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An Exploratory Perspective to Measure the Emergence Degree for a Specific Technology Based on the Philosophy of Swarm Intelligence

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Abstract-How to evaluate or measure the emergence degree or level for a specific technology is rarely discussed in the prior studies, and it should be a valuable issue for the relevant areas on technology forecasting, foresight, and technological strategies for macro and micro economies, particularly for those emerging economies who are chasing the technology advances in the developed countries. A conceptual framework inspired by swarm intelligence theory is introduced to measure the emergence degree or level for a specific technology. Swarm intelligence belongs to complex systems theory, and has evolved into a helpful tool for heuristic algorithms and optimization computation, and brought forward an insightful perspective on the evolution and emergence of natural or social systems in the past decades. To verify the proposed framework for measuring emergence degree of a specific technology based on the basic philosophy of swarm intelligence, a case study analyzes an annual set of emerging technologies of the World Economic Forum. The theoretical and empirical analyses could present a fresh vision to investigate the essence of technology emergence, and provide some supplemental thoughts for the policy-making on those emerging or new technologies.

Keywords: technology emergence; swarm intelligence; emerging technology; technology evolution; emergence degree; TOPSIS

1 Introduction

During past decades, a variety of emerging technologies have had a profound impact on the eco-social system through technical evolution, or revolution. The studies on technological paradigm and technology evolution offer important facets to strategic management, innovation, and Science and Technology (**S&T**) policies (Dosi, 1982; Teece, 1986; Devezas, 2005; Chen et al., 2012; Aharonson and Schilling, 2016). Forecasting and foresight on emerging technologies have become increasingly critical prerequisites for subsequent policy-making, especially for national strategic S&T policies (Martin, 2010; Li, 2017). Identification of emerging technologies is also valuable to mission-oriented policy design (Mazzucato, 2016).

However, very few studies ever mentioned whether technology emergence can be divided into different degree or levels. In another words, while a specific technology observing by a director of R&D department, how to know this technology has emerged, or not emerged yet, or is emerging now, and so forth. Besides, while this R&D director is observing several technologies, how to compare the emergence degree or level among the different technologies. Obviously, measuring emergence degree or level of the different technologies is meaningful for the decision context of R&D investment, and could also be valuable for the policy-making of STI (Science, Technology and Innovation).

Basically, modeling the complex socioeconomic system of technological development relies heavily (not exclusively) on the notion of S-shaped growth. Some empirical work has shown the S-shaped growth model to be particularly fitting (Devezas, 2005; Li, 2015). While discussion continues on the shape and linearity of development (Suominen and Seppänen, 2014), the existence of clear phases seems supported.

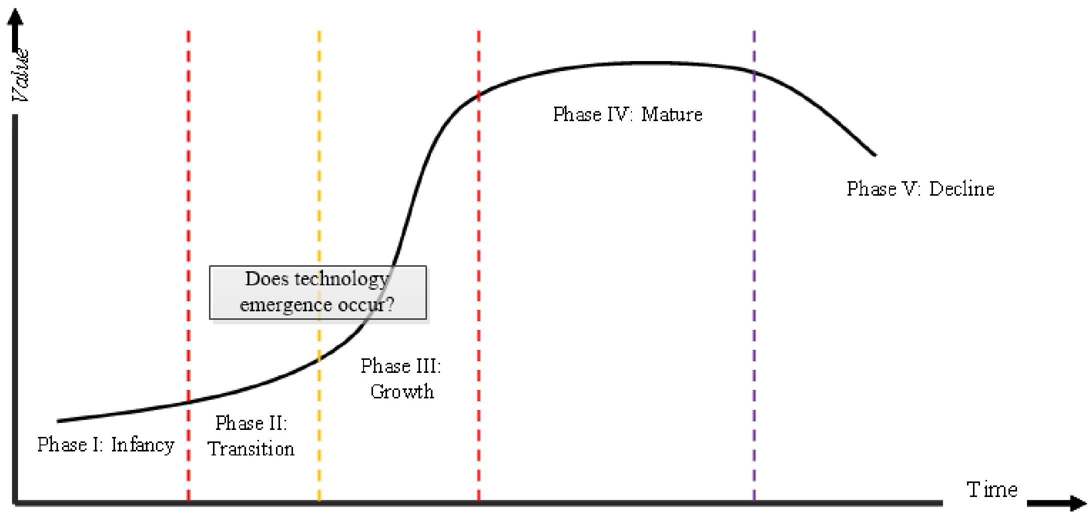

Figure 1. S-curve of technology evolution.

Regarding the Figure1, Li (2015) implied that policies promoting technology development should be characterized by the phase of a technology in its evolution. In this evolution, bibliometric indicators, such as patents, are seen as being important indicators of evolutionary stage progression. Existing indicators are not without issues and often fall to flaws in assumptions (Suominen and Seppänen, 2014). For example with patents, there is a debate on the unilateral effect of patent indicators; a better solution could rely on the hybrid or multi-dimensional indicators (Porter, 1999; Daim et al., 2006; Érdi et al., 2013; Li, 2015).

However, contemporary studies on identifying the evolution phase of technology still rely on domain experts' opinions using methods such as Delphi. Large-scale interviewing of domain experts is challenged by its resource intensity. Meanwhile, integrating different opinions and resolving differences among experts could also present theoretical or computational difficulties in the context of group or multi-variant decisions. Accurately identifying and measuring technological emergence of a specific technology, whether with qualitative or quantitative methods, or a combination, remains a challenge.

Central to the challenge of measuring the technological emergence is to identify or measure whether emergence has occurred or has been occurring for a specific technology. We can model trajectories of well-known phenomena, but when it comes to novelties we are hard-pressed to "explain the arrival" of a new technology. The connotation regarding technology emergence or emerging technology is still fragmented and lacking of uniform definitions (Rotolo et al., 2015; Li et al., 2018).

To describe and measure the technology emergence, many ideas and indicators involving technology evolution ,emerging technologies, "tech mining" and so forth have been proposed and introduced (Porter, 1999; Li 2015; Carley et al., 2018; Porter et al, 2019). However, such relevant issues on the dynamic mechanism, observing dimensions and measuring the emergence degree or levels for a specific technology etc., still have the room for exploration and discussions. Because in the prior literature on technology emergence, the analytical results are only two choices: yes(1) or no (0). For example, through the patent analysis or text mining about a certain topic of technology, it can be concluded that the emergence on the specific technology occurred, or not. While observing the different technologies, how to compare the emergence degree or levels between technologies has to face the challenge. Therefore, measuring the emergence degree or levels for a specific technology could be a promising concept, and also could provide the supplemental knowledge for the traditional theories on technological forecasting, foresight and STI policy-marking etc.

According to the theories of complex systems and actor-network of sociology (Callon, 1986; Harvey et al, 2015; Tao, 2018), if any participant of TE (technology emergence) is considered as the peer-to-peer actor or individual, the emergence of a specific technology could be taken into a phenomenon of self-organization activities at the large scale, just like the emergence of swarm intelligence. Inspired by the philosophy of swarm intelligence emergence, a conceptual framework of measuring technology emergence is proposed and the relevant metrics and indicators are also explored in this context.

2 Related Works Review

Regarding the emergence of a specific technology, behind the emergence could be the large-scale activities related to the specific technology, which include technology R&D, technology transfer, technological entrepreneurship and the involvement of human resources and organizations enabling rapid growth in a macro (time and space) perspective. Aiming at the TE, the theories of complex system, e.g. self-organization, system dynamics and swarm intelligence and so forth, could provide an exploratory angle or perspective, and the sociology also could be another reference vision, for instance, behavioral side of individuals and actor-network theory and so on (Callon, 1986; Sayes, 2014). Regarding the swarm intelligence theory, it is not only to describe the collective behavior on the flocks of birds, fish or cattle, but has evolved into the helpful means of simulation on system dynamics, social-eco system evolution, and optimization computation and on in the past decades (Soni et al., 2019; Mohammed et al., 2020).

Comparing the perspective of sociology, e.g. actor-theory or social networking, the emergence of swarm intelligence based on complexity theory, could provide some new ideas on the measuring or evaluating the emergence of technology (Reynolds, 1987; Holland, 1998; Chen et al, 2016;Tao, 2018). In the basic framework of SIE(swarm-intelligence emergence), there are such important features or dimensions as *large-scale activities*, *relatively rapid growth of involved participants* (herds, schools, flocks, or even people) and *highly efficient transmission of signal* (Reynolds, 1987 ; Vices et al., 1995). Based on the theory of emergent evolution, Tao (2018) argued that the similar phenomenon of swarm intelligence also can happen in human society or human behavior in the macro vision. Actually, the classic theory of herd behavior or the effect of sheep-flock had ever also been mentioned in several articles on business and management (Lieberman & Asaba, 2006; Chen, 2008).

In addition, emergence also could be one of basic concepts in modern complexity science, which includes theories such as synergetics, catastrophe theory, complex system, self-organization, and swarm intelligence and so forth (Linstone, 1999; Fraser & Greenhalgh, 2001; Samet, 2012). Within complexity theory, Holland (1998) ever argued that the essence of ***Emergence*** is from small to big, from simple to complex. Therefore, an interesting question is inspired by swarm intelligence, i.e. these three features of swarm-intelligence emergence can be applied or introduced to evaluate or measure the TE? And then, the relevant question is, inspired by complexity theory, is if TE can be observed from the perspective of swarm-intelligence.

To further explore the measurement or evaluation on emergence degree for a specific technology, a quantitative method grounded in the philosophy of swarm intelligence emergence is proposed and discussed. Swarm Intelligence (SI), or swarm computation, collective intelligence, is a theory is derived from observations on the dynamic behavior of fish schools, bird flocks and animal herds, that can avoid the attack of predators and improve their survival rates through large-scale aggregation, distributed control and synchronous moving as a whole (Reynolds, 1987; Vices et al., 1995), and some social behavior of human also can be depicted by swarm intelligence (Chen, 2008; Tao, 2018; Soni et al., 2019).

In traditional studies of technology evolution, TE and emerging technologies, most perspectives or methodologies focus on relevant theories of evolutionary economics, innovation, and dynamic capability; notably relying on complex systems and complexity theories is rare from the current debate. The prior studies relating to "technology emergence" were retrieved from multiple databases using the queries seen in Table 1.

Table 1. Boolean search on technology emergence literature from three data sources.

	Boolean Query	Data source	Search result	Timespan &Indexes
#1	TS="technolog* Emergence"	Web of Science (WOS) Core	48(**44***)	Timespan: 1986-2018. Indexes: SCI-EXPANDED,

		Collection		SSCI, CPCI-S, CPCI-SSH, CCR-EXPANDED, IC.
#2	TS=(“emerg* technolog*” OR “tech* emergence” OR “emergence of* technolog*” OR “emerg* scien* technol*”) **	Web of Science (WOS) Core Collection	15,433	Timespan: 1986-2018. Indexes: SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH, CCR-EXPANDED, IC.
#3	TS=(“tech* emergence” OR “emergence of* technolog*” OR “emerg* scien* technol*”)		192	
#4	TS=(“emerg* technolog*”)		15,269	

***Excluding some noisy data, only 38 relevant articles remain from the first query; further checking of those cited papers in second level retrievals results in another 6 articles being included. Therefore, the matched count reaches 44 under a simple Boolean query regardless of a more complicated formula -- e.g., considering the synonyms and co-word analysis.**

**** In #2 query, the search terms are from the article of Rotolo et al. (2015). Actually, the #3 query and #4 query are also derived from # 2 query; while we excluded the term “emerg* technolog*”, 192 publications remain, in which only 61 publications present the significant relevance to TE after we carefully read the abstract of each publication.**

Regarding the TE and ET (emerging technology), Rotolo et al. (2015) thought that these two terms have similar connotation, and are often used in the same discourse or context. However, TE could be considered a phenomenon for a specific technology, and ET is often used to describe or define a specific new technology. Based on the formula of Query #2, two refined queries are shown in Table 2.

Table 2. Two refined queries based on Query #2 in Table 1.

	Boolean Query	**Data source**	**Search result**	**Refined by**
#5	TS=(“emerg* technolog*” OR “tech* emergence” OR “emergence of*	Web of Science (WOS) Core Collection Timespan: 1986-2018. Indexes: SCI-	9,059	DOCUMENT TYPES: (ARTICLE OR REVIEW)
#6			1,815	DOCUMENT TYPES: (ARTICLE OR REVIEW) AND

	technolog*" OR "emerg* scien* technol*")	EXPANDED, SSCI, CPCI-S, CPCI-SSH, CCR-EXPANDED, IC.		WEB OF SCIENCE INDEX: (WOS.AHCI OR WOS.SSCI)

In this paper, the differences between TE and ET are not the key issues; in turn, how to evaluate the emergence degree for a specific technology still has the room for exploration and debating; therefore, the quantitative framework for measuring the emergence degree of a specific technology is proposed and discussed, and the efforts could provide a supplementary perspective to enhance the theoretical roots of TE and ET.

Once the search scope about TE or ET is refined to social science and arts & humanities, there are about 1800 articles or reviews. The descriptive analyses on the results of #6 query are shown in Tables 3.

Table 3. Top 10 journals of the relevant articles on TI and ET based on # 6 query

Source Titles	Record Count
Technological Forecasting and Social Change	128
Scientometrics	45
Public Understanding of Science	32
Nanoethics	30
Technology Analysis and Strategic Management	25
International Journal of Technology Management	23
British Journal of Educational Technology	22
Energy Policy	21
Research Policy	21
Sustainability	19
Total	**366**

From the results in Table 3, the relevant articles on TE or ET were primarily published in such journals: *Technological Forecasting and Social Change*, *Scientometrics and Public Understanding of Science*, etc. Regarding these 366 papers published in journals presented in Table 3, the co-occurrence of author keywords is shown in the Figure 3, which is visualized by the tool of VOSviewer.

Figure 2. Co-occurrence of author keywords extracted from the papers in Table 3 [1].

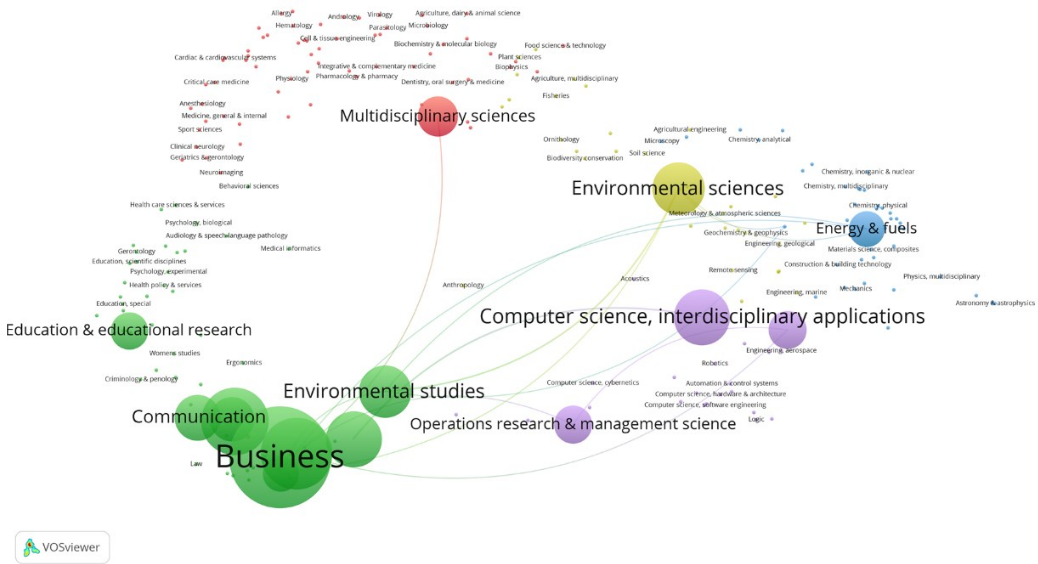

Figure 3. The distribution over WoS Categories of these papers in Table 3 [2].

Based on the analytical results shown in Figure 2 and Figure3, the main categories of TE studies include *business*, *communication*, *environmental sciences*, *interdisciplinary applications of computer science* etc., and the high frequent terms involve *technology forecasting*, *innovation system*, *foresight*, *patent analysis*, *text mining* and *bibliometrics* and so on. Therefore, TE seems to be an operational construct. It appears to be taken as synonymous

[1] The tool of VantagePoint [*http://www.theVantagePoint.com*] is utilized in cleaning & analyzing the data.

[2] The tool of VOSviewer [*https://www.vosviewer.com/*] is utilized in the Figure 4 based on the cleaning data generated by VantagePoint [*http://www.theVantagePoint.com*].

or derived from concepts such as emerging technology (Mogoutov and Kahane, 2007; Bozeman et al., 2007; Rotolo et al., 2015), technological entrepreneurship (Woolley, 2010), and tech mining (Hopkins and Siepel, 2013; Newman et al., 2014). The lack of theory can stem from the use of the construct in a retrospective way to observe or analyze emerged technologies, e.g., nanotechnology and biotechnology.

In addition to the lack of an acknowledged definition of TE, quantifying TE also is not easy and riddled operational challenges (Burmaoglu et al., 2019; Porter et al., 2019). Ávila-Robinson and Miyazaki (2013) suggested an approach to discern technology emergence through a proxy effect of dynamics of scientific knowledge bases. Some studies prefer to treat emergence of a certain technology in terms of occurrence phenomenon and later depict the linkages between TE and specific characteristics. For example, Woolley (2010) explored the relationship between TE and entrepreneurship activities across multiple industries and discussed that entrepreneurship first occurs in upstream industries, then enables the founding of firms in downstream industries and related sectors. Goeldner et al. (2015) discussed the emergence of care robotics based on patent and publication analysis. Raimbault et al. (2016) and Shapira et al. (2017) discussed the emergence of synthetic biology through the perspective of science mapping and bibliometrics.

Recently, complex system and co-evolution theories are introduced to propel the theory building and conceptualization on TE. Burmaoglu et al. (2019) argued that the emergence concept should be qualitatively reviewed using the different dimensions drawn from philosophy of science, complexity, and economics. Ávila-Robinson et al. (2019) proposed an approach to investigate factors influencing the way emerging stem cell therapies emerged, based on an co-evolutionary and system-oriented perspectives.

In this study, we consider the basic idea of TE and propose that TE should be a relatively independent conception or dynamic phenomenon in a certain period. In fact, both potential emerging and disruptive technologies can approach concrete emergence (Danneels, 2004; Christensen et al., 2015; Li et al., 2017); even old or traditional technologies could reach emergence in specific periods for some reasons. Therefore, technology emergence can be treated as an interesting phenomenon for a specific technology.

In terms of TE, its essence could be a variety of activities related to a specific technology, involving R&D, marketing, and commercialization and so forth. Meanwhile, the hidden and profound driving-force of TE could be the natural motivation to improve the competency, dynamic capability, or survival possibility under changing circumstances. Therefore, TE is also a spontaneous, self-organized and decentralized flocking or clustering of many different entities, which could be SMEs (small-medium enterprises), MNEs (multi-nation enterprises), microbusiness organizations, or research institutions. In addition, compared to other contemporary technologies, the technology related to TE should experience more rapid growth in certain acknowledged dimensions or perspectives.

TE could be seen as a burst of macro-behavior or phenomena during a relatively short period -- the drivers or reasons for which rely on large-scale synchronous and self-organizing activities at the micro or individual level, which is inspired by the philosophy of swarm intelligence (Reynolds, 1987).

Reynolds (1987) proposed the classic "Boids" swarm intelligence (SI) model designed to simulate the emergence of swarm intelligence. The Boids model only includes three simple heuristic-rules: (a) *separation*; (b) *cohesion*; and (c) *alignment*. With these, the Boids model can simulate the complicated behavior of flocks, herds, and schools. Vicser et al. (1995) attempted to provide a theoretical exploration of macro emergence of swarm intelligence based on statistical mechanics. Emergence can be seen as a classic concept or analytical tool in the framework of complex systems theory (Holland, 1998; Sharkey, 2006; Berrondo and Sandoval, 2016; De et al., 2017). Actually, emergence theory is not only conducted to explain the social and natural phenomena on self-organization, system evolution, self-optimization etc., even our universe could be a specific emergence (Holland, 1998) Integrating TE with SI, we can define TE as the macro phenomenon through the simple behaviors of large-scale sets of individuals who are involved in the evolution or development of the specific technology.

In the prior studies related to TE, technology evolution, or emerging technology management, they are preferable to consider TE as the occurred reality, especially in empirical or case analyses, and the emergence degree of technology were seldom mentioned. Whether the emergence of the technologies discussed (e.g., care robotics (Goeldner et al., 2015), synthetic biology (Raimbault et al, 2016; Shapira et al., 2017) really occurred could be raised, along with how we can evaluate the emergence degree for a specific technology. In other words, it is also very difficult for us to refuse or deny those hypothesized TEs. Little is known of how to identify whether a specific technology has emerged, or exactly when the emergence occurred (Carley et al., 2018). Several subsequent questions arise: when, why, and how the technology "emerges" in an observed period? Assessing or identifying whether or when the emergence for a specific technology has occurred is definitely valuable for strategic management and policy-making decisions. Therefore, several relevant questions are raised:

1) What metrics besides patents can be utilized to measure emergence for a specific (new/emerging/disruptive) technology? Enriched indicators for TE are still the critical issue for the relevant studies on TE, ET or technology forecasting by far (Porter et al., 2019; Ranaei et al., 2020).
2) How do we compare the emergence degree or levels among different contemporary technologies? Through the perspective of policy-making or strategic planning, can the emergence degree or levels between technologies be compared under the uniform standard or framework?
3) How to explain the differences in emergence degree among technologies during a specific period or in some specific regions (e.g., nations, states, provinces, cities, or territories)? For example, while the emergence of a certain technology has really occurred, i.e. the emergence degree is very close to 1.0, the focus of the policy-making is to facilitate the commercialization; inversely, if the emergence degree is closer to zero, the R&D incentive could be a better option. However, if the emergence degree is close to 0.5, the relevant incentive policy maybe needs the compromising. Therefore, if we could get a more precise emergence degree or level about the specific technologies, the corresponding policy-making would be more targeted.

In general, in evaluating the degree of TE, patents and publications are popular data sources (Porter and Detampel, 1995; Chang et al., 2009; Woolley, 2010; Small et al., 2014; Raimbault et al., 2016). In addition to the growth of patents and publications involving the specific technology, more indicators such as technological entrepreneurships and public awareness have also been proposed.

3 To Measure Technology Emergence

To further explore the definition, boundaries, connotations, and measurement of TE, we follow the research design described in Figure 3.

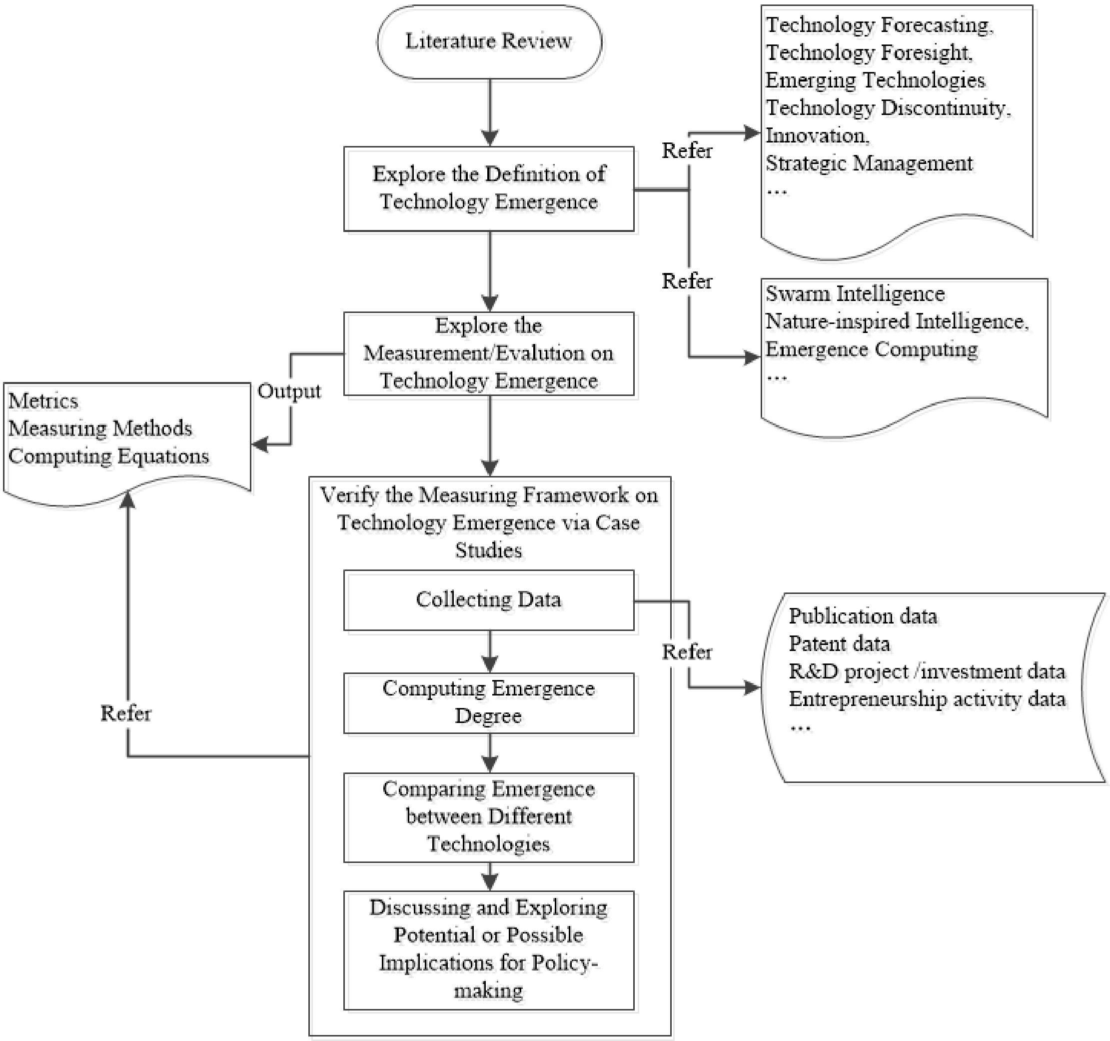

Figure 3. Research flow and methods in this article

In Figure 3, we intend to explore issues related to the evaluation of TE within a quantitative and integrated methodology. The gap between policy-making and a theoretical framework for evaluating TE appears significant. In essence, accurately evaluating TE involves multidisciplinary knowledge and crossing multi-research areas -- e.g., technology forecasting, emerging technology management, dynamic capabilities and strategic management, and discontinuity of technology evolution.

To mitigate the gap between policy-making and a TE framework, the exploration in this paper includes such aspects as: (*a*) to further explore the conceptualization and operationalization of technology emergence, (*b*) to propose an integrated quantitative framework to evaluate the degree of emergence for a specific technology, and (*c*) to verify the proposed evaluation framework through empirical case studies.

In the theoretical TE framework drawing on the philosophy of swarm intelligence, emergence is a dynamic macro-phenomenon relying on self-organization and nonlinear collective activities; in addition to deterring and confusing the predators through a huge shape, the efficiency of signal transmission can also be significantly improved, and then enhance the survival rate of individuals in the whole (Reynolds, 1987; Parpinelli and Lopes, 2011; Nguyen et al., 2012).

In human society, under the pressure of market competition, technology-life cycling, or the encouragement from macro-strategies or policies, more small-sized stakeholders (including small or micro-enterprises and independent makers or researchers) could be attracted to engage in relevant activities on the specific technology development. After all, joining a potential technology emergence could result in finding more opportunities and facilitating the survival and development of those small start-ups. In turn, a variety of R&D, entrepreneurship and commercialization activities surrounding the specific technology could really facilitate emergence, having a concrete impact on the established market(s) and further creating new market branches and innovation opportunities.

Although the conceptualization of TE could be linked to theories of technology evolution and technology lifecycle, it appears more similar to a victory or a burst phenomenon of a certain technology in competition with many contemporary technologies. Therefore, technology evolution and technology lifecycle sound more similar to generalized theories for any technology development. In terms of TE, considering the potential impact and implications of TE on strategic management and policy-making, it should be treated as an instrumental concept and explored via evaluating methods and tools.

Based on the above, technology emergence could be considered as a phenomenon involving relatively large-scale swarming or clustering of individuals' activities or behaviors involving a certain technology under the mechanisms of self-organization, synchronization, and collaboration. Furthermore, these activities or behaviors could cover such factors as R&D, technology spillover, triple-helix (collective University-Industry-Government engagement), and commercialization. **Meanwhile, technology emergence has**

brought forward a substantial and explicit impact on the established market and has even produced new market branches or segments. Therefore, the concept of TE could involve such three dimensions of swarm behavior:(*a*) one dimension is behavior of researchers who are affected by trend topics and publication trends; (*b*) the second one is behavior of market players who are directing their R&D efforts for gaining competitive advantage; (*c*) and the third dimension is behavior of society that technology diffusion rate is related to higher rate of technology acceptance.

Based on the above concept of TE, as well as integrating the emergence ideas of swarm intelligence (Reynolds, 1987; Parpinelli & Lopes, 2011), TE could also have such characteristics as:

1) Comparatively large **-scale of participants** (e.g., small-medium sized enterprises, individual makers, and research institutes); i.e. in the observed period /territory/sector/domain, the scale of participants on a specific technology could be larger than the most of contemporary technologies. For example, from 2016 to 2019, the participant scale of 3D printing presents very popular than many manufacturing technologies (Maresch & Gartner, 2020; McCausland, 2020);
2) Comparatively rapid **growth of R&D** activities, also extending to active technology commercialization and intermediary services;
3) Comparatively efficient signal/information transmission about the specific technology emergence, which could be divided into two dimensions: (a) technology spillover, **diffusion across multi-categories** or multi-fields have become reality by the large-scale following, learning behaviors among the participants or stakeholders; (b) **public awareness** on the observed technology have begun to increase.

TE could be observed and evaluated through four dimensions/perspectives: R&D scale in major fields, growth of R&D activities, diffusion across categories and public awareness. A new evaluating framework on TE building upon the basic philosophy of swarm intelligence theory is shown in Figure 4.

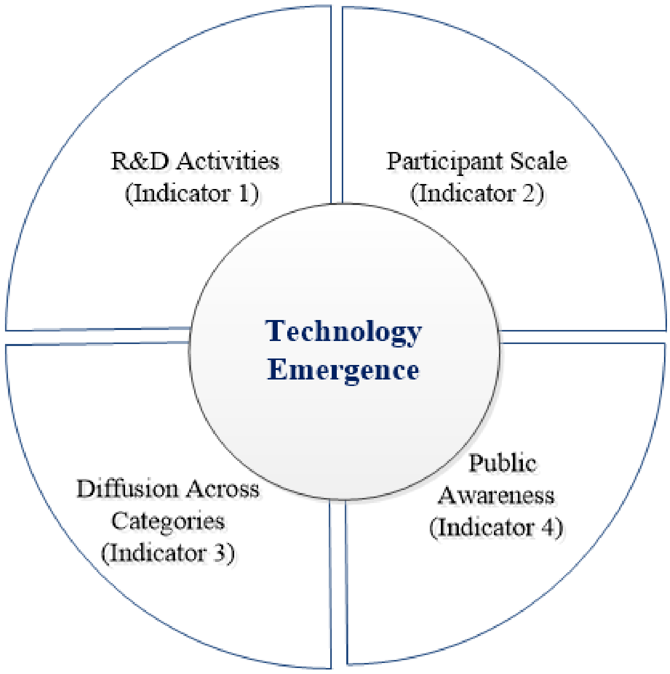

Figure 4. Evaluating TE through the perspective of swarm intelligence theory

Figure 4 could offer an integrative, four-dimensional perspective to measure technology emergence, drawing on SI attributes that are introduced in the above; however, these proposed dimensions or indicators could be controversial and compromised. Whatever measuring TE or evaluating the emerging technologies, more and insightful dimensions or indicators are still the research fronts (Porter et al, 2019) . We then consider each dimension in trying to develop computational tools to help track and measure TE. The nomenclature for this SI-oriented TE framework is shown in Table 4.

Table 4. Nomenclature for Equations to Measure Technological Emergence

Nomenclature	Description
m	The amount of particular measurements -- e.g., R&D projects, publications, or patents
n	The involved items on those selected measurements -- e.g. categories, International Patent Classifications (IPCs), source titles, etc.
w_i	The weight of a measurement i ($i \in [1, m]$)
w_j	The weight of item j ($j \in [1, n]$)

S_{ij}	The proportion of publications or patents related to the specific technology in the main categories, publication sources, or IPCs, e.g. a specific technology belongs to many categories, and the relevant patents could involve several IPCs, the proportions could be useful indicator. While more and more investment on this technology, the proportions of those relevant publications and patents on the specific technology could increase over time.
G_{ij}	The annual growth that could involve, for instance, R&D investments, projects, academic publications, and/or patents. While a certain technology becoming popular or emerging, the annual growth of the relevant R&D activities could grow over year.
D_i	The distributions of R&D projects, publications, or patents in different categories/IPCs and so forth. It is natural that the R&D activities could diffuse into many different areas over time. For example, with the emergence of nanotechnologies, more and more areas are involved. So, this indicator is expected to partly depict the knowledge/technology diffusion.
PP_i	The public awareness about topic/technology i , which could be compared with the referenced topic/ technology, and then the similarity or distance formulas (e.g., Cosine similarity, Pearson correlation coefficient, or Euclidean distance) can be derived.

（1）R&D Scale in Major Fields

The differences between two categories could be considered to measure or evaluate the participant scale. For example, significant differences between categories can be seen in Figure 5 when retrieving published articles indexed in different categories of the WOS (Web of Science).

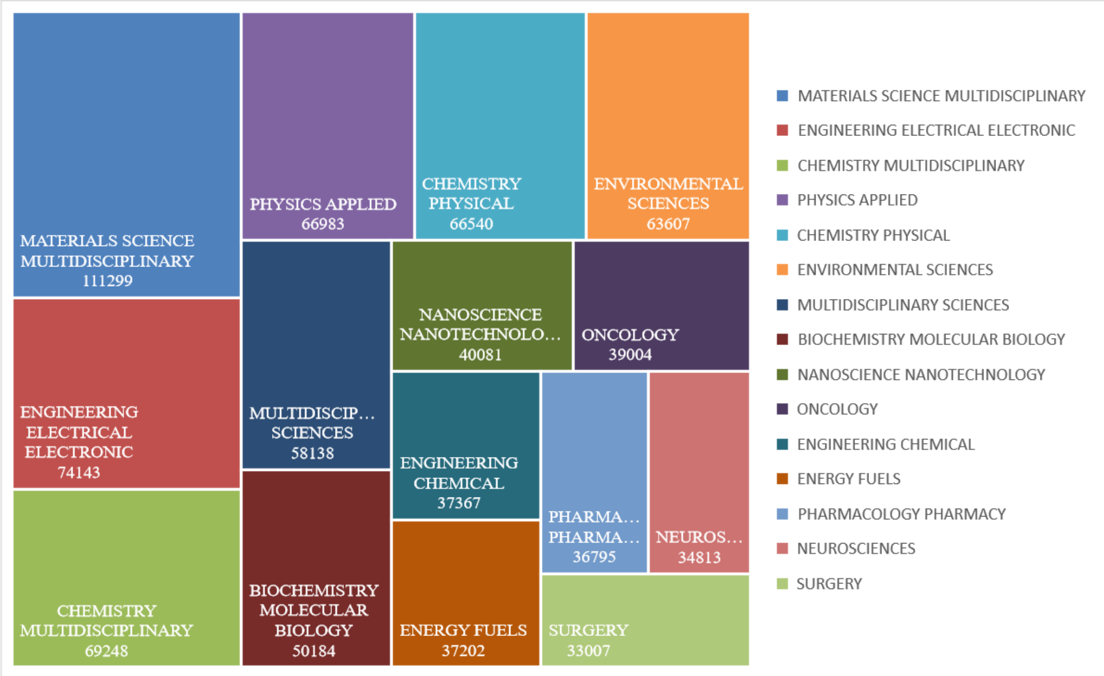

Figure 5. The top 15 categories of articles indexed by WOS in 2018.

In 2018 (as of examination), published articles indexed by the WOS core collection reached 1,604,798. Articles classified into *MATERIALS SCIENCE MULTIDISCIPLINARY* tallied 111,299. However, articles belonging to *ENGINEERING MULTIDISCIPLINARY* were just 13,695, and articles relating to *ENGINEERING OCEAN* only reached 2,001. In general, patent distribution in different categories or IPCs evidences an even wider range – some IPCs are huge and others are tiny. Therefore, computing the proportions of main categories, main publication sources, or IPCs is supposed to be significant for measuring, evaluating and comparing the emergence degree, which is related to a specific technology or scientific topic. Based on this consideration, computing the indicator of participant scale is shown in Equation (1).

$$Indicator_{scale} = \frac{\sum_{i=1}^{m} w_i \left(\sum_{j=1}^{n} w_j \sqrt{\prod_{j=1}^{n} S_{ij}^{\,w_j}} \right)}{\sum w_i} \tag{1}$$

In equation (1), S_{ij} is the proportion of publications or patents related to the specific technology in the main *categories*, *publication sources*, or *IPCs*; w is the weight; m represents the amount of the involved indicators -- e.g., R&D projects, publications, and patents; and n represents the included categories, IPCs, or source titles (for example, the proportions of the relevant publications in the top 5 (n=5) source titles).

（2）**R&D Growth**

Regarding the evaluation of R&D activities, average speed of growth in a specific period could be a better choice than simply computing the ratio of the given-period amount and base-period amount; the proposed computation method is shown in Equation (2).

$$Indicator_{growth} = \frac{\sum_{i=1}^{m} w_i \left(n\sqrt{\prod_{j=1}^{n}(1+G_{ij})} - 1 \right)}{\sum w_i} \tag{2}$$

In Equation (2), G_{ij} represents the annual growth that could involve, for instance, R&D investments, projects, academic publications, and patents. w_i is the weight; n is the number of years; m represents the amount of those involved measurements -- e.g., patents, R&D projects, and publications.

（3）**Diffusion Across Categories**

To evaluate the diffusion across categories, the distributions of R&D investments, projects, academic publications, and patents in different categories can be tallied.

$$Indicator_{diffusion} = \frac{\sum_{i=1}^{m} w_i D_i}{\sum w_i} \tag{3}$$

In fact, the method depicted by Equation (3) could be an overly simplified solution that could be biased or controversial. For instance, the number of the relevant publications on nanotechnology is greater than 1.5 million in WOS, and those publications involve most all categories of WOS. Therefore, the proportion of involved categories is proposed to be an indicator of technology emergence. Theoretically, if we can find all relevant data, including R&D investments, projects, academic publications, and patents, Equation (3) could present more convincing information. However, R&D publications and patents could be more standard and broadly available data sources. For example, the classification methods of R&D projects differ significantly among countries or territories, even among different government departments in one country.

（4）**Public Awareness**

In certain relevant studies on social communication, public awareness, perceptions and concerns about emerging technologies are relatively important issues due to their potential impacts on social-economic systems (Renn and Benighaus, 2013; Read et al., 2016). In traditional methodology on public perceptions or awareness of technology development or emergence, randomized sampling or online surveys based on the Internet are prevalent methods. In addition to public surveys, theoretically, the retrieval frequency of the specific or observed technology from a search engine (e.g., Google or Baidu), as well as the number of hot reports or headlines, on the specific or observed technology are also valuable data sources to observe the degree of emergence of a specific technology. Of course, collecting data from search engines and news media, as well as guaranteeing the integrity of the collected data, are not easy for general academic research. For example, although Google Trends (http://www.google.com/trends) can provide the trend of search frequency for a specific word or term, how to integrate those trend curves of multiple words or terms surrounding a specific technology or topic into a synthetic trend curve seems out of the realm of current technical support from Google Trends. Meanwhile, to obtain an accurate trend of news headlines on a specific technology from all news media could face the same challenge as Google Trends, as well as other technical problems (e.g., how to integrate the data from online and traditional media, or how to identify, weigh, and calculate the news headlines for different media platforms).

Based on the considerations above, a flexible computation method is proposed and presented in Equation (4).

$$Indicator_{public-concern} = \frac{\sum_{i=1}^{m} w_i \, PP_i}{\sum w_i} \tag{4}$$

Equation (4) presents an idea which supposes that data of public surveys, topic search frequencies or news headlines related to the observed technology can be collected under specific circumstances. For example, if the topic search trends can obtain the special technical support from Google and the data collection of news headlines can obtain third-party credible investigation, the public perceptions or awareness about the specific technology could be better choice.

Conversely, if public survey data are the only data source for Equation (4), a well-known technology (e.g., nanotechnology) could be used as the baseline or reference - i.e., public perceptions or awareness about those observed technologies can be compared with the referenced technology, and similarity or distance formulas (e.g., Cosine similarity, Pearson correlation coefficient, and Euclidean distance) could be utilized.

Currently, large volumes of data are generated daily by social media, such as Facebook, Twitter, and WeChat; our ability to extract the relevant data regarding the specific technology from these social media platforms can also constitute a valuable supplement.

Briefly, the conceptual framework on identifying and evaluating technology emergence illustrated above provides some rethinking and explorations at the operational level. In Figure 4, four dimensions (or four indicators) are proposed based on the basic philosophy of swarm intelligence and complex science, and they are expected to further measure or compare emergence degree between different technologies, and the related computation methods for these four observation dimensions are also discussed To further verify the proposed framework, a case study is next presented.

Besides, regarding the weights (ω_i) in the Equation (1)-Equation (4), in the context of practical operation, the Delphi method can be considered, or the questionnaire interview of domain experts can be conducted to assign the weights for the different indicators or metrics. In the following case study, the weights is assigned by the empirical or subjective rules, which can be improved in the future work.

4 Case Study

4.1 Data Collection

During the past decades, forecasting emerging, disruptive, or breakthrough technologies has become a critical issue, and several relevant intellectual institutes attract broad attention -- for example, *Word Economic Forum (WEF) in Davos*, *MIT Technology Review* and *Scientific American*. Since 2003, the term -- “emerging technologies” has been substituted by “breakthrough technologies” in a relevant annual report of *MIT’s Technology Review*; and since 2010, *Scientific American* has reported a top 10 emerging technologies provided by the specific workgroup of WEF, which engages thousands of experts in different research areas. To test the four indicators of emergence proposed above, we utilize the 2013 top ten emerging technologies in WEF's annual report. Relatively speaking, the annual top 10 emerging technologies announced by the WEF attract large-scale attention, engaging academic and non-academic circles.

This annual forecasting of emerging technologies provided by the WEF is supposed to impact policy-making at the national level. The 2013 top emerging technologies anticipated by the WEF are shown in Table 5.

Table 5. 2013 top 10 emerging technologies anticipated by WEF[3]

	Anticipated Emerging Technologies (Abbr.)
#1	Online Electric Vehicles (OLEV)
#2	3-D printing and remote manufacturing (3DP)
#3	Self-healing materials (SHM)
#4	Energy-efficient water purification (EEWP)
#5	Carbon dioxide (CO2) conversion and use (CDCU)
#6	Enhanced nutrition to drive health at the molecular level (ENDM)
#7	Remote sensing (RS)
#8	Precise drug delivery through nanoscale engineering (PDDNE)
#9	Organic electronics and photovoltaics (OEP)
#10	Fourth-generation reactors and nuclear-waste recycling (FGR&NWR)

Actually, the mentioned ETs by WEF could be attributed to the macro technologies or technology clusters that differ from the mono-technology, to measure emergence of the technologies presented in Table 5, we draw on R&D publication data from the WOS Core Collection, and the data source for patents is Derwent Innovation Index (DII). Regarding the data on public awareness, a questionnaire is designed and the survey is outsourced to a third-party investigation company. In the questionnaire, nanotechnology and graphene are also included as comparative baseline and verification factors in addition to the 10 technologies presented in Table 5.

[3] https://www.weforum.org/agenda/2013/02/top-10-emerging-technologies-for-2013/

4.2 Analytical results

To compute the four indicators on evaluating and measuring technology emergence, the publications and patents of the anticipated technologies are retrieved from WOS and DII through Boolean queries, and the search strings are shown in Table 6.

Table 6. Search strings for the forecasted emerging technologies in Table 5

	Boolean queries of publications in WOS Core Collection*	Boolean queries of patents in Derwent Innovations Index**
OLEV	TS=("Electric Vehicle" OR "electric car" OR "electric bus") AND TS=("pick-up coil" OR "Wireless charg*" OR "wireless power" or "electromagnetic field broadcast*")	TS=("Electric Vehicle" OR "electric car" OR "electric bus") AND TS=("pick-up coil" OR "Wireless charg*" OR "wireless power" or "electromagnetic field broadcast*")
3DP	TS=((3D OR 3-D OR "3 dimension*" OR "three dimension*" OR additive) NEAR/2 (print* OR fabricat* OR manufactur* OR product*))	TS=("3D print*" OR "3-D print*" OR "3 dimension* print*" OR "three dimension* print*" OR "additive manufactur*" OR "additive fabricat*" OR "additive production*")
SHM	TS=("Self-healing material*" OR "self healing material*" OR "self repair* material*" OR "self-repair* material*")	TS=("Self-healing material*" OR "self healing material*" OR "self repair* material*" OR "self-repair* material*")
EEWP	TS= ((“sea water” OR “seawater” OR “waste water” OR “wastewater”) near/10 (desalinat* OR purification OR purify*)) AND TS =(energy or fuel) AND TS=efficien*	TS= (sea water OR seawater OR waste water OR wastewater) AND TS= (desalinat* OR purification OR purify*) AND TS =(energy or fuel) AND TS=efficien*.
CDCU	TS= (“carbon dioxide” near/5 (conver* OR captur* OR sequestration))	TS= "carbon dioxide" AND TS= (conver* OR captur* OR sequestration)
ENDM	TS= (“malnutrition” OR “nutrient deficienc*”) AND TS=(“Enhanced nutrition” OR “molecular nutrition” OR “essential amino acid*” OR “molecular level” OR "genomic*") and TS=(people or human)	TS= (malnutrition OR "nutrient deficienc*") AND TS=("Enhanced nutrition" OR "molecular nutrition" OR "essential amino acid*" OR "molecular level" OR "genomic*") and TS=(people or human)

RRS	TS=("remote sensing*" OR "low power sensing" OR "low power-sensing" OR "vehicle-to-vehicle sensing" OR "vehicle to vehicle sensing")	TS=("remote sensing*" OR "low power sensing" OR "low power-sensing" OR "vehicle-to-vehicle sensing" OR "vehicle to vehicle sensing")
PDDNE	TS=”drug deliver*” and TS=nano*	TS="drug deliver*" and TS=nano*
OEP	TS=((“electronic*” OR “photovoltaic*”) near/3 organic*) OR TS=(“organic material*” AND (electronic* OR photovoltaic*))	TS="organic material*" AND TS=(electronic* OR photovoltaic*)
FGR&NWR)	TS=((”fourth generation” OR “fourth-generation ”) near/3 (reactor OR nuclear)) OR TS=(("liquid metal-cooled” OR "liquid metal cooled") near/3 (reactor OR nuclear)) OR TS=((“nuclear-wast*” OR “nuclear wast*”) near/3 recycle*)	TS=(("fourth generation" OR "fourth-generation") AND (reactor OR nuclear)) OR TS=(("liquid metal-cooled" OR "liquid metal cooled") AND (reactor OR nuclear)) OR TS=((nuclear-wast* OR nuclear wast*) AND recycle*)

In Table 6, except for three-dimensional printing, prior studies did not yield a published Boolean formula for the other technologies. Therefore, the Boolean queries and search results are exploratory, and could be controversial.

Table 7. Simple Boolean Queries on the technologies presented in Table 6 (2010-2016) **

Technologies	Publications in WOS	Patents in DII
Online Electric Vehicles (OLEV)	357	774
3-D printing and remote manufacturing (3DP)	19008	12576
Self-healing materials (SHM)	538	152
Energy-efficient water purification (EEWP)	641	1570
Carbon dioxide (CO2) conversion and use (CDCU)	6254	15370
Enhanced nutrition to drive health at the molecular level (ENDM)	84	16
Remote sensing (RS)	69971	5589
Precise drug delivery through nanoscale engineering (PDDNE)	49609	2967
Organic electronics and photovoltaics (OEP)	14413	2454
Fourth-generation reactors and nuclear-waste recycling (FGR&NWR)	249	105

**** Because the 2013 top 10 emerging technologies anticipated by WEF are selected, 2013 activity is taken to be the middle point and then the retrieval period is tracked back to 2010.**

(1) Computing the indicator of scale based on Equation (1)

Regarding the idea of Equation (1), the proportion of the relevant publications and patents on the observed technology in the main categories of source titles and IPC codes can be taken as the elements. In this instance, the main source titles (e.g., journals and conferences) of publications, as well as the main IPC codes of the relevant patents, are selected. For example, the retrieval results for Online Electric Vehicles (OLEV) are shown in Table 8.

Table 8. The proportions of publications and patents related to OLEV in top 5 sources and IPC codes

	Publications	Top 5 Sources*	Count	Proportion **	Patents	Top 5 IPC codes	Count	Proportion**
OLEV	357	IEEE ECCE	17	0.0036	774	H02J-017/00	455	0.0290

	IEEE Trans on PE	14	0.0024	B60L-011/18	389	0.0128
	Annual IEEE APECE	11	0.0030	H02J-007/00	366	0.0041
	IEEE Trans on IE	11	0.0016	H02J-007/02	349	0.0207
	IEEE VPPC	10	0.0132	H02J-050/12	158	0.0884

*IEEE ECCE: IEEE Energy Conversion Congress and Exposition; IEEE Trans on PE: IEEE Transactions on Power Electronics; Annual IEEE APECE: Annual IEEE Applied Power Electronics Conference and Exposition; IEEE Trans on IE: IEEE Transactions on Industrial Electronics; IEEE VPPC: IEEE Vehicle power and propulsion conference.

**The proportions mean that the publications or patents on OLEV can take what percentage in the specific public source (journal or conference) or in a certain classification code of patent. For example, from 2010 to 2016, about 14 articles on OLEV are published in *IEEE Trans on PE*, the proportion is 0.0024(0.24%).

In relevant studies on TE, technology forecasting and technology foresight, an indicator of patent activity seems to be much more frequently utilized than publication data, and a simple retrieval trial is shown in Table 9.

Table 9. The occurring frequency of patents and publications in a relevant article set on TE

Boolean query	Search result	Keyword	Occurring Frequency**
TS=("technolog* emerg*" OR "technolog* forecast*" OR "technolog* foresight" OR "technolog* evolution*") AND DOCUMENT TYPES: (Article) Timespan: 1997-2017. Indexes: SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH, CCR-EXPANDED, IC.	1334	patent	216
		Bibliometrics/ publication	86

**The occurring frequencies on patent and bibliometrics are calculated in such meta-data columns of WOS as AB (Abstract), ID (Indexing Keywords) and DE (Author Keywords).

Based on the information presented in Table 9, patents are supposed to present more technology intelligence, so patent data are given more weight than publication data. Here, the weight of patents is supposed to be 0.7 -- that refers to the occurring frequencies in Table 8, and then the weight of the publication data is 0.3. **Definitely, a more appropriate weighting method should be based on survey or expert interviews; therefore, this arbitrary weighting could be debatable and compromised**. However, as a case instance, this simple weighting of patent and publication activity offers a convenient solution. Next, the indicator of scale can be calculated in the following Equation (5).

$$Indicator_{scale}(OLEV) = \frac{0.3 * \sqrt[5]{\prod_{j=1}^{5} OP(\textbf{publications})} + 0.7 * \sqrt[5]{\prod_{j=1}^{5} OP(\textbf{Patents})}}{0.3 + 0.7} = 0.0147\ (w_j = 1) \quad (5)$$

In Equation (5), OP stands for *Proportion* in Table 8; clearly, a more nuanced weighting approach would be warranted. For example, w_j can be reassigned into variations based on the impact factors of journals or the reputation of conferences in the domain areas, and w_i can also be changed for specific reasons and even be changed into a dynamic variable.

Following the calculation method presented in Equation (5), the scale indicators of the anticipated technologies presented in Table 5 are shown in Table 10.

Table 10. Computing results of scale indicators about anticipated emerging technologies

	Anticipated Emerging Technologies (Abbr.)	Indicator of scale
#1	Online Electric Vehicles (OLEV)	0.0147
#2	3-D printing and remote manufacturing (3DP)	0.3338
#3	Self-healing materials (SHM)	0.0043
#4	Energy-efficient water purification (EEWP)	0.0216
#5	Carbon dioxide (CO2) conversion and use (CDCU)	0.0723
#6	Enhanced nutrition to drive health at the molecular level (ENDM)	0.0004
#7	Remote sensing (RS)	0.0415
#8	Precise drug delivery through nanoscale engineering (PDDNE)	0.0505
#9	Organic electronics and photovoltaics (OEP)	0.0178
#10	Fourth-generation reactors and nuclear-waste recycling (FGR&NWR)	0.0241

From the results shown in Table 10, based only on the perspective of participant scale, the top 10 emerging technologies forecasted by WEF show great differences. The #2 technology, 3DP, has attracted many more countries, research institutes and enterprises than the #6 technology, ENDM. Comparing these two potential emerging technologies, some interesting phenomenon can be unveiled. For example, the top 5 countries authoring the publications and top 5 patent assignees related to 3DP and ENDM are shown in Tables 11 and 12.

Table 11. Top 5 countries authoring publications and patent assignees related to 3DP up to 2016

Top 5 countries/territories	publications	Top 5 assignees	patents
USA	5498	HEWLETT PACKARD DEV CO LP	142
PEOPLES R CHINA	3141	PRINT RITE UNICORN IMAGE PROD CO LTD ZHU	137
GERMANY	1644	UNITED TECHNOLOGIES CORP	136
JAPAN	1321	STRATASYS INC	111
ENGLAND	1219	CAL COMP ELECTRONICS COMMUNICATIONS CO	86

Table 12. Top 5 countries authoring publications and patent assignees related to ENDM up to 2016

Top 5 countries/territories	publications	Top 5 assignees	patents
USA	35	PRONUTRIA INC	5
INDIA	12	PRONUTRIA BIOSCIENCES INC	4
AUSTRALIA	6	BASU S	2
ITALY	6	BERRY D A	2
BRAZIL	4	CHEN Y	2
ENGLAND	4	HAMILL M J	2
FRANCE	4	POLLENERGIE	2
MEXICO	4	SILVER N W	2
NETHERLANDS	4		
PEOPLES R CHINA	4		

Compared to the more popular technology, 3DP, ENDM is more similar to a niche technology in the global scheme; however, ENDM could have equal or greater impacts on the socio-economic, environmental, and ecological systems than 3DP. ENDM is an attempt to improve the efficiency of nutrition absorption at the molecular level in the human body through sophisticated technologies involving bioscience, nutriology, and nanoscience. Next, ENDM could significantly reduce the total consumption of food for human beings, especially in territories experiencing food shortages and with possible starving periods in the future (Darntonhill et al., 2004; Morine et al., 2014; Rondanelli et al., 2016).

(2) Computing the indicator of growth based on Equation (2)

To compute the growth indicator, the geometric mean is also utilized in Equation (2). For example, the annual growth rates of publications and patents related to 3DP technology are shown in Table 13.

Table 13. Annual growth of publications and patents related to 3DP

	Forecasted emerging technologies	Period	Annual Growth of publications	Annual Growth of patents
#2	3-D printing and remote manufacturing (3DP)	2010-2011	1.0954	1.4819
		2011-2012	1.3100	1.5528
		2012-2013	1.2608	2.0366
		2013-2014	1.5904	3.5116
		2014-2015	1.3609	2.9224
		2015-2016	1.5351	1.4852

Based on the data presented in Table 13, the growth indicator can be calculated based on Equation (2). For example, while using the same weighting methods as described for the previous indicator, the computation of the growth indicator on 3DP is shown in Equation (6).

$$Indicator_{growth}(3DP) = \frac{0.3 * \sqrt{\prod_{j=1}^{6} AG(\textbf{ publications })} + 0.7 * \sqrt{\prod_{j=1}^{6} AG(\textbf{Patents})}}{0.3 + 0.7} = 0.8304 \quad (6)$$

Similarly, the growth indicators of the 10 technologies presented in Table 5 can be calculated and are shown in Table 14.

Table 14. Computing results of growth indicators about the anticipated technologies presented in Table 5.

	Anticipated Emerging Technologies (Abbr.)	Indicator of growth
#1	Online Electric Vehicles (OLEV)	0.7706
#2	3-D printing and remote manufacturing (3DP)	0.8304
#3	Self-healing materials (SHM)	0.3330
#4	Energy-efficient water purification (EEWP)	0.1506
#5	Carbon dioxide (CO2) conversion and use (CDCU)	0.0753
#6	Enhanced nutrition to drive health at the molecular level (ENDM)	0.0159
#7	Remote sensing (RS)	0.1668

#8	Precise drug delivery through nanoscale engineering (PDDNE)	0.1093
#9	Organic electronics and photovoltaics (OEP)	0.0364
#10	Fourth-generation reactors and nuclear-waste recycling (FGR&NWR)	0.2647

Based on the growth indicators presented in Table 14, during the period of 2010 to 2016, OLEV and 3DP achieved relatively rapid growth; inversely, ENDM and OEP experienced much slower growth.

(3) Computing the indicator of Diffusion across categories or IPC codes

To compute the diffusion indicator presented by Equation (3), the annual increase of publication categories and the annual increase of patent IPC codes related to the observed technology are taken into account; the annual increases for WOS categories and IPC codes related to the 10 technologies presented in Table 6 are shown in Table 15.

Table 15. Annual growth of WOS categories and IPC codes related to those technologies in Table 6.

	Emerging Technologies forecasted by WEF	Annual Increase of the relevant WOS categories*	Annual Increase of the relevant IPC codes*	Period
#1	OLEV	0.3286	0.5000	2010-2016
#2	3DP	0.0553	0.6481	
#3	SHM	0.0609	0.2250	
#4	EEWP	0.2449	0.2993	
#5	CDCU	0.0452	0.0552	
#6	ENDM	0.0998	0.1690	
#7	RS	0.0212	0.0925	
#8	PDDNE	0.0217	0.0565	
#9	OEP	0.0322	0.0465	
#10	FGR&NWR	0.0410	0.1387	

*The annual increase of the relevant WOS categories or the relevant IPC codes on those different technologies is just calculated by the average growth in the assigned period. For example, the relevant IPC codes on 3DP achieved 64.81% annual growth from 2010 to 2016, a very impressed figure.

Based on the data presented in Table 15 and the weighing method discussed above, the diffusion indicators for the anticipated emerging technologies can be computed and are shown in Table 16.

Table 16. Computing results of diffusion indicator about the anticipated technologies presented in Table 5.

	Anticipated Emerging Technologies (Abbr.)	Indicator of diffusion
#1	Online Electric Vehicles (OLEV)	0.4486
#2	3-D printing and remote manufacturing (3DP)	0.4703
#3	Self-healing materials (SHM)	0.1758
#4	Energy-efficient water purification (EEWP)	0.2830
#5	Carbon dioxide (CO2) conversion and use (CDCU)	0.0522
#6	Enhanced nutrition to drive health at the molecular level (ENDM)	0.1482
#7	Remote sensing (RS)	0.0711
#8	Precise drug delivery through nanoscale engineering (PDDNE)	0.0461
#9	Organic electronics and photovoltaics (OEP)	0.0422
#10	Fourth-generation reactors and nuclear-waste recycling (FGR&NWR)	0.1094

Additionally, based on the results presented in Tables 15 and 16, another interesting phenomenon could be revealed in that most of these anticipated technologies have slow increases of WOS categories, except for OLEV and EEWP. This could mean that academic studies on those technologies are relatively concentrated in a narrow domain. However, the activities related to patents could present more diversity, and therefore the growth of IPC codes could more significantly present diffusion than the academic outputs.

(4) Computing the indicator of public awareness

To probe public awareness about the emerging technologies anticipated by WEF, shown in Table 6, a simple questionnaire is designed. The survey is conducted by a professional company that is one of the largest China companies in online surveying. The degrees of public awareness are defined in five level Likert-scale. In this questionnaire, another three technologies (biomass energy, graphene, nanotechnology) are included as potential verification factors (or, a reference group) in addition to the ten possibly emerging technologies presented in Table 6,

After we submit the questionnaire and our requirement regarding the number of valid responses to the platform of this company, the total fee of the online survey is calculated; after the survey fee is delivered to this platform, a large number of electronic requests regarding the survey will be sent to the terminals of potential respondents via such devices as mobile phone and laptop.

In this survey, the number of valid responses is required to be no fewer than 1000; when the threshold is approached, all push messages concerning the survey will be stopped. Finally, 3074 survey requests were sent in an approximately random manner; 1154 responses were collected in approximately one month and 1151 responses are complete. Descriptive statistics about this survey are shown in Figures 6 and 7, as well as Table 17.

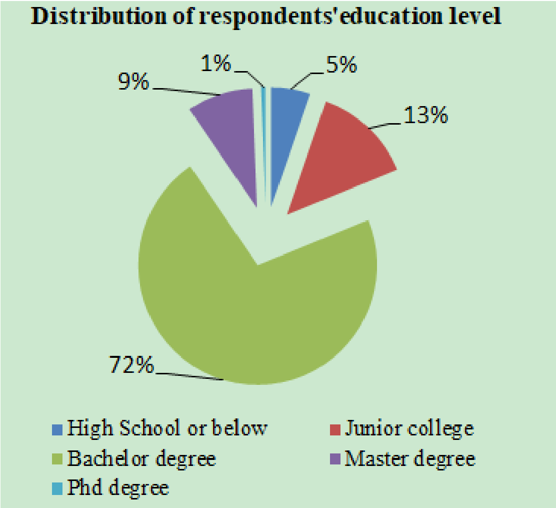

Fig. 6. Distribution of respondents' education level

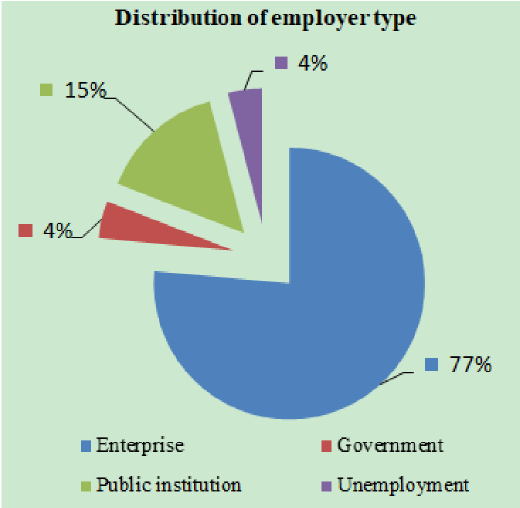

Fig. 7. Distribution of employer type

From Figures 6 and 7, the majority of respondents have bachelor's degrees and are employed by a wide variety of enterprises. This online survey shown in Table 17 could be biased for the reason that most respondents are literate and familiar with the Internet and cell phones.

Table 17. Basic statistics of the online survey about public concerns on emerging technologies

Item	Mean*	Std. Deviation
Online Electric Vehicles (OLEV)	2.97	0.986
3-D printing and remote manufacturing (3DP)	3.24	0.885
Self-healing materials (SHM)	2.64	1.060
Energy-efficient water purification (EEWP)	3.20	1.003
Carbon dioxide (CO2) conversion and use (CDCU)	2.71	1.091

Enhanced nutrition to drive health at the molecular level (ENDM)	2.59	1.111
Remote sensing (RS)	3.21	1.003
Precise drug delivery through nanoscale engineering (PDDNE)	2.88	1.017
Organic electronics and photovoltaics (OEP)	3.02	1.064
Fourth-generation reactors and nuclear-waste recycling (FGR&NWR)	2.54	1.092
Graphene	2.75	1.115
Biomass energy	2.81	1.095
Nanotechnology	3.39	0.890

***The scale for each question is based on Likert-scale, i.e. form 1-very unfamiliar to 5-very familiar.**

In this survey shown in Table 17, as one of the classical emerging technologies, nanotechnology, has been well-studied for prior plentiful studies in many different areas (Schummer, 2004; Porter et al, 2007; Islam and Ozcan, 2017).

In this case study, we introduced a computing method of determining public awareness on specific technologies. First, the response pattern of 1151 respondents on nanotechnology is taken into the reference group. Second, the similarity between response patterns of the other observed technologies and the response pattern of nanotechnology are calculated. Because the tests of normality and independence between items are qualified, *Pearson* correlations are utilized to present the similarity between the observed technology and nanotechnology. The test instances of normality and independence are shown in Tables 18 and 19, and the computing results of the *Pearson* correlations are shown in Table 20.

Table 18. An instance on tests of normality between OLEV and Nanotechnology

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Online Electric Vehicles (OLEV)	.212	1151	.000	.906	1151	.000
Nanotechnology	.212	1151	.000	.886	1151	.000

[a] Lilliefors Significance Correction

Table 19. An instance on tests of independence (Chi-Square Tests) between OLEV and Nanotechnology

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	307.777 [b]	16	.000
Likelihood Ratio	250.220	16	.000

Linear-by-Linear Association	189.964	1	.000
N of Valid Cases	1151		

[b] 2 cells (8.0%) have expected count less than 5. The minimum expected count is 1.39.

Table 20. Pearson correlations between Nanotechnology and the observed technologies presented in Table 6.

				3-D printing and remote manufacturing (3DP)	Online Electric Vehicles (OLEV)	Self-healing materials (SHM)	Energy-efficient water purification (EEWP)	Carbon dioxide (CO2) conversion and use (CDCU)	Enhanced nutrition to drive health at the molecular level (ENDM)	Remote sensing (RS)	Precise drug delivery through nanoscale engineering (PDDNE)	Organic electronics and photovoltaics (OEP)	Fourth-generation reactors and nuclear-waste recycling (FGR&NWR)
Nano-technology	Pearson Correlation			0.459	0.406	0.404	0.501	0.409	0.429	0.508	0.488	0.497	0.388
	Sig. (2-tailed)			0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N			1151	1151	1151	1151	1151	1151	1151	1151	1151	1151
	Bootstrap	Bias		0.000	0.001	-0.001	0.000	0.000	0.001	-0.001	0.000	-0.002	0.000
		Std. Error		0.027	0.026	0.026	0.024	0.026	0.026	0.026	0.025	0.024	0.027
		95% Confidence Interval	Lower	0.405	0.356	0.348	0.451	0.359	0.376	0.455	0.441	0.446	0.335
			Upper	0.512	0.457	0.456	0.546	0.459	0.476	0.558	0.535	0.542	0.442

According to the computation of degree of technology emergence based on the proposed conceptual framework and quantitative formulas above, the emergence degrees for the emerging technologies anticipated by WEF could be evaluated and compared from four perspectives or dimensions, which are shown in Table 21.

Table 21. Evaluation of emergence degree of those technologies presented in Table 5 via four indicators

	Anticipated Emerging Technologies	Indicator of scale	Indicator of growth	Indicator of diffusion	Indicator of public awareness
#1	OLEV	0.0147	0.7706	0.4486	0.406
#2	3DP	0.3338	0.8304	0.4703	0.459
#3	SHM	0.0043	0.3330	0.1758	0.404
#4	EEWP	0.0216	0.1506	0.2830	0.501
#5	CDCU	0.0723	0.0753	0.0522	0.409
#6	ENDM	0.0004	0.0159	0.1482	0.429
#7	RS	0.0415	0.1668	0.0711	0.508
#8	PDDNE	0.0505	0.1093	0.0461	0.488
#9	OEP	0.0178	0.0364	0.0422	0.497
#10	FGR&NWR	0.0241	0.2647	0.1094	0.388

To further visualize the analysis results presented in Table 21, one classic multi-criteria decision-making method (MCDM), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) and its variations or the similar methods, e.g. IF-TOPSIS (Aloini et al., 2018), PROMETHEE (Behzadian et al., 2010; Vetschera & Almeida, 2012) also should be helpful. Here, the basic TOPSIS is conducted to ranking process (Shih et al., 2007; Behzadian et al., 2012; Li and Porter, 2018), which is shown in Equations (7)-(10).

$$\exists V = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & .. \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}_{m\times n} \xrightarrow[x'_{ij}]{Normalization} V' = \begin{bmatrix} x'_{11} & x'_{12} & \cdots & x'_{1n} \\ x'_{21} & x'_{22} & \cdots & x'_{2n} \\ \cdots & \cdots & \cdots & .. \\ x'_{m1} & x'_{m2} & \cdots & x'_{mn} \end{bmatrix}_{m\times n} \quad (7)$$

In Equation (7), the normalization formula is shown in Equation (8).

$$x'_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m}(x_{kj})^2}}, i = 1, 2, \ldots\ldots, m; \ j = 1, 2, \ldots\ldots, n \tag{8}$$

In TOPSIS, the positive ideal-solution $S^{*(+)}$ and negative ideal-solution $S^{*(-)}$ are two reference points in the multi-dimension Euclidean space for those observed objects.

$$\begin{aligned} S_j^{*(+)} &= max(x'_{ij}), \ j = 1, 2, \ldots\ldots, n \\ S_j^{*(-)} &= min(x'_{ij}), \ j = 1, 2, \ldots\ldots, n \end{aligned} \tag{9}$$

In the following step, the relative proximity to the two ideal-points (i.e. $S_j^{*(+)}$ and $S_j^{*(-)}$) for each point (observed or evaluated object) can be calculated by Equation (10).

$$C_i^* = \frac{\sqrt{\sum_{j=1}^{n}(x'_{ij} - S_j^{*(-)})^2}}{\sqrt{\sum_{j=1}^{n}(x'_{ij} - S_j^{*(+)})^2} + \sqrt{\sum_{j=1}^{n}(x'_{ij} - S_j^{*(-)})^2}}, i = 1, 2, \ldots\ldots, m \tag{10}$$

Based on the data in Table 21 and the TOPSIS method depicted in Equations (7)-(10), the ranking result of emergence degree for the emerging technologies anticipated by WEF in 2013 is visualized in Figure 8.

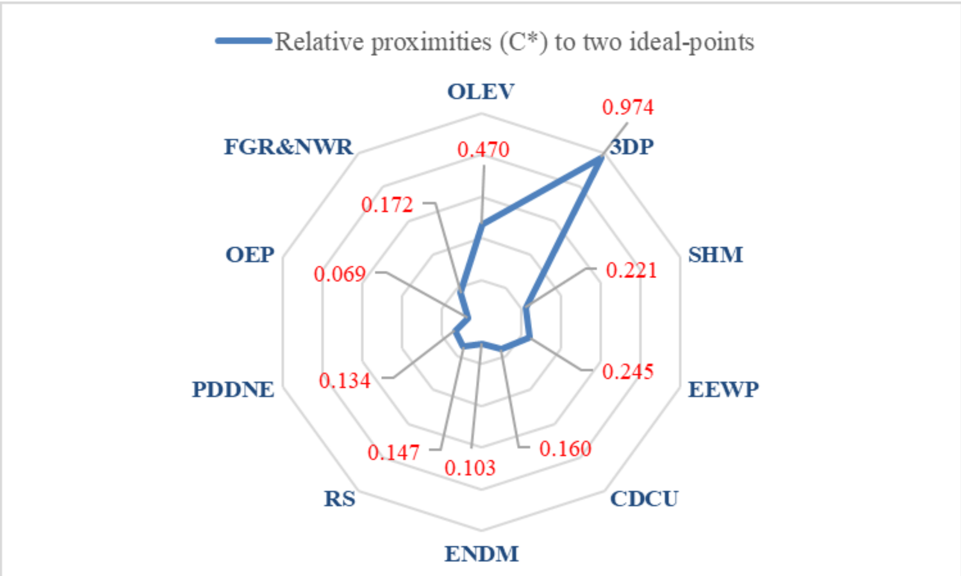

Figure 8. Evaluation and rank on emergence of anticipated emerging technologies presented in Table 5.

Based on the information in Figure 8, it can be concluded that 3DP reflects significant emergence. The emergence status or degree for the ten emerging technologies anticipated by WEF in 2013 could be divided into several different levels, shown in Table 22.

Table 22. A proposed level partition for TE's degree or status

Emergence degree or status	Anticipated Emerging technologies	Range of Relative Proximity (C*)
Level 5	3DP	(0.8, 1.0]
Level 4	None	(0.6, 0.8]
Level 3	OLEV	(0.4, 0.6]
Level 2	SHM, EEWP	(0.2, 0.4]
Level 1	CDCU, ENDM, RS, PDDNE, FGR&NWR	(0.1, 0.2]
Level 0	OEP	(0.0, 0.1]

Actually, the evaluation results of the emergence degree of these technologies seem to be reasonable and roughly coincide with our intuition. The relevant technology on three-dimension printing (3DP) presents a much more significant emergence phenomenon than the other nine technologies. This seems to coincide with 3DP seeming to have the support of national strategies, such as Germany's "Industry 4.0", China's "Made in China 2025", and US "Reindustrialization."

The result presented in Table 22 could be controversial and even biased for possible technical reasons. It is offered as an illustration. However, the proposed conceptual framework of measuring technology emergence via these four dimensions deriving from the philosophy of swarm intelligence could be effective.

In addition, the comparison of degree of emergence among different technologies presented in Figure 8 and Table 22 could attract interest in deeper exploration of underlying reasons. For example, the US and India are the most active countries in the relevant areas of ENDM for different reasons. Relatively speaking, the studies on ENDM from India are more about malnutrition than obesity. Meanwhile, as a developing country and having the largest population by far, China's relevant R&D outputs on ENDM are pretty rare. Actually, China could still face dual challenges of malnutrition and obesity. In other words, the relevant R&D activities on ENDM in China could have more room for expansion than in most other territories.

5 Discussion and Limitations

In past decades, forecasting emerging technologies has been important for many countries. Several developed and developing nations have funded strategic projects of technology foresight – e.g., including the U.K., Japan and China (Georghiou, 1998; Mu et al.,2008; Breiner et al., 2010). However, very few studies have thoroughly analyzed the measurement and evaluation of TE. In turn, TE is often taken into an established or apparent phenomenon (Goeldner et al., 2015; Raimbault et al, 2016).

Regarding how to measure emergence degree of a specific technology and compare the emergence degree between technologies, combining with the basic philology of swarm intelligence theory, an exploratory framework on TE and the relevant methods of computation are proposed and illustrated. TE thus becomes a dynamic concept that can be measured, evaluated and compared under a quantitative framework. To explain and verify the proposed conceptual framework for TE, a case study on the emerging technologies anticipated by the WEF in 2013 is conducted. Although only such data as publications, patents and simple questionnaires are collected, the empirical analysis still demonstrates the effectiveness of the proposed framework on technology emergence. Therefore, the marginal contributions of this paper could have:

(1) In prior studies, the possible differences between technology emergence and emerging technologies are seldom discussed. Evaluating TE or ET is still exploratory, and many issues on emergence degree or level of a specific technology need to be addressed.

(2) We note some interesting TE phenomena. For example, on May 24th, 2019, SpaceX launched 60 satellites into space, and the Starlink plan was formally triggered. However, the core technologies of Starlink seem like the re-emergence of MOTOROLA's iridium program from about 20 years ago. 3D printing/additive manufacturing technology also could be the natural evolution of traditional rapid prototyping technology (Li and Porter 2018). Therefore, some old or obsolete technologies also could re-emerged in the future; and then TE seems have the broader boundary than emerging technologies.

(3)Regarding the studies on TE, the multi-dimensional and insightful indicators are still the research fronts. Inspired by the philosophy of swarm-intelligence theory, an evaluation model and several dimensions that can be conducted to observe and measure TE are proposed; these could be a valuable supplement on the relevant theories or analytical methods on technology forecasting, foresight and technology evaluation and so on

(4) In this paper, we attempt to define the levels of TE; five levels are proposed in the

case study, which could be another valuable point that can approximately map the connections between TE and technology evolution (S-curve) by quantitative means. Meanwhile, the proposed framework and indicators can effectively differ technology emergence from technology maturity. Consequently, more precise advice or policies for technology development could be approached.

In summary, the theoretical and empirical explorations on technology emergence illustrated in this paper, as well as the proposed framework and measurement methods for TE, offer a approach. This could hold promise for analyses to inform technology policy and management. We note some promising ways. First, traditional theories and conceptualizations of TE or ET could be further extended. Second, under the proposed framework, the operationalization of TE can be based on data such as publications, patents, and questionnaires and so forth. Third, the proposed conceptual framework and evaluation method for technology emergence not only can be utilized to evaluate or measure the emergence status for a specific technology, but can also be used to compare the relative degree of emergence among different technologies. Therefore, the explorations on TE measurement could facilitate the operationalization of TE and support exploration of possible effects on proximal areas such as technology life-cycle, technology paradigm, technology foresight, etc.

Finally, emergence differences among technologies can present a signal to potential stakeholders and could affect subsequent policy-making. To enhance the emergence level for a specific technology, policy-making can probe the deeper reasons based on our proposed conceptual framework and evaluation methods. For example, if the participant scale of OLEV can be enlarged, the emergence level of OLEV might be significantly promoted. Regarding ENDM, how to stimulate China's enthusiasm seems to be very important for enhancing emergence. In terms of the relevant technology on OEP, how to attract diversified attention from different areas, as well as how to further encourage and enhance interdisciplinary research and cooperation could effectively promote emergence. In addition, although 3DP technology presents a higher emergence level than the other nine technologies, the relevant public concerns of 3DP seem to be less than the others examined. Therefore, relevant studies of public perception, social communication and risk analysis on 3DP technology might warrant more attention from academic and enterprise circles (Li and Porter, 2018).

Additionally, we acknowledge that this research has limitations. Although the theory of swarm intelligence is referenced, the explorations of TE remain weak and controversial, especially regarding its dynamic mechanisms. In the case study, except for 3DP, that reflects a published search string (Huang et al. 2017; Li and Porter 2018), the other nine technologies rely solely on descriptive information provided by the WEF and our subjective judgment (**see Appendix)** to retrieve pertinent records. Therefore, the search results on publications and patents about those technologies are possibly biased. In following studies, the search terms should be further refined through several bibliometric practices, e.g., further text analyses (to gauge the implications for precision and recall of adding or deleting terms to the Boolean search string, and possibly considering citation patterns as well (Porter et al, 2008; Li and Chu, 2017; Li et al., 2017).

Considering the flexibility of the proposed conceptual framework for TE, slight bias or errors could be tolerable. Generalization of the conceptual framework for TE depicted by Figure 4 has good prospects, but demands further assessment. Comparison with other computational possibilities would add substantial validation (Rotolo et al., 2015; Ávila-Robinson & Sengoku, 2017; Burmaoglu et al., 2019).

In follow-on studies, more accurate methods of weighting must be explored, which involves weighting the different data sources (e.g., publications, patents, projects, and questionnaires), as well as weighting different dimensions or indicators (e.g., scale, growth, diffusion and public concerns).

Acknowledgement

Appendix

Table A1. Descriptions of the top 10 emerging technologies anticipated by WEF in 2013

	Emerging Technologies (Abbr.)	Summary Descriptions
#1	Online Electric Vehicles (OLEV)	Wireless technology can now deliver electric power to moving vehicles. In next-generation electric cars, pick-up coil sets under the vehicle floor receive power remotely via an electromagnetic field broadcast from cables installed under the road. The current also charges an onboard battery used to power the vehicle when it is out of range.
#2	3-D printing and remote manufacturing (3DP)	Three-dimensional printing allows the creation of solid structures from a digital computer file, potentially revolutionizing the economics of manufacturing if objects can be printed remotely in the home or office. The process involves layers of material being deposited on top of each other in to create free-standing structures from the bottom up.
#3	Self-healing materials (SHM)	One of the defining characteristics of living organisms is their inherent ability to repair physical damage. A growing trend in biomimicry is the creation of non-living structural materials that also have the capacity to heal themselves when cut, torn or cracked.
#4	Energy-efficient water purification (EEWP)	Where freshwater systems are over-used or exhausted, desalination from the sea offers near-unlimited water but a considerable use of energy – mostly from fossil fuels – to drive evaporation or reverse-osmosis systems. Emerging technologies offer the potential for significantly higher energy efficiency in desalination or purification of wastewater, potentially reducing energy consumption by 50% or more.
#5	Carbon dioxide (CO2) conversion and use (CDCU)	Long-promised technologies for the capture and underground sequestration of carbon dioxide have yet to be proven commercially viable, even at the scale of a single large power station. New technologies that convert the unwanted CO2 into saleable goods can potentially address both the economic and energetic shortcomings of conventional CCS strategies.
#6	Enhanced nutrition to drive health at the	Even in developed countries millions of people suffer from malnutrition due to nutrient deficiencies in their diets. Now modern genomic

	molecular level (ENDM)	techniques can determine at the gene sequence level the vast number of naturally consumed proteins which are important in the human diet. The large-scale production of pure human dietary proteins based on the application of biotechnology to molecular nutrition can deliver health benefits such as muscle development, managing diabetes or reducing obesity.
#7	Remote sensing (RS)	The increasingly widespread use of sensors that allow often passive responses to external stimulate will continue to change the way we respond to the environment, particularly in the area of health. Examples include sensors that continually monitor bodily function – such as heart rate, blood oxygen and blood sugar levels – and, if necessary, trigger a medical response such as insulin provision.
#8	Precise drug delivery through nanoscale engineering (PDDNE)	Pharmaceuticals that can be precisely delivered at the molecular level within or around a diseased cell offer unprecedented opportunities for more effective treatments while reducing unwanted side effects. Targeted nanoparticles that adhere to diseased tissue allow for the micro-scale delivery of potent therapeutic compounds while minimizing their impact on healthy tissue, and are now advancing in medical trials.
#9	Organic electronics and photovoltaics (OEP)	Organic electronics – a type of printed electronics – is the use of organic materials such as polymers to create electronic circuits and devices. In contrast to traditional (silicon-based) semiconductors that are fabricated with expensive photolithographic techniques, organic electronics can be printed using low-cost, scalable processes such as ink jet printing, making them extremely cheap compared with traditional electronics devices.
#10	Fourth-generation reactors and nuclear-waste recycling (FGR&NWR)	Current once-through nuclear power reactors use only 1% of the potential energy available in uranium, leaving the rest radioactively contaminated as nuclear "waste". Spent-fuel recycling and breeding uranium-238 into new fissile material – known as Nuclear 2.0 – would extend already-mined uranium resources for centuries while dramatically reducing the volume and long-term toxicity of wastes, whose radioactivity will drop below the level of the original uranium ore on a timescale of centuries rather millennia.

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