traditional methods. Therefore, how to find more complete information or knowledge about risk scenarios remains the critical challenge of risk analysis and risk management.

In the past two decades, nanotechnology has been one of the most prevailing emerging technologies and has attracted much attention and research on related risk analysis, perception, and governance. However, the innovation and business activities associated with nanotechnology precede policy development and environmental regulations, and the governance gap on the risk of nanotechnology is significant (Renn and Roco 2006; McComas and Besley 2011; Read et al. 2016). Shatkin and Ong (2016) argue that the nanotoxicology and risk assessment of nanomaterials have seriously lagged behind the development of the nanotechnology industry, particularly alternative testing methods and strategies for the risk assessment of manufactured nanomaterials. In terms of the risk analysis of nanotechnology, some iconic studies focus on three dimensions: the environment, health, and safety (EHS). EHS involves too many categories and research areas to construct a concise terminology, and topic modeling on risk analysis of EHS for a specific emerging technology appears to remain a difficult issue.

From the perspective of risk assessment, because the data from emerging technologies are too sparse and uncertain, a multi-criteria decision analysis (MCDA) is proposed to support early decisions for emerging technologies (Bates et al. 2016). In terms of the risk perception of the public, reducing knowledge deficits is correlated with positive perceptions of the risk of emerging technologies in the early and controversy-free period, and the risk perception of emerging technologies could be malleable to an extent (Satterfield et al. 2009; Pidgeon et al. 2011). When analyzing public opinion on emerging technologies, the risk perception and benefit evaluation should be aggregated into a systematic approach, which could reduce the public’s global bias to risk (Binder et al. 2012).

The factors of risk perception of emerging technologies could involve many different aspects, including psychological, social, and cultural aspects, and these factors shape individual and social risk perceptions (Renn and Benighaus 2013). Based on the literature on the risk of emerging technologies, the majority of the research comes from the social sciences, environmental science, engineering, communication, and toxicology; therefore, the risk management of emerging technologies is a multi-disciplinary or inter-disciplinary field.

Although it is difficult to find a uniform and undisputed definition of risk management for emerging technologies (Kipper and Rampolla 2012), researchers related to the social sciences, public administration, and environmental science. Researchers could be more concerned about the impact of emerging technologies on socioeconomic and environmental-ecological systems (An and Ahn 2016; Jeong et al 2016).

For complicated reasons, including economic development and the desire to encourage the development of new technologies and related entrepreneurial activities, the policies of risk prevention and remediation for emerging technologies always seem to lag in time (Renn and Roco 2006; Gavankar et al. 2015). In an academic context, the relevant studies on the risk analysis of emerging technologies are fragmented and distributed in many different disciplines, and the indications of risk are considered too insignificant for policy decision-making, particularly in the early stages. Uncovering the related research and initiatives on the risk analysis of emerging technologies in a more efficient manner can provide justification for policy-makers and attract more attention from diversified communities, including academia, social services, and environmental governance.

In summary, there are several significant gaps between prior relevant literature and the issues proposed by this article:

(1) Risk analysis is a typical multidisciplinary topic in the social sciences. Relatively, risk analysis for a specific emerging technology lags behind industrial application and commercialization. Although studies of risk analysis combined with emerging technologies are also important issues—particularly for public administration, S&T policy, technology management, and so forth—the topic terms (keywords) about "risk analysis" still lack a general consensus and academic investigation. Thus, the relevant literature search on the risk analysis for a specific emerging technology must favor a more personal experience than quantitative methods. Basically, the relevant studies on risk analysis for a specific emerging technology are

sparse, interdisciplinary, and dispersed in many different categories, particularly in the early stages.

(2) Meanwhile, topic modeling and the topic terminology for 3D printing also remain unexplored. Therefore, determining the topic descriptors on 3D printing could face challenges involving many different engineering categories (e.g., mechanical engineering, material science, manufacturing, automation, etc.). Therefore, capturing the highly relevant terms for 3D printing also has significant value for subsequent studies.

(3) In addition, how to locate the relevant studies concerning risk analysis of a specific emerging technology could be transferred into another more generalized question (e.g., how can we find the most relevant research literature between two different topics via a quantitative and efficient method?).

To mitigate the gaps between the current studies and the concrete needs in many relevant facets, several research questions could be raised:

Question 1: What keywords/terms are highly relevant on the topic of risk analysis within an academic context?

Question 2: In terms of highly relevant keywords on risk analysis, how can we determine the relevant studies/literature for the risk analysis of 3D printing or find the best strategies for literature retrieval?

Question 3: If a new analytical framework for capturing the literature on the risk analysis of 3D printing is proposed, then how could its advantages or implications be interpreted?

Further, to address the questions raised above, an integrated framework based on a technique of the variation of TF*IDF and several new metrics for a Boolean query is designed; meanwhile, an empirical case study related to 3D printing is implemented.

3. Methodology and Analytical Framework

To mitigate the gaps noted above, the analytical, deductive process is designed and presented in Figure 2, in which each step will be addressed in the following.

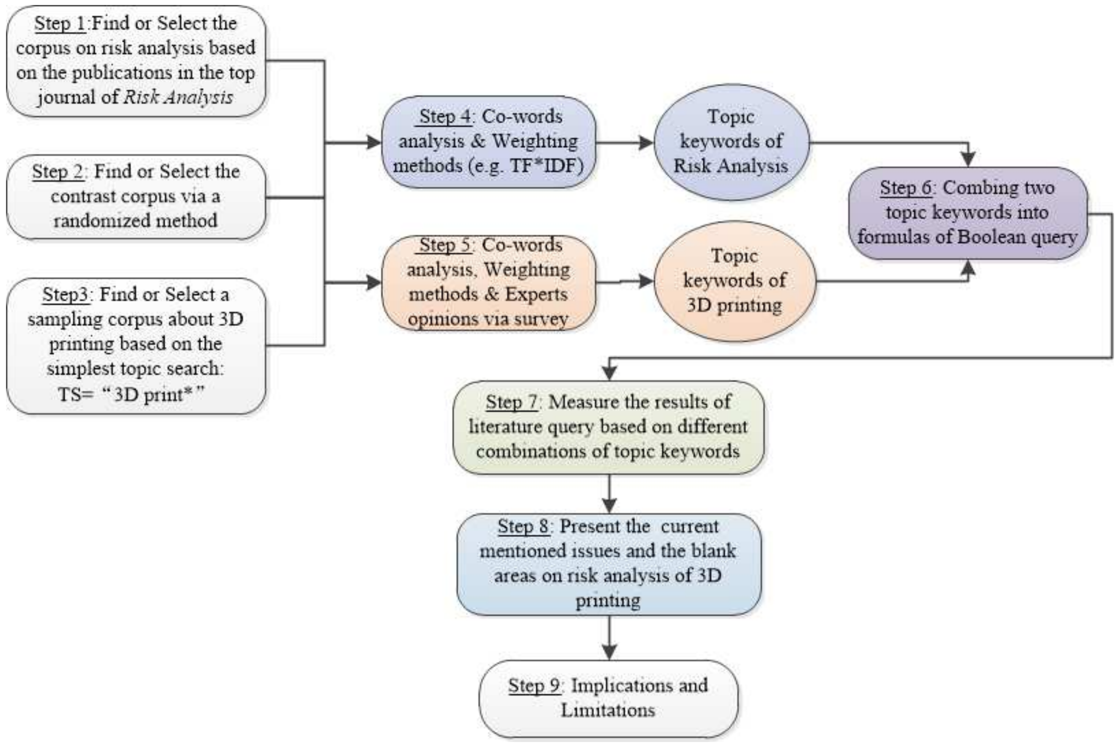

Figure 2. Analytical and deduction flow of this article

In Figure 2, because 3D printing technology is involved in many different categories, a survey for domain experts is added into step 5. Additionally, the topic models for risk analysis and emerging technologies should be built to efficiently extract the related knowledge, and then, the risk signs for an emerging technology could be used to determine the inter-knowledge between the two topics.

Definition 1. It is assumed that a sign of risk in an emerging technology can be defined as a simple tuple, as shown in equation (1).

$$\textit{Risk-Signal for a specific topic} = \langle \textit{Documents}, \textit{Terms} \rangle \quad (1)$$

Definition 1 could apply to most traditional topic models. For example, if the elements in equation (1) are described and presented by the probability distribution, then Definition 1 could apply to an LDA model. On the other hand, if the documents represent the nodes, and the terms represent the edges in a specific knowledge-map, then Definition 1 could partially match the basic conception of the knowledge-map (Kim et al. 2003; Vickery 2013). In terms of the documents, they could be an aggregating concept that could include multiple types of documents (e.g., articles, patents, news, blogs, etc.). The terms represent the words that are highly related to the specific topic. Because the two elements in equation 1 are time-varying, they are functions that are consistent with the dynamic evolution.

Based on equation 1, the inter-knowledge among different topics could be interpreted by the intersection of two multi-dimensional sets and their relevant functions (from the perspective of the set theory) or the overlapping areas of two different knowledge graphs (based on knowledge mapping). Here, set theory is first utilized to leverage the elaborations, and knowledge mapping theory is then interpreted.

Definition 2. The inter-knowledge for any two different topics can be represented by the intersection of the document and term sets, which are the elements defined in equation 1 (i.e., the multi-dimensional and time-varying elements, as shown in equation 2).

$$Inter\text{-}Knowledge(T_i\ , T_j) = \{\bigcup_{k=1}^{n} doc_k \mid term_i \in doc_k \ \&\ term_j \in doc_k\} \tag{2}$$

Based on equation 2 and temporarily ignoring the dynamic portion of the knowledge, accurately identifying the static intersection content between two different research themes is still complicated because the research topic or theme is thought of as a derivative concept that obeys a specific probability distribution (Blei et al. 2003). However, in the practice or activities of retrieving information, the relatively simple concept of a topic is a convenient, intuitive approach that is often facilitated by accessing the knowledge (e.g., the topics of "3D printing," "risk management," and "risk analysis").

Based on equations 1 and 2, directed toward a specific emerging technology, the intersection between the topic of "risk analysis" and the emerging technology could be valuable knowledge for exploring signs of risk, particularly in the early stage of the technology life cycle. Therefore, we first define the topic terms for "risk analysis" or highly relevant issues. Because the journal *Risk Analysis* is a leading forum for risk analysis based on the comprehensive perspectives of multi-disciplinary social sciences, the articles published in this journal are selected as the corpus of risk analysis. The time span for access is from 2000 to 2016 in the Web of Science (WOS) database.

In the criteria for extracting the topic terms of risk analysis, the basic philosophy of TF*IDF (Term Frequency * Inverse Document Frequency) (Zhang et al. 2011) is referred to and extended. Based on traditional TF*IDF theory, a specific term related to a certain topic should present a much higher frequency in a relevant document compared to an irrelevant document. Therefore, TF*IDF is a useful tool for weighting the different terms for topic discrimination. Furthermore, to extract the contrast sample of the corpus, a stratified sampling method is utilized to extract the common corpus. From 2000 to 2016, a random 1,000 articles were extracted in each year from the WOS database and the number of articles in the contrast corpus was 17,000. Based on the two corpora, the extended or variation of TF*IDF is shown in equation 3.

$$Variation(tf * idf) = (\frac{n_i}{\sum n_i}) * (\log \frac{|D|}{1 + |\{j : t_i \in d_j\}|}) \tag{3}$$

In equation 3, n_i is the frequency of the term appearing in the related corpus on the specific topic, and $\sum n_i$ is the sum of the frequency of all terms in the topic corpus. $|D|$ is the number of documents in the contrast sample, and $|\{j : t_i \in d_j\}|$ represents the frequency of a specific term appearing in the contrast sample. Considering the expertise of the authors in the relevant research fields, the author keywords are used as the critical source of topic terms. However, in the data sample extracted from the WOS database, some of the records did not contain author keyword data due to unknown technical reasons, according to Clarivate Help response. Therefore, after data cleaning, 9,866 records in the contrast sample have valid content in the Author Keywords field. The percentage of documents in the contrast sample that have author keywords is 58.03%. Based on cleaning the data and equation 3, the top 50 terms for risk analysis are shown in Table 1.

Table 1. Top 30 terms for risk analysis, based on equation 3

Author Keyword	Term frequency	Variation(TF*IDF)	Common Word
risk perception	0.11099	0.92539	**risk**
risk assessment	0.1001	0.72582	
risk communication	0.06068	0.4914	
risk	0.04305	0.39592	
risk analysis	0.03683	0.31319	
risk management	0.0389	0.28206	
uncertainty	0.03631	0.25843	**uncertainty**
trust	0.02956	0.22428	**trust**
terrorism	0.02075	0.17645	**terrorism**
decision analysis	0.014	0.12876	**decision analysis**
uncertainty analysis	0.01504	0.1218	**uncertainty**
exposure assessment	0.01141	0.10494	**exposure**
microbial risk assessment	0.01089	0.10015	**microbial**

vulnerability	0.01089	0.10015	**vulnerability**
variability	0.01245	0.09724	**variability**
risk perceptions	0.01037	0.09537	**risk**
quantitative risk assessment	0.00985	0.09059	**quantitative risk**
benchmark dose	0.00985	0.09059	**benchmark dose**
sensitivity analysis	0.01141	0.08657	**sensitivity analysis**
precautionary principle	0.00934	0.0859	**precautionary principle**
homeland security	0.00934	0.0859	**homeland security**
modeling	0.01349	0.08585	**modeling**
climate change	0.01141	0.07758	**climate change**
decision making	0.01037	0.07679	**decision making**
probabilistic risk assessment	0.0083	0.07633	**risk**
expert elicitation	0.0083	0.07633	**expert elicitation**
Campylobacter	0.00882	0.075	**Campylobacter**
Bayesian network	0.00882	0.075	**Bayesian**
expert judgment	0.0778	0.07155	**expert judgment**
food safety	0.00882	0.07143	**food safety**

In Table 1, some general keywords are in the top 30 terms in the risk analysis topic (e.g., modeling, trust, and decision analysis). This phenomenon could be due to the following: (1) the core corpus for risk analysis is not sufficient, or the contrast corpus is too small or has a certain bias of representation; or (2) these words are actually important for the specific topic, although the contrast corpus is the entire WOS database, which contains over 24 million records between 2000 and 2016.

Further, according to the top 100 terms ordered by the variation of TF*IDF, some highly relevant terms on risk analysis could be determined after excluding several significant general words (e.g., modeling, trust, decision making, etc.). The Boolean search formula for the topic of risk analysis is shown in Table 2.

Table 2. Boolean formula for "risk analysis" based on the top 100 terms ordered by the variation of TF*IDF

No	Search Formula for a topic in Web of Science
0#	*TS=(risk* OR uncertainty OR terrori* OR exposure OR vulnerability OR "microbial" OR variability OR "benchmark dose" OR "homeland security" OR "precautionary" OR "climate chang*" OR "expert judgment" OR "food safety" OR epidemiolog* OR "dose response" OR "natural hazard*" OR "particulate matter" OR "nuclear waste" OR "invasive specie*" OR "extreme event*" OR "air pollution" OR "cross*

	contaminat" OR "ecolog*" OR "cancer" OR "health*" OR "environment*" OR "global warming" OR toxic*)*

Regarding how to evaluate the identification or filtering of the relevant research on risk analysis and emerging technology, the assessment criteria for signal recognition and knowledge discovery provide the inspiration. In the traditional theory of knowledge discovery and the relevant classification and clustering algorithms, two proportion values involving accuracy and recall are often utilized to evaluate the performance of the algorithms; furthermore, the harmonic mean of accuracy and recall also prevails in presenting the integrated perspective to compare multiple models or algorithms (Domingos 1999; Lee et al. 2016). Meanwhile, the Signal-Noise Ratio (SNR) and Signal-Gain Cost (SGC) are also referred to, in order to evaluate the performance of Boolean queries. The relevant indicators are presented in equations 4, 5, 6, 7, and 8:

$$Accuracy=\begin{cases}\dfrac{|M_i|}{|D_i|}, & while|D_i|>0\\ 0, & while|D_i|=0\end{cases} \tag{4}$$

In Equation 4, the metric of *Accuracy* is utilized to present the proportion of matching records in the i^{th} Boolean query experiment, in which $|M_i|$ represents the matched records and $|D_i|$ presents all records.

$$Recall=\begin{cases}\dfrac{|M_i|}{|M|}, & while\ |M|>0\\ 0, & while\ |M|=0\end{cases} \tag{5}$$

In Equation 5, *Recall* is a metric that is often utilized to present the ratio for matched records in the i^{th} Boolean query experiment with the total matched records (TMR)-|M|. To some extent, |M| could be approximately substituted for by a benchmark value.

$$Utility=\begin{cases}0, & while|D_i|=|M|=0;\\ \dfrac{1}{\omega_1\dfrac{|D_i|}{M_i}+\omega_2\dfrac{|M|}{M_i}}, & and\ \omega_1+\omega_2=1;\ \omega_1,\omega_2\in[0,1]\end{cases} \tag{6}$$

In Equation 6, the metric of *Utility* can facilitate the combination between *Recall* and *Accuracy* to evaluate the comprehensive performance among different Boolean queries for a specific topic search. For example, if the Recall is the preference for a topic search, then the weight of Recall (i.e., ω_2) in Equation 6 could be much larger than the weight of Accuracy, (i.e., ω_1, or vice versa).

$$Signal\text{-}Noise\,Ratio\,(SNR) = \begin{cases} \dfrac{|M_i|}{|D_i| - |M_i|}, & while\,|D_i| - |M_i| > 0 \\ 0, & otherwise. \end{cases} \tag{7}$$

Equation 7 represents a typical metric of information theory and presents the ratio of matching records to noise data.

$$Signal\text{-}Gain\ Cost\,(SGC) = \begin{cases} \dfrac{1}{SNR}, & while\,SNR > 0 \\ \delta \to \infty, & while\,SNR = 0 \end{cases} \tag{8}$$

In Equation 8, SGC is the reciprocal of SNR within the mathematical form, which can more intuitively present the cost (noise amount) per matched record in a Boolean query experiment.

The metrics of *Accuracy*, *Recall,* and *Utility* are often utilized to evaluate different algorithms in computer science, and *SNR* and *SGC* are also two general measurements in classical information theory consideration. How these metrics are integrated could be meaningful and helpful for the following case study. Basically, how to discover the relevant studies on risk analysis of 3D printing is a complicated query because of its interdisciplinary characteristics, and because real signals could be sparse and dispersed in many different categories; in other words, tremendous noise seems to be inevitable in Boolean queries on this topic.

4. Empirical Study: Discovering the Relevant Literature on the Risk Analysis of 3D Printing in WOS

To verify the analytical framework introduced, a promising emerging technology, 3D printing, is used as the case study (Rayna and Striukova 2016). The technology of 3D printing is still in its early stages (Laplume et al. 2016). Theoretically, the topic model for 3D printing should be built before the literature is retrieved; however, several topic terms clumped around 3D printing are still controversial.

4.1 Data Collection

To obtain more accurate topic terms on 3D printing, step 5 in Figure 2 is decoupled into several subsequent steps and depicted in Figure 3.

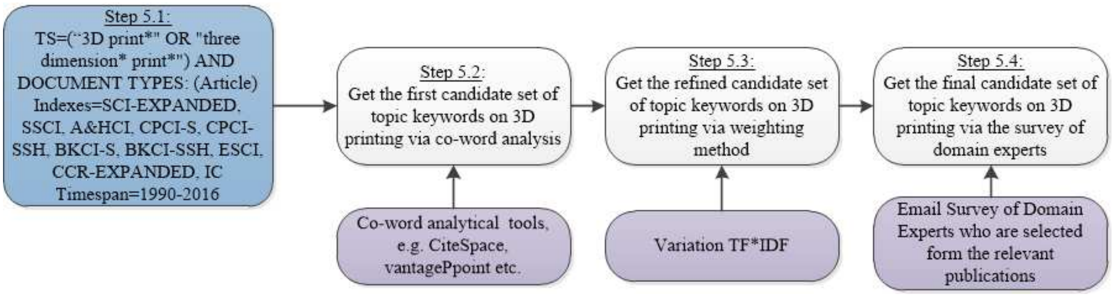

Figure 3. The flow of capturing the topic terms on 3D printing

Based on the processing presented in Figure 3, topic keywords on 3D printing are determined, based on which the relevant query result is shown in Table 3. Although four subsequent steps in Figure 2 are processed, the bias could not be completely eliminated, and the set of topic keywords on 3D printing in Table 3 remains a compromise.

Table 3. Boolean search formula for 3D Printing recommended by domain experts

No	Search formula in Web of Science	Count	Scope
1#	*TS=("3D Printing" or "Solid Freeform Fabrication" or "Rapid Prototyping" OR "Additive Manufacturing" OR "Three Dimensional Printing" OR "3D Bioprinting" OR "Direct ink writing" OR "Direc-write assembly" OR "solvent-cast 3D printing" OR "UV-assisted 3D printing" OR "radiation-assisted 3D printing" OR "liquid deposition modeling" OR "two-photon polymerization" OR "4D printing")*	*18,182*	*Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC Timespan=1996-2016*

Additionally, the Boolean formula could cause debate to some extent for different expert groups or different perspectives. Based on the search strategy for 3D printing in Table 3, 18,182 publications in the WOS between 1996 and 2016 seem relevant for 3D printing, and the control experiments through combining the “3D printing” terms with the topic of “risk analysis” are shown in Table 4.

Table 4. Retrieval results combing 0# formula with 1# formula

No	**Search formula**	**Records**	**Matched Records**	***Accuracy***	***Recall***	***Utility*** **(ω1=0.3, ω2=0.7)**	***SNR***	***SGC***
2#	1# and 0#	2868	38	1.325%	100%	4.284%		

Before Boolean querying the 2# experiment between risk analysis and 3D printing (although the noise data had been considered), such low accuracy and recall ratio are beyond the prior estimation. Additionally, the query result raises interesting questions: (1) Which topic keywords on risk analysis are actually helpful for this topic search, and which keywords generate primarily noise? (2) How can we describe the noted areas and most likely keep blank areas based on the subsequent experiments? and (3) Can the relevant Boolean formulas be refined to improve the search performance based on the quantitative criteria?

To further explore these questions 38 matched publications are taken as the benchmark value. The 38 matched records identified by abstract reading could have biased judgments due to the authors' knowledge background and personal cognitive habits; therefore, they are a relatively compromised benchmark value for the following experiments and discussions.

4.2 Identifying the current noted areas on the risk analysis of 3D printing technology

Clearly, in Table 4, the tremendous noise data show that some topic terms for risk analysis merely bring noise rather than actually relevant records, or offer relationships that we fail to discern. To further identify the noted and blank areas on the risk analysis of 3D printing, sequential Boolean queries are implemented by adding the topic keywords of risk analysis one by one, and the accumulated noise data and matched records are calculated. The sequential Boolean queries are shown in Table 5, and the result is shown in Figure 4.

Table 5. Boolean queries for single keywords on risk analysis combined with 1# formula

No	Term of risk analysis	Count	Accumulation	Matches	Accumulated Matches	Accuracy	Recall	SNR	SGC
3#	1# and TS=risk*	248	248	12	12	4.84%	31.58%	5.08%	19.67
4#	1# and TS= uncertainty	108	356	1	13	0.93%	2.63%	0.93%	107.00
5#	1# and TS= terrori*	4	360	0	13	0.00%	0.00%	0.00%	-
6#	1# and TS = exposure	276	636	3	16	1.09%	7.89%	1.10%	91.00
7#	1# and TS= vulnerability	7	643	1	17	14.29%	2.63%	16.67%	6.00

8#	1# and TS= microbial	20	663	0	17	0.00%	0.00%	0.00%	-
9#	1# and TS= variability	78	741	0	17	0.00%	0.00%	0.00%	-
10#	1# and TS= “benchmark dose”	0	741	0	17	-	0.00%	-	-
11#	1# and TS= “homeland security”	3	744	0	17	0.00%	0.00%	0.00%	-
12#	1# and TS= precautionary	0	744	0	17	-	0.00%	-	-
13#	1# and TS= "climate chang*"	3	747	0	17	0.00%	0.00%	0.00%	-
14#	1# and TS= "expert judgment"	0	747	0	17	-	0.00%	-	-
15#	1# and TS= "food safety"	4	751	1	18	25.00%	2.63%	33.33 %	3.00
16#	1# and TS= epidemiolog*	3	754	0	18	0.00%	0.00%	0.00%	-
17#	1# and TS= "dose response"	4	758	0	18	0.00%	0.00%	0.00%	-
18#	1# and TS= "natural hazard*"	0	758	0	18	-	0.00%	-	-
19#	1# and TS= "particulate matter"	2	760	0	18	0.00%	0.00%	0.00%	-
20#	1# and TS= "nuclear waste"	1	761	0	18	0.00%	0.00%	0.00%	-
21#	1# and TS= "invasive specie*"	1	762	0	18	0.00%	0.00%	0.00%	-
22#	1# and TS= "extreme event*"	0	762	0	18	-	0.00%	-	-
23#	1# and TS= "air pollution"	0	762	0	18	-	0.00%	-	-

24#	1# and TS= "cross contaminat*"	1	763	0	18	0.00%	0.00%	0.00%	-
25#	1# and TS= "ecolog*"	28	791	1	19	3.57%	2.63%	3.70%	27.00
26#	1# and TS= "cancer"	145	936	0	19	0.00%	0.00%	0.00%	-
27#	1# and TS= "health*"	273	1209	4	23	1.47%	10.53%	1.49%	67.25
28#	1# and TS= environment*	1583	2792	11	34	0.69%	28.95%	0.70%	142.91
29#	1# and TS= "global warming"	1	2793	0	34	0.00%	0.00%	0.00%	-
30#	1# and TS=toxic*	75	2868	4	38	5.33%	10.53%	5.63%	17.75

To clearly present the query results in Table 5, the columns of Match and Accumulated Matches are shown in Figure 4.

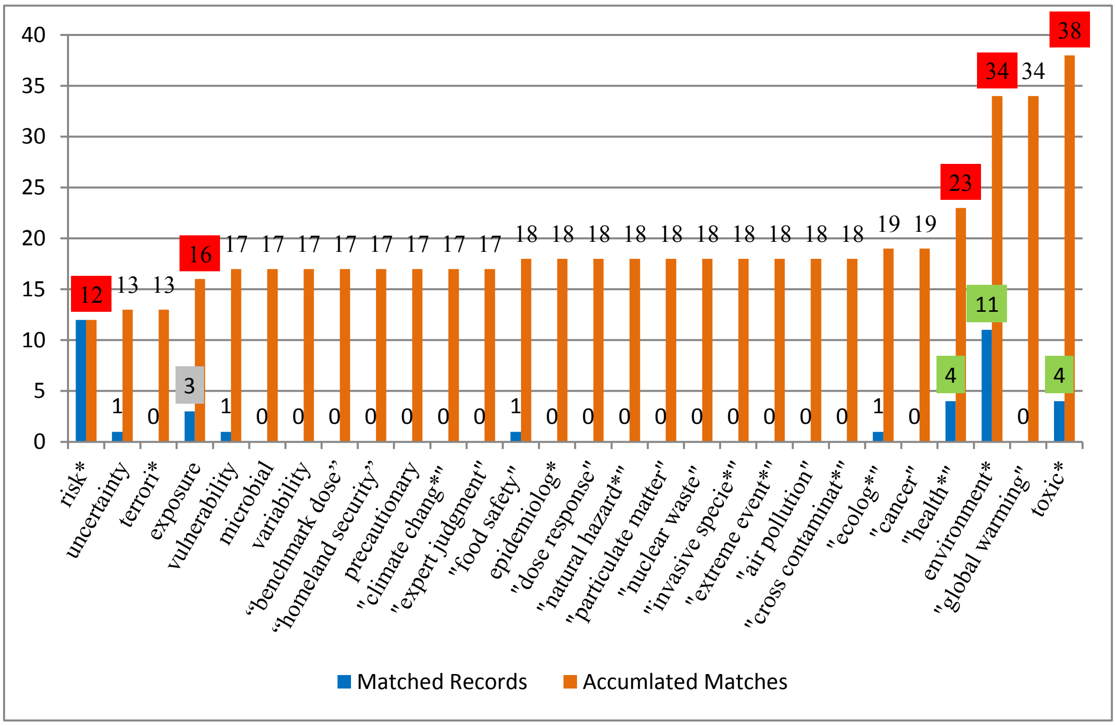

Figure 4. Matched and Accumulated Match results of the Boolean query in Table 5

From the results depicted in Table 5 and Figure 4, in the set of topic keywords on risk analysis, several types of terms for the Boolean query of risk analysis on 3D printing could be classified, such as:

(1) a complete noise term (CNT) that only adds noise in a Boolean query without any real

signal;

(2) a high SGC term (HST), which could bring some matched records (real signal) accompanied by high costs (much more noise);

(3) a relatively efficient term (RET), which brings a real signal with a relatively low cost (less noise); and

(4) a double zero term (DZT), which cannot be matched to any record.

The classification results based on the descriptions of the three types of CNT, HST, and RET are presented in Table 6.

Table 6. Classification of the topic keywords on risk analysis based on Table 5 and Figure 3

Type	Terms	Average SGC	Matched records
CNT	“terrori*”, “microbial”, “variability”, “epidemiolog*”, "dose response", "particulate matter", "nuclear waste", "invasive specie*", "cross contaminat*", "cancer", "global warming"	-	0
HST	“uncertainty”, “exposure”, "health*", “environment*”	102.04	19
RET	“risk*”, “vulnerability”, "ecolog*", "food safety", “toxic*”	14.68	19
DZT	“benchmark dose”, “precautionary, ”“expert judgment”, “natural hazard*”, “extreme event*”, “air pollution”	-	0

Based on the information presented in Table 6, although there are very few studies on the risk analysis of 3D printing, issues such as the environment, health, food safety, and toxicity are explored and discussed to some extent. However, other aspects of risk analysis (e.g., terrorism, cross contamination, cancer, precautionary governance, etc.) could be blind spots at the current stage based on the WOS data. Although the keyword for “air pollution” is not explicitly found in the matched records, several publications noted that the “emission of ultra-fine particles” of 3D printers could be considered in the relevant exploration.

4.3 Refining the Boolean Query Formula based on the Risk Analysis of 3D printing technology

Clearly, aiming at these four types of topic keywords noted in Table 6, to improve the performance of the Boolean query, handling strategies could be considered such as: (1) excluding CNT and DZT; and (2) refining HST based on the application context. Some attempts to refine the Boolean query are shown in Table 7.

Table 7. Attempts to refine the Boolean query on risk analysis of 3D printing

No	Search formula	Records	Matches	*Accuracy*	*Recall*	*Utility (%)* (*ω1=0.3, ω2=0.7*)
31#	1# and TS=(risk* OR uncertainty OR exposure OR vulnerability OR "food safety" OR "ecolog*" OR "health*" OR "environment* impact" OR toxic*)	1095	38	3.47%	100.00%	10.70
32#	1# and TS=(risk* OR vulnerability OR "food safety" OR "ecolog*" OR "health*" OR "environment* impact" OR toxic*)	733	34	4.64%	89.47%	13.79
33#	1# and TS=(risk* OR uncertainty OR exposure OR vulnerability OR "food safety" OR "environment* impact" OR toxic*)	796	38	4.77%	100.00%	14.32
34#	1#AND TS=(risk* OR vulnerability OR "food safety" OR "environment* impact" OR toxic*)	420	35	8.33%	92.11%	22.94

To compare the query results presented in Table 7, several extra Boolean queries based on common-sense synonyms of risk are implemented and shown in Table 8.

Table 8. Extra Boolean queries based on common-sense synonyms of risk

No	Search formula	Records	Matches	*Accuracy*	*Recall*	*Utility (%)* (*ω1=0.3, ω2=0.7*)
35#	1# and TS=(risk* OR uncertainty OR exposure OR vulnerability OR food OR ecolog* OR toxic*) AND TS=(safe* OR health* OR environment*)	193	15	7.77%	39.47%	17.75
36#	1# and TS=environment* and TS=(risk OR impact OR threat* OR influence)	219	20	9.13%	52.63%	21.67
37#	1# and TS=environment* and TS=(risk OR impact OR threat*	229	20	8.73%	52.63%	20.99

	OR influence OR pollution OR contaminat*)					
38#	1# and TS=(health* OR environment* OR safe* OR food OR air OR soil OR water) and TS=(risk OR impact OR threat* OR pollution OR contaminat* OR danger*)	312	22	7.05%	57.89%	18.30
39#	1# and TS=(risk* OR exposure OR vulnerability OR "food safety" OR "environment* impact" OR "environment* perspective" OR toxic* OR threat* OR "cyber* security")	720	31	4.31%	81.58%	12.78
40#	1# and TS=(risk* OR "pontential exposure" OR vulnerability OR "food safety" OR "environment* impact" OR toxic* OR "cyber* security" OR safety)	592	28	4.73%	73.68%	13.71

Identifying the relevant literature on risk analysis for a specific emerging technology is beyond the scope of a traditional topic query in the WOS or other academic databases. Here, through 40 query experiments, the topic keywords of risk analysis could be significantly helpful for finding the relevant studies on the risk analysis of 3D printing.

5. Discussions and Limitations

This article is simply inspired by the challenge of developing an ordinary query based on basic Boolean operators; however, the final work put into this article is far beyond our estimation. Even the literature retrieval in WOS based on simple Boolean computing and how to completely find the interdisciplinary studies that bring together two different topics remain a challenge, aiming at which some explorations are introduced in this article.

The paper offers some possible advances:

(1) The topic terms on risk analysis and 3D printing are explored based on an integrated framework involving techniques such as co-word analysis, variation of TF*IDF, and the survey of domain experts.

(2) Some metrics often utilized in computer science are proposed to evaluate the performance of a Boolean query of an interdisciplinary research literature.

(3) With the commercialization process of 3D printing, capturing the potential risk signals is critically important for anticipatory governance and the policy-makers involved. Based on the literature discovered in WOS, possible threats to the environment, human health, and social security (such as emissions of ultra-fine particles from some commercial 3D printers), the potential toxicity of 3D printed parts, the decryption of biological features, and the possible infringement of intellectual property warrant further monitoring and in-depth research.

(4) The analytical framework proposed by this paper should seemingly generalize to similar explorations – e.g., how to discover the relevant studies on risk analysis of synthetic biology, or how to identify the relevant literature on the risk analysis of graphene technologies?

Meanwhile, in addition to the possible meanings and implications noted, some limitations of this paper are significant and must be addressed:

First, the risk analysis corpus could cause controversy concerning the data source, even though *Risk Analysis* is the leading relevant journal, because the concept of "leading" is fuzzy and disputed. However, *Risk Analysis* is a professional journal in the relevant area; therefore, the articles published in *Risk Analysis* should be a qualified, if not complete, data source for the corpus. Theoretically, the contrast corpus based on the basic sampling methods could be acceptable to some extent. An alternative solution for the contrast corpus could be developing an interface to access Google Scholar or a third-party, large, and authoritative corpus.

Second, because the search strategies for 3D printing and risk analysis could be controversial and the publication data from WOS could be insufficient, the case study needs to be compared to other databases (e.g., Scopus and Google Scholar.) However, there is no combination of search criteria that can find all of the relevant literature based on Boolean operators. Therefore, obtaining uniform and undisputed term combinations on 3D printing should be explored in depth in future research.

In terms of a specific emerging technology, capturing the risk signal and delivering the risk signal for policy-making remain very difficult for researchers and decision-makers. With regard to Kaplan's theory of risk analysis (Kaplan 1997) and the latest relevant research (McComas 2011; Read et al. 2016), the discovery of risk scenarios is still the most difficult for all of the related issues compared to the other two elements: likelihoods and consequences. Occasionally, creative or innovative ideas, models, and techniques on risk scenarios are necessary (Kaplan 1997). In this paper, an integrated framework based on traditional methodologies of bibliometrics and knowledge discovery is proposed to identify the risk signals of a specific emerging technology, which are scattered and hidden in many different disciplinary publications, particularly in the early stages.

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Appendix

Table 9. 38 publications related to the risk analysis of 3D printing

Articles	Main Categories of WOS
Santos, A. L., Almeida, H. A., Bártolo, H., & Bártolo, P. J. (2012, July). A decision tool for green manufacturing while utilizing additive process. In ASME 2012 11th Biennial Conference on Engineering Systems Design and Analysis (pp. 155–161). American Society of Mechanical Engineers.	Mechanical Engineering
Baechler, C., DeVuono, M., & Pearce, J. M. (2013). Distributed recycling of waste polymer into RepRap feedstock. *Rapid Prototyping Journal,* 19(2), 118–125.	Mechanical Engineering Multidisciplinary Material Science
Huang, S. H., Liu, P., Mokasdar, A., & Hou, L. (2013). Additive manufacturing and its societal impact: a literature review. *The International Journal of Advanced Manufacturing Technology,* 1–13.	Automation & Control Engineering Manufacturing Engineering
Stephens B., Azimi P., El Orch Z., et al. (2013). Ultrafine particle emissions from desktop 3D printers. *Atmospheric Environment,* 79:334–339.	Environmental Sciences; Meteorology & Atmospheric Sciences
Le Bourhis, F., Kerbrat, O., Hascoët, J. Y., & Mognol, P. (2013). Sustainable manufacturing: evaluation and modeling of environmental impacts in additive manufacturing. *The International Journal of Advanced Manufacturing Technology*, 69(9–12), 1927–1939.	Automation & Control Engineering Manufacturing Engineering
Kreiger, M., & Pearce, J. M. (2013). Environmental life cycle analysis of distributed three-dimensional printing and conventional manufacturing of	Multidisciplinary chemistry Chemical engineering

polymer products. *ACS Sustainable Chemistry & Engineering,* 1(12), 1511–1519.	Green & Sustainable Science & Technology
Kellens, K., Renaldi, R., Dewulf, W., Kruth, J. P., & Duflou, J. R. (2014). Environmental impact modeling of selective laser sintering processes. *Rapid Prototyping Journal,* 20(6), 459–470.	Mechanical Engineering Multidisciplinary Material Science
Short, D. B., Volk, D., Badger, P. D., Melzer, J., Salerno, P., & Sirinterlikci, A. (2014). 3D Printing (Rapid Prototyping) Photopolymers: An Emerging Source of Antimony to the Environment. *3D Printing and Additive Manufacturing,* 1(1), 24–33.	Manufacturing Engineering Mechanical Engineering
Yoon, H. S., Lee, J. Y., Kim, H. S., Kim, M. S., Kim, E. S., Shin, Y. J., ... & Ahn, S. H. (2014). A comparison of energy consumption in bulk forming, subtractive, and additive processes: Review and case study. *International Journal of Precision Engineering and Manufacturing-Green Technology,* 1(3), 261–279.	Manufacturing Engineering Mechanical Engineering Green & Sustainable Science & Technology
Depoorter, B. (2014). Intellectual property infringements & 3d printing: Decentralized piracy. *Hastings Law Journal,* 65(6), 1483–1503.	Law
Mani, M., Lyons, K. W., & Gupta, S. K. (2014). Sustainability characterization for additive manufacturing. *Journal of research of the National Institute of Standards and Technology,* 119, 419–428.	Instrument & Instrumentation Applied Physics
Short, D. B., Sirinterlikci, A., Badger, P., & Artieri, B. (2015). Environmental, health, and safety issues in rapid prototyping. *Rapid Prototyping Journal,* 21(1), 105–110.	Mechanical Engineering Multidisciplinary Material Science
Hu JF. (2015).Thoughts on 3D printing. Proceedings of the 2015 international conference on education, management, information and medicine (EMIM 2015), 8:499–502.	Business; Economics; Management
Yampolskiy M., Schutzle L., Vaidya U., et al. (2015). Security challenges of additive manufacturing with metals and alloys. *Critical Infrastructure Protection IX,* 466:169–183.	Computer Science
Zhu F., Skommer J., Friedrich T., et al. (2015). 3D printed polymers toxicity profiling - A caution for biodevice applications. *MICRO+NANO MATERIALS, DEVICES, AND SYSTEMS,* 9668:1–7.	Nanoscience & Nanotechnology
Hunt EJ., Zhang CL., Anzalone N., et al. (2015). Polymer recycling codes for distributed manufacturing with 3-D printers. *Resources Conservation and Recycling,* 97: 24–30.	Environmental Engineering & Sciences
Kim Y., Yoon C., Ham S., et al. (2015). Emissions of Nanoparticles and Gaseous Material from 3D Printer Operation. *Environmental Science & Technology,* 49(20):12044–12053.	Environmental Engineering; Environmental Sciences
Afshar-Mohajer N., Wu CY., Ladun T., et al. (2015). Characterization of particulate matters and total VOC emissions from a binder jetting 3D printer. *Building and Environment,* 93:293–301.	Construction & Building Technology; Environmental Engineering
Zhu F., Friedrich T., Nugegoda D., et al. (2015). Assessment of the biocompatibility of three-dimensional-printed polymers using multispecies toxicity tests. *BIOMICROFLUIDICS,* 9(6):1–5.	Biochemical Research Methods; Biophysics;

Flank S., Ritchie GE., Maksimovic R. (2015). Anticounterfeiting Options for Three-Dimensional Printing. *3D Printing and Additive Manufacturing,* 2(4):181–189.	Manufacturing Engineering; Materials Science
Oskui SM.,Diamante G., Liao CY., et al. (2016). Assessing and Reducing the Toxicity of 3D-Printed Parts. *Environmental Science & Technology Letter* 3(1):1–6.	Environmental Engineering; Environmental Sciences
Vimal K., Vinodh S., Brajesh P., et al. (2016). Rapid prototyping process selection using multi criteria decision making considering environmental criteria and its decision support system. *Rapid Prototyping Journal,* 22(2): 225–250.	Mechanical Engineering Multidisciplinary Material Science
Yi JH., LeBouf RF., Duling MG., et al. (2016). Emission of particulate matter from a desktop three-dimensional (3D) printer. *Journal of Toxicology and Environmental Health-Part A-Current Issues,* 79(11): 453–465.	Environmental Sciences; Occupational Health; Toxicology
Barron S., Cho YM., Hua A., et al. (2016). Systems-Based Cyber Security in the Supply Chain. *Proceedings of 2016 IEEE Systems and Information Engineering Design Symposium (SIEDS),* pp. 20–25.	Computer Science
Azimi P., Zhao D., Pouzet C., et al. (2016). Emissions of Ultrafine Particles and Volatile Organic Compounds from Commercially Available Desktop Three-Dimensional Printers with Multiple Filaments. *Environmental Science & Technology,* 50(3):1260–1268.	Environmental Engineering; Environmental Sciences
Zhang LY., Dong HW., El Saddik A. (2016). From 3D Sensing to Printing: A Survey. *ACM Transactions on Multimedia Computing Communications and Applications,* 12(2):1–23.	Computer Science,
Izdebska J., Zolek-Tryznowska Z. (2016). 3D food printing - facts and future. *AGRO Food Industry Hi-Tech,* 27(2):33–37.	Biotechnology & Food Science & Technology
Panda, B. N., Garg, A., & Shankhwar, K. (2016). Empirical investigation of environmental characteristic of 3-D additive manufacturing process based on slice thickness and part orientation. *Measurement,* 86, 293–300.	Multidisciplinary Engineering Instruments & Instrumentation
Galbally, J., & Satta, R. (2016). Three-dimensional and two-and-a-half-dimensional face recognition spoofing using three-dimensional printed models. *IET Biometrics,* 5(2), 83–91.	Computer science, Artificial intelligence
Zeltmann SE.,Gupta N.,Tsoutsos NG., et al.(2016). Manufacturing and Security Challenges in 3D Printing. *JOM,* 68(7):1872–1881.	Materials Science
Do Q., Martini B., Choo KKR. (2016). A Data Exfiltration and Remote Exploitation Attack on Consumer 3D Printers. *IEEE Transactions on Information Forensics and Security,* 11(10):2174–2186.	Computer Science
Nagarajan, H. P., Malshe, H. A., Haapala, K. R., & Pan, Y. (2016). Environmental Performance Evaluation of a Fast Mask Image Projection Stereolithography Process Through Time and Energy Modeling. *Journal of Manufacturing Science and Engineering,* 138(10), 101004.	Manufacturing engineering Mechanical engineering
Neely, E. L. (2016). The Risks of Revolution: Ethical Dilemmas in 3D Printing from a US Perspective. *Science and engineering ethics,* 22(5), 1285–1297.	Multidisciplinary Sciences Multidisciplinary Engineering Ethics

	History & Philosophy of Science
Liu, Z., Ning, F., Cong, W., Jiang, Q., Li, T., Zhang, H., & Zhou, Y. (2016). Energy Consumption and Saving Analysis for Laser Engineered Net Shaping of Metal Powders. *Energies,* 9(10), 763.	Energy & Fuels
Tang, Y., Mak, K., & Zhao, Y. F. (2016). A framework to reduce product environmental impact through design optimization for additive manufacturing. *Journal of Cleaner Production,* 137, 1560–1572.	Environmental engineering Environmental sciences Green & sustainable science & technology
Ford, S., & Despeisse, M. (2016). Additive manufacturing and sustainability: an exploratory study of the advantages and challenges. *Journal of Cleaner Production,* 137, 1573–1587.	Environmental engineering Environmental sciences Green & sustainable science & technology

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Jeong YJ., Park I., Yoon B. (2016). Forecasting technology substitution based on hazard function. *Technology Forecasting and Social Change,* 104: 259–272.

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