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# An Approach to Identify Emergent Topics of Technological Convergence: A case study for 3D printing

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**Abstract**: Technological Convergence (TC) reflects developmental processes that overlap different technological fields. It holds promise to yield outcomes that exceed the sum of its subparts. Measuring emergence for a TC environment can inform innovation management. This paper suggests a novel approach to identify Emergent Topics (ETopics) of the TC environment within a target technology domain using patent information. A non-TC environment is constructed as a comparison group. First, TC is operationalized as a co-classification of a given patent into multiple 4-digit IPC codes (⩾2-IPC). We take a set of patents and parse those into three sub-datasets based on the number of IPC codes assigned 1-IPC (Non-TC), 2-IPC and ⩾3-IPC. Second, a method is applied to identify emergent terms (ETs) and calculate emergence score for each term in each sub-dataset. Finally, we cluster those ETs using Principal Components Analysis (PCA) to generate a factor map with ETopics. A convergent domain -- 3D printing -- is selected to present the illustrative results. Results affirm that for 3D printing, emergent topics in TC patents are distinctly different from those in non-TC patents. The number of ETs in the TC environment is increasing annually.

**Keywords**: Technological Convergence (TC); Emergent topics (ETopics); Emergent terms (ETs); International Patent Classification (IPC); 3D printing

# 1 Introduction

Actions such as sharing similar technological characteristics accelerate the erosion of distinct barriers among industries. Technologies commercialized in one industry could significantly influence, or even shape, the nature of a product and process evolution in other industries. This growing trend is broadly known as Technological Convergence (Lei, 2000). Regarding the converging environment, sourcing the essential technological knowledge from beyond their own industry is often necessary and key to successful innovation management.

New and emerging technologies appear frequently in the converging environment, at the boundaries of different technology fields. Martin (1995) has emphasized the foresight of the most promising research areas and emerging technologies that can yield longer-term economic and social benefits. He also introduced the notion of "convergence of technological fields" as one characteristic of general emerging technologies. Emerging technologies have the potential to be highly generative and may open up whole new areas of technology and science (Breitzman & Thomas, 2015). In academia, the existing literature is oriented toward patent-based approaches for the identification of emerging technologies (Lee et al. 2017). Yet, there is a lack of exploration for emerging technologies in the convergence environment. We have asked the research question: Is there an analytical approach to help identify and distinguish emergent topics in the convergence environment?

Patent databases are being employed as they are increasingly giving insights into technological development. Technology classification system could be seen as an appropriate unit of analysis for exploiting the information contained in the patent databases (Dibiaggio & Nesta, 2005; Leydesdorff, 2008). Convergence can be found in patent data through growing overlap among Standard Industrial Classification (SIC) codes or International Patent Classification (IPC) codes and through an increase in patent citations among different classes (Pennings & Puranam, 2001). Many researchers make use of the IPC codes to illustrate the patterns of converging technologies (Dosi, 1982; Matti & Tuomo, 2011; Shim et al., 2016; Verbeek et al., 2002). IPC hierarchically structures patents into section (1-digit), classes (3-digit), subclasses (4-digit), main groups, and subgroups. The technical fields and background of the patent documents appear significant in the classification task at the IPC subclass level (Lim & Kwon, 2017). Therefore, this paper defines the TC environment as the dataset in which patents are assigned with multiple 4-digit IPCs. Conversely, the non-TC environment is the dataset in which patents are assigned with single 4-digit IPCs.

This analysis was conducted through spotlighting Emergent Topics (ETopics) in a TC environment and comparing to those in a corresponding non-TC environment. The emergent terms identified from patent databases could contribute to technology forecasting (Roper et al., 2011), enable firms to innovate new technologies and hold competitive skills. ETopics can also serve technology assessment interests in developing awareness of potential socio-economic implications in advance of the implementation of emerging technologies, to instigate possible policy actions (Porter et al., 1980; Roco et al., 2011).

Both ETs and TCs are becoming a priority and part of the research agenda of many national governments (Jeong & Lee, 2015; Rotolo et al., 2017). Constructing efficient approaches to explore R&D emergence and convergence can accelerate discoveries, solutions, and innovations. This paper provides an original approach for identifying emergent terms of TC. From an academic perspective, the systematic approach proposed can be applied to other sectors to reveal the emergence of TCs as many industries are facing trends of fusing technologies and convergence processes (Karvonen & Kässi, 2011). From a practical standpoint, the findings of the approach can help strategic decision makers understand what is emerging in the convergence pattern within a technological domain. Firms can also use the emergence information in a technological convergence environment to manage intellectual property to gain competitive advantage.

The paper is organized as follows: Section 2 provides a brief overview of emerging technologies and technological convergence. Section 3 describes our analytical approach. The empirical study and the results are given in section 4. Section 5 concludes with an outlook on possible future research and implications for R&D management.

## 2 Theoretical background

### *2.1 Emerging technologies*

A WOS (Web of Science) search for articles with the title "emerg* technology(ies)" returns over 2600 records; thus it can be seen that this topic has attracted a lot of interest from governments, companies, and individual scientists (Small et al., 2014). Many researchers have offered definitions and explored the characteristics of "emerging technologies". Day and Schoemaker (2000) defined emerging technology as a science-based innovation that has the potential to create a new industry or to transform existing ones. Porter et al. (2002) defined emerging technologies as being able to exert much enhanced economic influence in the coming (roughly) 15-year horizon. Goldstein (1999) ascribed the following characteristics to emergence: radical novelty; coherence, correlation, wholeness; global or macro; dynamical; and ostensive, perceivable. Srinivasan (2008) pointed out that fast growth, convergence, dominant designs and network effects are the characteristic of emerging technologies, and the only certainty with emerging technology is the high degree of uncertainty associated with them. Halaweh (2013) summarized 6 characteristics of emerging technology: uncertainty, network effect, costs, unobvious impact, limited to creator or inventor country, and not fully investigated and researched. Boyack et al. (2014) noted that "there is nearly universal agreement on two properties associated with emergence – novelty (or newness) and growth. We find two additional properties on which there is less, but still moderate, agreement – emergence is noticeable and unexpected". Rotolo et al. (2015) summarized five distinguishing characteristics of an emerging technology: (a) radical novelty; (b) relatively fast growth; (c) coherence; (d) prominent impact; and (e) uncertainty and ambiguity. The last characteristic pertains to the technology showing high potential, but its value has not been well-demonstrated (Cozzens et al., 2010). Emergence can be treated with some or all of these characteristics (Van Merkerk & Robinson, 2006).

More and more quantitative methods, mainly bibliometrics (Chang et al., 2009; Glänzel & Thijs, 2012; Guo et al., 2012; Huang et al., 2015; Boyack et al.2014), are conducted as a complement to expert-centric approaches in analyzing emergence in science and technology. There are mainly two directions: one is identifying the existing technologies as emergence (Cho & Shih, 2011; Joung & Kim, 2017; Ju & Sohn, 2015), and the other is predictive analysis before they emerge (Daim et al. , 2006; Kyebambe et al., 2017; Erdi et al., 2013; Bengisu & Nekhili, 2006).

Lee et al. (2017) reviewed a rich patent-based literature to identify emerging technologies. He expounded that the approaches, including curve fitting techniques and stochastic models (estimating probability distributions of patent citations), don't enable identification of emerging technologies at early stages of technology development.

In this paper, we detailed the introduction of the emergence indicator proposed by Search Technology and Georgia Tech group members (Garner et al., 2017). They have been involved in Foresight and Understanding from the Scientific Exposition (FUSE) Program for emergence and framing candidate indicators (Alexander et al., 2012). Their emergence indicator offers replicability and feasible generation.

### *2.2 Technological Convergence Based on IPCs*

A prevailing view on the convergence phenomenon is that industries and markets would merge through a growing overlap among technologies, services, and firms. This concept associated with technological development has become the focus of many studies (Hacklin, 2007; No & Park, 2010; Stieglitz, 2003). The term TC refers to a process, whereby the different sectors come “to share a common knowledge and technological base” (Athreye & Keeble, 2000; Rosenberg, 1976). Patent data have been used to measure TC (Fai & von Tunzelmann, 2001; Gambardella & Torrisi, 1998; Matti & Tuomo, 2011; Curran & Leker, 2011).

As we mentioned, IPC codes are a hierarchical way of assigning the category to which every patent belongs. There are eight sections, 130 classes, 642 sub-classes, and 73,915 groups (“International Patent Classification (IPC) - IT support area - Edition 20180101 - Statistics”). The IPC separates the whole body of technical knowledge, which may be regarded as proper to the field of patents for invention using hierarchical levels (e.g., section, class, subclass, group, and subgroup) in descending order of hierarchy. One patent can be assigned to more than one sub-class if the patent finds application in various industrial domains. If all the patents are not concentrated in a few sub-classes, research can be said to be diversified. The definition of TC operationalized in this study is based on the co-classifications of 4-digit IPC codes. The occurrence of a combination of two IPC subclasses is considered to indicate a converged technology (Caviggioli, 2016). Patent documents with two or more distinct patent subclasses might indicate the presence of a convergence development. On the contrary, a patent classified with a single 4-digit IPC code would show no indication of technology convergence. This fundamental concept of IPC co-classification analysis is also adopted (Song et al., 2017) to depict the relationships among technology classes, as they help to illustrate how technological knowledge structures are interconnected and yield insight into the technological orientation and changes therein.

## 3 Proposed Methodology

This work investigates the emergence related to the convergence environment in a specific technology domain. We first develop a proxy for technological convergence using 4-digit IPCs in the patents. The techniques we employ to identify ETs have been used and validated in a number of previous studies (e.g. Carley et al., 2017; Garner et al., 2017; Carley et al., 2018) and our emergence indicator (catalogued below) is most compatible with the datasets used in our study, providing results in quantifiable format. Finally, Principal Components Analysis (PCA) factor mapping is used to provide not only visualization, but a deeper understanding of how ETs are related to one another.

Figure1 shows the overall process of the proposed approach. The framework is designed to be executed in three steps: (1) Parse the dataset based on the number of 4-digit IPCs; (2) Generate emergence indicators (ETs); (3) Cluster ETs by PCA. Finally, Non-TC environment is used as a comparison group to reveal the differences from TC.

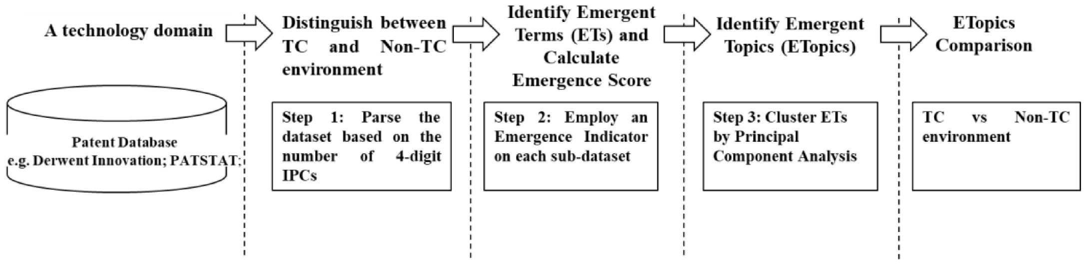


Figure 1. Overall Process to Generate Emergent Terms in relation to Technological Convergence

### *3.1 Distinguish between TC and Non-TC*

There are various free or commercial patent databases. USPTO, EPO, WIPO, JPO, SIPO, OECD, Google Patents, Derwent Innovation Index (DII), etc., are examples. The IPC system is used in more than 100 countries in the world; almost all the patent-related databases have IPC information. Besides IPCs, there are two important classification systems used by the largest patent offices (e.g., the EPO and US joint CPC system, and the Japanese FI system). Those two systems are also based on IPCs. Patents from a database such as DII can be downloaded and imported to VantagePoint [www.theVantagePoint.com] software. The software was employed to extract 4-digit IPCs of each patent record. The number of IPC technology classes assigned in one patent indicates the range of its technical application (Cozzens & Wetmore, 2010). This implies that patents with co-assignment of multiple IPCs are enriched in technological knowledge and, possibly, with higher value. Thus, we parsed the whole dataset at the subclass level into three sub-datasets based on the number of 4-digit IPC codes assigned, and we named the three sub-datasets as 1-IPC, 2-IPC, ⩾3-IPC (no less than 3 4-digit IPCs). For 1-IPC dataset, all the patents were assigned with single 4-digit IPCs in this dataset, and so on. Here, we examined various ways to parse the dataset to distinguish the TC environment and non-TC environment. We also tried to examine emergent terms in 4-IPC, 5-IPC, etc., sub-datasets separately. Finally, we determined to use three sub-datasets, which provided better comparison.

### *3.2 Identify Emergent terms*

A more thorough treatment of how we calculate emergent terms is provided by Carley et al. (2017; 2018). The emergence indicator we employ here contains five specific methodological steps (Porter et al., 2018, Figure 1). Here we add some formulations for elaboration. Appendix A indicates how our emergence indicator calculation runs as a script in Vantagepoint.

Here, t refers to a 10-unit time period (usually years, but we are investigating use of other temporal units, such as quarters); numbers refer to those 10 periods; 1 refers to the earliest and 10 to the latest period. Where, t=4…10 should be taken as an active period ($t_{active}$) comprising 7 temporal units, and t=1…3 should be taken as a base period ($t_{base}$) of 3 units. To a specific term i:

$n_{it}$ : number of records contain term i in time t; $x_{it} = \begin{cases} 1 & \text{if term i appears in time period t} \\ 0 & \text{otherwise} \end{cases}$ ;

$N_t$ : number of records in time period $t_{active}$ is the set of authors who use term i;

$|A| = m$, $A = \{a_1 ... a_m\}$, $1 \le j \le m, 1 \le k \le m, j \ne k$; $y_{jk} = \begin{cases} 0 & \text{a}_j \text{ and a}_k \text{ co-author one record} \\ 1 & \text{otherwise} \end{cases}$ ;

Criterion 1: [Term Persistence: a term must appear in at least 3 time periods (years) and in at least 7 records.]

If $\sum_t x_{it} \geq 3$ and $\sum_t n_{it} \geq 7$ then that term meets the specified "Persistence" criteria.

Criterion 2: (Novelty and Growth: the term cannot appear in as many as 15% of the base period records; it must appear in at least twice as many records in the active period as in the base period.)

If $\frac{\sum_{t=1}^{3} n_{it}}{\sum_{t=1}^{10} n_{it}} \leq 0.15$ and $\sum_{t=4}^{10} n_{it} \geq 2 \times \sum_{t=1}^{3} n_{it}$ then that term meets the specified Novelty and Growth criteria.

Criterion 3: (Community: terms need to be used by more than one author who doesn't co-author on the same set of records.)

Term i meets the specified Community criterion if $m \geq 2$ and $\sum_{j=1}^{m} \sum_{k \neq j} y_{jk} \geq 1$

Criterion 4: Calculation of EScore for Term i

$$\text{Active Trend}_i = \left(\sum_{t=8}^{10} \frac{n_{it}}{\sqrt{N_t}} - \sum_{t=4}^{6} \frac{n_{it}}{\sqrt{N_t}}\right) \div 2$$

$$\text{Recent Trend}_i = \left(\sum_{t=9}^{10} \frac{n_{it}}{\sqrt{N_t}} - \sum_{t=7}^{8} \frac{n_{it}}{\sqrt{N_t}}\right) \times 10 \div 2$$

$$\text{Slope}_i = \frac{\frac{n_{i10}}{\sqrt{N_{10}}} - \frac{n_{i7}}{\sqrt{N_7}}}{3} \times 10$$

$$\text{EScore}_i = 2 \times \text{Active Trend}_i + \text{Recent Trend}_i + \text{Slope}_i$$

Criterion 5: (We examined various levels of the resulting term scores for various datasets, settling on a threshold of 1.77 for a term to be considered emergent)

If $EScore_i \geq 1.77$ then the term is considered to be emergent. The value 1.77 was chosen based on empirical observations. A reasonable threshold was judged to fall between EScores of 1.5 and 2. We selected 1.77 as the square root of Pi (in the middle, and a touch of whimsy).

***3.3 Identify Emergent Topics***

As we set the threshold for selecting ETs, there are a large number of emergent terms. We aim to reduce the dimension and refine the information for ETs. The objective of this clustering is to minimize associations among clusters and maximize the relationships within clusters. Different clustering algorithms have different starting points and mechanisms of selection; however, these will not bring about large differences in the actual clusters developed (Newman, et al., 2014). Principal Components analysis (PCA) is a useful technique for extracting the main relationships implicit in a dataset (Zhu & Porter, 2002; Zhu et al. 1999; Watt et al., 1998). We use PCA clustering the ETs that frequently occur together in the dataset records in one ETopic. The factor loadings for each ET, also called component loadings in PCA, are the correlation coefficients between the terms and Topics (PCA factors). We go on to compare those ETopics between our single-IPC sub-dataset and multiple-IPC sub-dataset.

## 4 Empirical study

This study focuses on technical fields with converging technologies. Our purpose is a comparative look at ETs in a TC environment and in a non-TC environment, in one target domain. We noticed that three-dimensional (3D) printing technology itself is based on diverse technologies such as laser beams and materials. Li & Porter (2018) developed an integrated framework involving several new metrics for a Boolean query to analyze the risk for 3D printing. They validate the dramatical growth in publications related to 3D printing in WOS (Web of Science) and the multiple categories involving in 3D printing technology. We confirm that 3D printing technology is a converging and emerging technology that produces 3D objects using a 3D printer (Park et al., 2016).

### *4.1 Datasets*

We chose DII as our source for data. It offers patent information that is more comprehensive, accurate, and searchable than the primary patent records as provided via databases such as PATSTAT because their records are rewritten by humans, so interpreted better than first level data. Patent records are converted into a standard format, errors corrected and each record assigned to a patent family and industry code. Crucially, patents in DII are enriched with enhanced titles and comprehensive abstracts in English (https://clarivate.com/wp-content/uploads/2017/12/Derwent-Innovation-for-Research.pdf).

The search query we set for 3D printing was SSTO= (((3D OR 3-D OR (3 ADJ dimension*) OR (three ADJ2 dimension*) OR additive) NEAR (print* OR fabricat* OR manufactur* OR product*))) (Huang et al., 2017). Ultimately, we got 30,122 patent records for 3D printing.

Figure 2 depicts the growth trend for 3D printing. Because of the time lag for patents being filed, the number of records in the basic patent years 2016 and 2017 should be incomplete. Surprisingly, Figure 2 shows that the number of 3D printing patents in 2017 is larger than that of 2016, and then 2015, respectively.

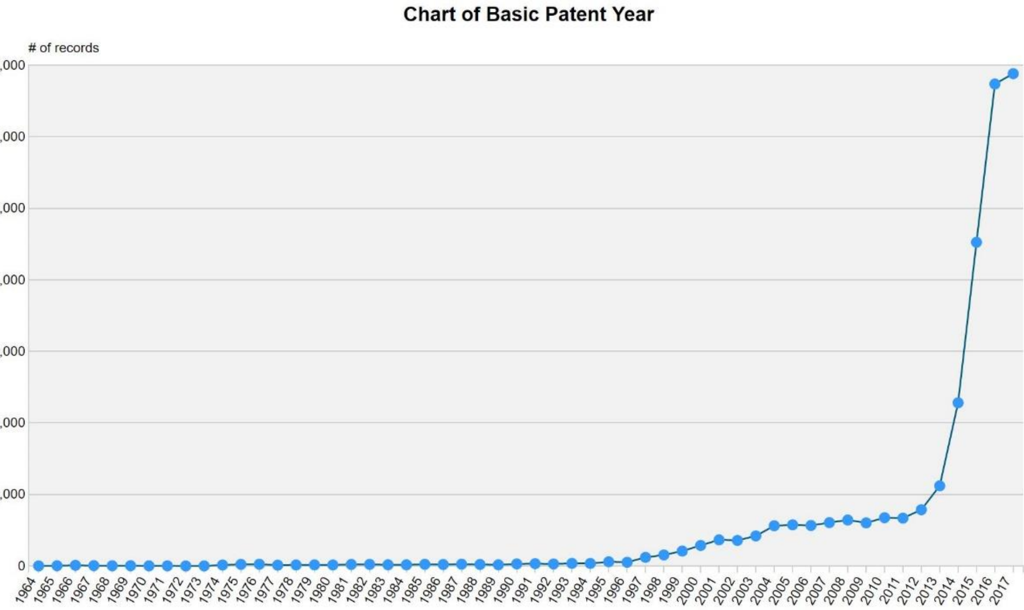


Figure 2. Development over time for 3D printing patents

***4.2 Growth Trend of TC and non-TC***

In order to understand the dynamic changes for the TC phenomenon in 3D printing, we analyzed the share of patents in the three sub-datasets, as mentioned in the methodology section: 1-IPC, 2-IPC, ⩾3-IPC (each year) (Figure 3). The reason we chose the beginning year as 2006 is that the IPC reform in 2006 (IPC-8) causes a difference in labeling among the patent documents published before and after the reform. For the documents published before the reform, only one single main IPC was assigned to a patent. After the reform, no formal distinction was made between the main and secondary classifications (Song et al. 2017).

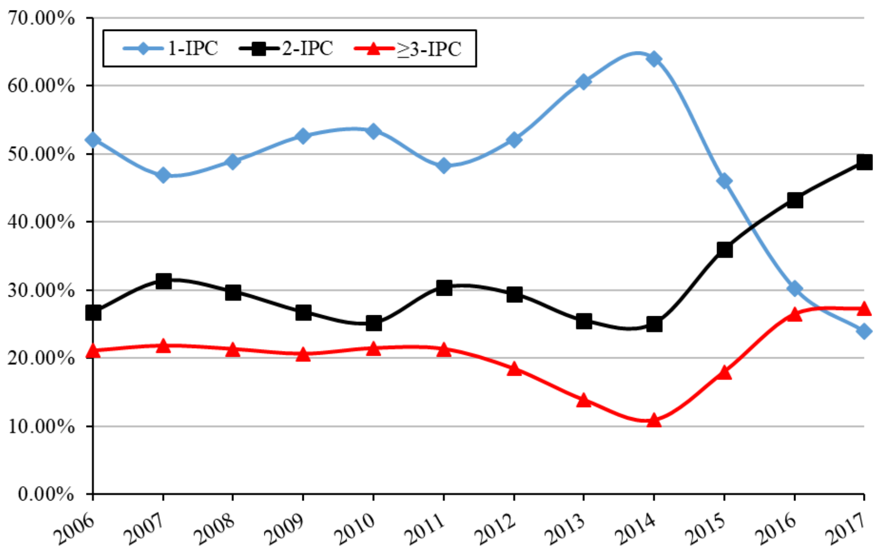


Figure 3. Share of patents according to the different counts of IPC on 3D printing

The results in Figure 3 show that the share of 2-IPC and ⩾3-IPC sub-datasets for 3D printing has significantly risen within the past three years, further demonstrating the growing TC of this technological domain. The shares of 2-IPC and ≥3-IPC patents began increasing in 2015. Furthermore, convergence in 3D printing is more obvious and faster growing; the percentage of 2-IPC patents exceed the single IPC patents in 2016; and the ≥3-IPC exceed the 1-IPCs in the following year.

### *4.3 ETs in TC and non-TC environments*

The object of the analysis is to distinguish ETs in multiple IPC sub-datasets. When running VantagePoint's emergence indicator script on each sub-dataset, we selected a ten-year test period consisting of a base period (three years) plus an active period (seven years). We tested three different ten years periods: 2006–2015, 2007–2016, and 2008–2017.

At first, it is also of interest to investigate the number of ETs in each sub-dataset. Figure 4 is a Venn diagram that shows the overlapping ETs of the three sub-datasets in different time periods. The number inside the circle is the number of ETs we got, while numbers outside the circle represent ETs not in that dataset. The number in the area of overlap of two circles represents the number of ETs in both sub-datasets. In the same way, the number in the overlap of three circles is the intersection of three sub-datasets. The number of ETs in 2-IPC and ≥3-IPC circles increases year by year.

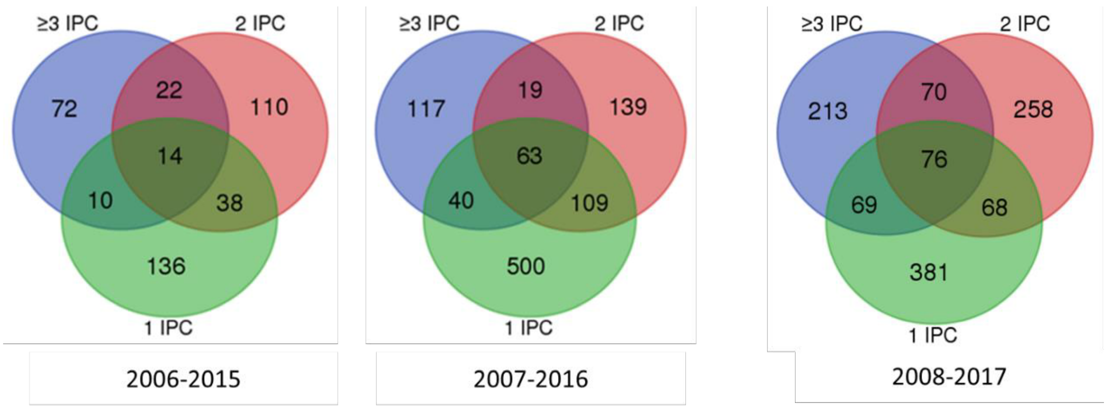


Figure 4. Venn diagram for 3D printing

Table 1 compares ET numbers between TC and non-TC, and the total number of ETs in each 10-year time period. The number of ETs in 2-IPC and ≥3-IPC sub-datasets is increasing annually for 3D printing. The number of ETs in 1-IPC sub-dataset decreases in 2017. It demonstrates the increasing emergence of TCs in the 3D printing domain.

**Table 1.** Total Number of ETs for 3D printing

| **Time period**<br>**# of IPC** | **2006–2015** | **2007–2016** | **2008–2017** |
|---|---|---|---|
| **Non-TC: 1-IPC** | 198 | 712 | 594 |
| **2** | 188 | 347 | 488 |
| **≥3** | 118 | 239 | 428 |
| **Total （exclude the overlapping terms）** | 402 | 987 | 1135 |

It is also interesting that the numbers of IPCs and ETs correlate negatively. We carried out the correlation analysis and found that the relationship between the number of ETs and the number of records correlates significantly (r = 0.814) based on our data (Table 2).

**Table 2**. Correlations

| | | # of IPCs | #of Records | #of ETs |
|---|---|---|---|---|
| **# of IPCs** | Pearson Correlation | 1 | -.697* | -.513 |
| | Sig. (2-tailed) | | .037 | .158 |
| | N | 9 | 9 | 9 |
| **# of Records** | Pearson Correlation | -.697* | 1 | .814** |
| | Sig. (2-tailed) | .037 | | .008 |
| | N | 9 | 9 | 9 |
| **# of ETs** | Pearson Correlation | -.513 | .814** | 1 |
| | Sig. (2-tailed) | .158 | .008 | |
| | N | 9 | 9 | 9 |

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3 shows the top 10 high emergence terms, giving the terms' Escore. We took a look at all the emergent terms in TC patents and found that they are largely different from those in non-TC patents.

**Table 3**. Top 10 High Emergence Score Terms in Three Sub-Datasets (2008-2017)

| **>=3 IPCs** | | **2 IPCs** | | **1 IPC** | |
|---|---|---|---|---|---|
| **Emergent terms** | **Score** | **Emergent terms** | **Score** | **Emergent terms** | **Score** |
| polylactic acid compatibilizer | 57.36 | platform print | 58.32 | polylactic acid | 31.92 |
| high plasticity | 43.31 | high precision | 34.04 | technical field | 29.27 |
| wt antioxidant | 38.75 | guide rail | 28.94 | print technology | 21.73 |
| screw extruder temperatures | 32.24 | screw rod | 28.48 | slide rail | 20.45 |
| manufacture additive | 32.23 | efficient print | 24.54 | Three dimensional print technology | 20.24 |
| multifunctional 3D printer | 29.90 | print quality | 23.41 | polyvinyl alcohol | 19.79 |
| taking compatibilizer | 29.64 | feeding pipe | 23.19 | simple manner | 19.78 |
| mechanical property distribution | 29.15 | connecting rod | 23.14 | stainless steel | 18.31 |
| controller operative | 28.98 | controller | 22.23 | feeding port | 18.15 |
| mixing modified acrylonitrile butadiene styrene | 27.87 | slide rail | 19.95 | plastic | 17.40 |

***4.4 Emergent Topics in a TC environment***

We use VantagePoint's PCA (Principle Components Analysis or "factor map" routine) to cluster those emergent terms. For the ≥3-IPC sub-dataset in the period 2008-2017, the PCA routine denotes 25 highly emergent topics (Figure 5). We would predict that those 25 topics that we distinguish as high emergence are more apt to remain especially active research topics over the next two or three years. The dropdowns are the ETs related to this ETopic.

### *4.5 Emergent Topics Comparison*

For each of these three sub-datasets, we obtained three factor maps belonging to the time periods 2006-2015, 2007-2016, and 2008-2017. We combined ETopics in 2-IPC and ⩾3-IPC sub-datasets together as ETopics in the TC environment. We've found that ETopics are updating rapidly over time in the 3D printing domain (Table 4). We give results in Table 4 to two 3D printing specialists[1] asking for their judgement. They have an agreement that our ETopics have covered the 3D printing domain comprehensively, including function, materials, and devices. Moreover, ETopics in TC patents have a broader range, including detailed preparation methods, devices, and improved materials. The emergent materials in the TC environment which are highlighted by the two experts are "polycarbonate," "titanium alloy," "waste plastic," and "Plant Fiber," etc. There are also many materials with auxiliary functions such as "radical photoinitiator," "release agents," and "chain extender." ETopics like "Notch Impact Strength" and "Low manufacturing" demonstrate the higher performance requirements for a 3D printer in the TC environment, while the ETs in 1-IPC describe the basic and universal devices, and theories for 3D printing. For instance, there are terms like "high precision," "work efficiency," "laser melting," and "laptop computer." Huang et al. (2017) has validated that composite materials became a new topic in the 3D printing of complex structures, which are thought of as a challenging but promising direction. Here we came to the consistent conclusion with Huang that among the ETopics in TC patents, composite materials related most strongly.

[1] The authors thank Dr. Ning Wang and PhD Candidate Mingyuan Ma from the University of Science & Technology Beijing for their assistance with this analysis. The two experts do not know each other. To avoid bias, we did not tell them our expectations. We also avoid implying that there is a right answer for the table.

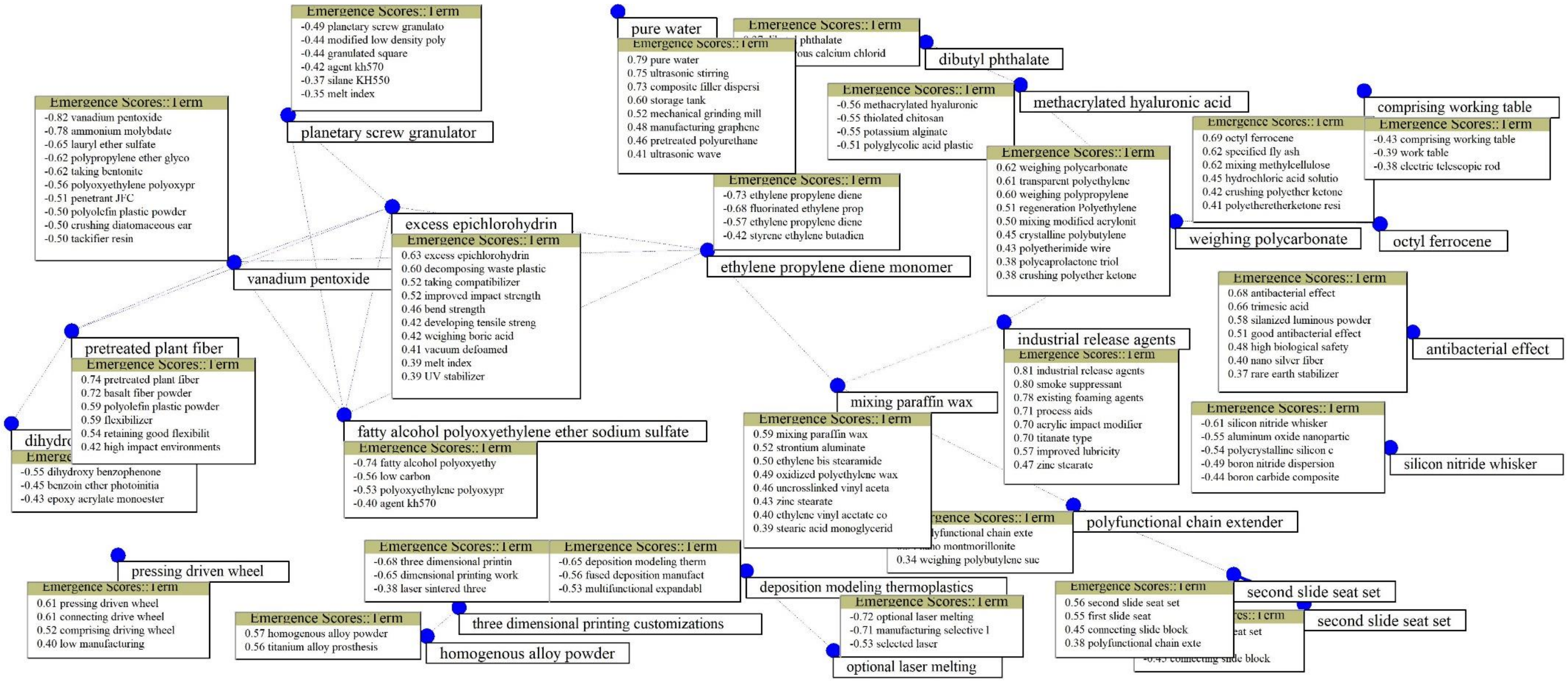


Figure 5. 3D printing Emergent Topics for 2008-2017 (≥3-IPC)

**Table 4**. ETopics Comparison between the TC Environment and non-TC Environment

| Time | TC | Non-TC |
|---|---|---|
| 2006–2015 | Melt Index; Polyvinyl Chloride; Excellent Mechanical Property; Montmorillonite; Process Aids; Single Screw; Silicon Carbide; Epoxy Acrylate; Laser Melting; Gas Turbine; Floss Layer; Synchronic Belt; Cost Effective Manner; Carbide Silicon; Acrylonitrile Butadiene Styrene; Work Efficiency; Isotetradecane; Laser Selective Melting; Impact Modifier; Fused Deposition Modeling; Epoxy Acrylate; Gas Turbine Engine; Twin Screw Extruder; Fluff Block; Aluminum Hydroxide; | Screw Rod; High Precision; Work Efficiency; Floss Layer; First Drive; Alloy Powder; Laptop Computer; Fused Deposition; Tributyl Phosphate; Guide Wheel; Service Life; Gas Turbine Engine; Automotive Industry; Laser Melting; Fluff Block; |
| 2007–2016 | Waste Plastic; Pure Water; Screw Extruder; Polycarbonate; Ethylene Vinyl Acetate; Work Efficiency; Twin Screw Extruder; Aluminum Oxide; Laser Melting; Polybutylene; Succinate Epoxy Acrylate; Vinyl Acetate; Viscosity Regulator; Titanium Alloy; Gas Turbine Engine; Fused Deposition;; Platform Print; Cost Effective Manner; Aluminum Nitride; Butadiene Styrene; Heating Block; Graphene; Fused Deposition Modeling; Synchronous Belt; Driven Wheel; Linear Silicone Oil; Gas Turbine Engine; Fluff Block; Laser Selective Melting; Gear Mesh; Epoxy Acrylate; Automation Degree; Sending Silk Wheel; | Release Agents; Connecting Rod; Lead Screw; Epoxidized Soybean Oil; Zinc Sulfide; Fused Deposition Model; Laptop Computer; Automation Degree High; Gas Turbine Engine; Tributyl Phosphate; Bone Tissue; First Drive; Light Oil; Alginate; Prolonged Service Life; Second Gear; Laser Additive Manufacturing; Tin Oxide; Fused Filament; STL File Format; Fluff Block; Pentaerythritol Tetraacrylate; First Conducting; Lithium Ion; |
| 2008–2017 | Notch Impact Strength; Pure Water; Hyaluronic Acid; Styrene Butadiene; Screw Extruder; Polyether Ether Ketone; Ethylene Bis Stearamide; Horizontal Guide; Vanadium Pentoxide; Laser Melting; Plant Fiber; Silicon Carbide; Ethylene Vinyl Acetate; Chain Extender; Trimesic Acid; Release Agents; Low Density Polyethylene; Fused Deposition Modeling; Low Manufacturing; Second Slide; Drive Wheel;; Laser Selective Melting;Sodium Gluconate; Strip Groove; Butadiene Styrene; Power Supply Module;Calcium Carbonate Powder; Heating Block;Fused Deposition Modeling; Resin Groove;Material Guide Pipe; Titanium Alloy Powder; Synchronous Belt; Water Pump; Retarder; Second Motor; Automation Degree; First Guide Rail; Vertical Guide; Radical Photoinitiator; | Alginate; Polystyrene; Work Efficiency; Epidermal Growth Factor; Epoxidized Soybean Oil; Fused Deposition Model; Polyvinyl Alcohol Solution; Tin Oxide; Compression Mold; Power Supply Module; Rheology Modifier; Polypropylene Fiber; Polyetherketoneketone; Gas Turbine Engine; First Bevel Gear; Cool Water Tank; High Density Polyethylene; Fused Filament Fabrication; Solid Polymer; Hot Isostatic; High Molecular; Universal Serial Bus; Engineering Bracket; Tissue Engineering Bracket; |

## 5 Conclusions and Discussions

In this paper, we developed a new framework aiming at monitoring emergent topics of technological convergence in a tech domain. First, we parsed the patents into different sub-datasets on the basis of the IPC classification system, which can be considered as the intellectual organization of the database of novel products and processes of economic value (Leydesdorff et al., 2017). Patents assigned with a single 4-digit IPC represent a non-TC environment, while patents with multiple IPC subclasses represent a TC environment. Second, we employed an emergence indicator, which identifies emergent terms. Then, PCA was used to cluster the emergent terms. Finally, we compared the emergent topics in the TC environment to the non-TC environment.

For 3D printing, both the share of TC patents and the number of ETs in the TC patents are increasing annually. Moreover, the ETopics of TC are almost completely different from those of the non-TC patent dataset. The TC ETopics have broader range. Updating ETopics in the TC patents over time indicates more complex and broader materials appearing within this domain.

To sum up, this proposed method can point attention to the cutting-edge topics in the converging R&D activities. R&D researchers and program managers could gain value from application of this two-part approach. First, it is informative to separate patents with more 4-digit IPC sub-class assignments as "TC." Analyzing them in contrast to non-TC (single IPC) patents may point toward dynamic directions for R&D. Second, identifying the ETopics in the TC domain can further illuminate promising technical elements warranting strong attention.

The limitations of this study present some challenging questions for future research. First, there is no universal agreement on the distinction between TC and non-TC. This paper contains a small study on the distinction work. We should further think about the conceptual extensions. Second, some of the emergent terms identified by the emergence indicator have synonyms in the terms list. How to best get a more efficient set of emergent topics and terms is a key part. Consolidating the emergent terms by clustering methods is helpful. Future research will try to compare PCA methods with other clustering methods.

The emergence indicator development will continue. Current thresholds for novelty, persistence, and community are undergoing sensitivity analyses to determine suitability. The "1.77" cutoff for inclusion as an ET is being assessed in multiple datasets. Preliminary indications are that these emergence indicators are quite robust, but that small modifications could improve their behavior. Other characteristics of emerging technologies may be considered for inclusion to reinforce the model. Shorter time periods such as quarters, instead of years, warrant exploration. In addition, how the emergent topics in TC patents perform should be further considered. Do they indeed show forth as especially active in patent activity over the coming few years?

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**Appendix A**. Screenshot of the Emergence Script Control Panel vantagepoint

## Calculate Emergence

Choose Terms field: Abstract (NLP) (Phrases) + Title (NLP) (Phrases) ▾

Choose Year field: Publication Year - 2008-2017 ▾

**Optional:**

Choose Organization field: ▾

**check that a field has meta tag set to Organization in dataset*

Choose Person field: ▾

**check that a field has meta tag set to Person in dataset*

Choose Country field: ▾

**check that a field has meta tag set to Country in dataset*

Choose Title field: ▾

Advanced

**Cleanup Terms List Options**

☐ Run General Cleanup?

Optional - Choose a stopwords file:

▾ Use Keyword List? Reset

☐ Use Fuzzy Match?

**Set Emergence Criteria**

Organization must have at least 70 % of records and 8 total records with emergent term.
Person must have at least 90 % of records and 3 total records with emergent term.
Country must have at least 45 % of records and 10 total records with emergent term.
☐ Group Top 10 Organization, Person, Country instead?

Calculate Emergence based on:
○ Percentage ○ Absolute Record Count ◉ Create Scores

Term must have at least:
7 Total Records
3 Years with at least 1 record
Ratio of Records in Recent Years to Baseline Years Records 2 :1
Remove items occurring in more than 15 % of Baseline years records
Number of Baseline Years to use in dataset 3
☐ Ignore latest year of data set? (in case of partial year)