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EVALUATING TECHNOLOGICAL EMERGENCE FOR STRATEGIC TECHNOLOGY (ETEST) MANAGEMENT: A HYBRID MODEL OF SCIENTOMETRICS AND MCDM APPROACHES

STRATEJİK TEKNOLOJİ YÖNETİMİ İÇİN TEKNOLOJİ TEZAHÜRÜNÜN DEĞERLENDİRİLMESİ (ETEST): BİLİMETRİ VE ÇKKV YAKLAŞIMLARININ BİRLİKTE KULLANILDIĞI MELEZ BİR MODEL

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ABSTRACT

Increasing intensity and rapid shifts on technology domain force policymakers and managers to think more on adaptive strategies by understanding the nature of emergence. However, even there were many conceptual models without consensus, understanding the nature of emergence may not lead to decision for managers or policymakers. There were some proposals aiming to design practical solutions but different fields, experts, or subjects may alter these proposed solutions and sometimes make them biased. In this study, it is aimed to propose a conceptual model by using combination of scientometrics and fuzzy Multi-Criteria Decision Making for evaluating emerging topics holistically. By using fuzzy approach, it is thought that expert decisions can be enhanced and with applying decision making process a compromise solution can be reached. Consequently, conceptual model is proposed and step-by-step methodology discussed.

Keywords: emergence, emerging topics, MCDM, scientometrics, fuzzy

JEL Codes: C54, O14

ÖZET

Teknoloji alanındaki artan yoğunluk ve hızlı değişimler politika yapıcıları ve yöneticileri tezahürün doğasını anlayarak uyumlu stratejiler üzerinde düşünmeye zorlamaktadır. Ancak, üzerinde fikir birliği olmayan birçok kavramsal model olsa da tezahürün doğasının anlaşılması yönetici ve politika yapıcıları karar vermeye yönlendiremeyebilecektir. Literatürde bazı pratik çözüm tasarlamayı amaçlamış öneriler bulunmaktadır. Ancak; farklı alanlar, uzmanlar veya konular bu önerilen çözümleri değiştirebilmekte ve bazen yanlı hale getirebilmektedir. Bu çalışmada, bütünsel olarak tezahür eden başlıkların değerlendirilebilmesi için Bilimetri ve Çok Kriterli Karar Verme yöntemlerinin birleştirilerek kullanıldığı kavramsal bir model önerilmesi amaçlanmıştır. Bulanık bir yaklaşım kullanılması ile uzman kararlarının iyileştirilebileceği ve uygulanan karar verme sürecinin uzlaşmacı bir çözüme kavuşturulacağı düşünülmektedir. Sonuçta, kavramsal model önerilmiş ve metodoloji adım adım açıklanarak tartışılmıştır.

Anahtar Kelimelers: Gelişmekte olan konular, MCDM, Bulanık

JEL Codes: C54, O14

1. INTRODUCTION

Technological change has been considered by researchers in literature especially with increasing need of innovation for development. Therefore, technology emergence has been studied conceptually (Alexander, Chase, Newman, Porter, & Roessner, 2012; Rotolo, Hicks, & Martin, 2015; Small, Boyack, & Klavans, 2014) and model-based (C. M. Chen, 2006). However, even the subject is emerging there has been no consensus and this makes the subject significant now.

Expert-dominated process is mostly acknowledged by policymakers in application. The analysis of heaps of scientific data there were many extracted topics and these topics have been evaluated verbally by experts based on their previous experiences and then these topics interpreted for future consequences. However, this process has not been handled by using multi-criteria decision making models.

In this study, it is aimed to propose a conceptual model by using combination of scientometrics and fuzzy Multi-Criteria Decision Making for evaluating emerging topics holistically. By using fuzzy approach, it is thought that expert decisions can be enhanced and with applying decision making process a compromise solution can be reached.

Study is outlined as follows. In the second section, literature on emerging topic detection models reviewed. Then, methodology is explained in third section. In the fourth section, finally, the model is discussed in conclusion and further implications are expressed.

1.1. Search and Evaluation of Technical/Technological Emergence

It can be asserted that cognitive-epistemological structure of science became topic of interest since 1955 (Garfield, 2006). It is thought that these studies were mostly inspired by the theories of scientific change (Fuchs, 1993; Kuhn, 1962; Shneider, 2009). Based on these theories, scientometricians have developed different models to analyze, visualize, and interpret the evolution of paradigms, collaboration structure of scientific domains, and anticipating emerging terms. Mainly, analyzing a scientific domain needs some steps to be performed. These are: (1) data retrieval, (2) data preprocessing, (3) creating the focused network, (4) analysis and generating the metrics, (5) visualization and interpretation. There were many different perspectives for almost all stages in the literature but at the end only the objective remained stable. Technically, most challenging issue in this process is discovering emerging topics accurately and reliably.

Therefore, emergence term detection has been a hot topic because of rapid change in science and technology. For the policy level, it can be asserted that policymakers needs emergence terms for keeping up-to-date technology policy process and navigating the policy discourse with a data-based perspective. For the firm level, searching new knowledge from internal or external databases is an important part of innovation process which was described by some of the authors as life or death issue for business firms. Based on Khanagha, Volberda, and Oshri (2017), managers couldn’t have opportunity to focus on emerging fields because of investment requirements. Together with its importance for policymakers and strategy specialists, emerging technology subject has been discussed in last decade conceptually on its attributes beyond its detection.

When conceptualization efforts were examined, Alexander et al. (2012)’s proposal was seen first with a definition for emergence by drawing an analogy with incremental and radical innovations from a technical change perspective. Moreover, they argued that technical emergence would occur as in technology growth models and proposed that the take-off phase with a steep trend might be called as radical emergence and then with a smoother curve it might be described as incremental emergence phase.

Second study was Small et al. (2014)’s and they cited Goldstein (1999)’s study and asserted some properties for emergence as radical novelty; coherence; wholeness; global or macro; dynamical; and ostensive. Then, they concluded that these definitions and properties put forward two universal accepted characteristics for emergence as novelty and growth.

In a latest article, Rotolo et al. (2015) defined the emerging technology concept as:

> *"a relatively fast growing and radically novel technology characterized by a certain degree of coherence persisting over time and with the potential to exert a considerable impact on the socio-economic domain(s) which is observed in terms of the composition of actors, institutions and the patterns of interactions among those, along with the associated knowledge production processes. Its most prominent impact, however, lies in the future and so in the emergence phase is still somewhat uncertain and ambiguous"*

When the definition analyzed it can be seen that there are five attributes as radical novelty; relatively fast growth; coherence; prominent impact; and uncertainty and ambiguity. Then, they proposed that fast growth could be evaluated by counting documents over time; radical novelty could be operationalized by clustering and co-word analysis; coherence could be assessed based on entropy measure. However, prominence may be accepted as a relative definition and it can be asserted that uncertainty and ambiguity may be overcome only by combining effective algorithms and expert opinions in hybrid approaches. As can be seen in conceptualization studies, there were some aspects like novelty, uncertainty, and fast growth on which scholars have reached consensus. However, these aspects described without operational definitions. When these aspects thought as decision criteria, they should be expected to be described operationally with a decision range (as upper level-lower level; bad side-good side) that decision makers can comment and grade it. In this sense, it is aimed to propose operational definitions for these aspects and use fuzzy linguistic model to overcome ambiguity of expert decisions to understand and rate emergence topics more reliably and accurately.

In another study, Li, Porter, and Suominen (2017) tried to explain the relationship between disruptive innovation/technology and emerging technology concepts by applying co-citation and bibliographic coupling networks. Finally, they saw that presence of emergence was dominant by volume of articles and the concept of disruptiveness relatively was discovered late-coming. Moreover, they expressed the lack of theoretical orientation in research regarding technological emergence. However, (Nagy, Schuessler, & Dubinsky, 2016) approached disruptive technology from a more operationalized perspective and proposed functionality, technical standards, and ownership criteria for distinguishing disruptiveness. When both studies were taken into account, it can be assessed that disruptive innovation demonstrate emerging characteristics and because of this, it can only be distinguished with its results.

When the subject is handled from a methodological point of view, it can be seen that topic detection and topic tracking are commonly used in the literature interchangeably. First, it is thought to clarify the meaning of these phrases. Ding and Chen (2014) differentiated these phrases with their aims. They proposed that the aim of the topic detection was identifying significant topics from a document collection but the aim of topic tracking was following the evolution of an identified topic. In this study, topic detection methodology is applied for finding the emergence terms in selected scientific domain.

Emergence topic/term detection methodologies may be considered as important processes especially for technology/innovation policy-makers and R&D strategists as explained before. Even it can be called as expert-dominated, increasing number of publications under scope makes using text mining algorithms required (Kontostathis, Galitsky, Pottenger, Roy, & Phelps, 2004). Kontostathis et al. (2004) classified the studies on emergence topic detection to two classes as fully-automatic and semi-automatic. They explained that fully automatic systems analyze the text corpus and create an emerging topic list then experts interpret and justify the results. Semi-automatic systems rely on user input as a first step in detecting emerging trend and almost all steps experts' supervision is needed.

One of the topic detection approach is a machine learning model. Pottenger and Yang (2001) made a radar analogy for detecting emerging trends in textual information. They expressed that a radar system and they thought that this radar analogy could assist in the differentiation of mobile vs. stationary objects, effectively screening out uninteresting reflections from stationary objects and preserving interesting reflections from moving objects. By using this analogy, they proposed their technique as identifying regions of semantic locality in a set of collections and screen out topic areas that are stationary in a semantic sense with respect to time and then by querying, hot topic regions of semantic locality could be identified and their characteristics by studying the underlying literature automatically associated with each such hot topic region could be determined. They applied a machine learning algorithm by using 7 inputs as;

> *"(1) number of occurrences of the concept in the trial year, (2) number of occurrences of the concept in the year before the trial year, (3) number of occurrences of the concept in the year two years before the trial year, (4) number of total occurrences of the concept before the trial year, (5) number of concepts in the cluster containing the concept before the trial year, (6) number of concepts in the cluster containing the concept in the year right before the trial year, (7) number of words with length at least four in the concept."*

They employed a 7x10x2 neural network for reaching a learning model for achieving better recall. In their model, domain experts filtered the final list. However, how linguistic judgments of domain experts were considered was not explained in the study. With this study it is aimed to fill this gap.

Another approach was emergence scoring methodology which was developed by Garner, Carley, Porter, and Newman (2017) and the proposed algorithm targeted four attributes of emergence as novelty, persistence, community, and growth. They applied five steps as:

> *"(1) retrieving dataset; (2) processing terms of interest; (3) generating EScores; (4) generating "player" emergence indicators; (5) applying the emergence scores and indicators."*

For generating emergence scores they prepared a script for VantagePoint commercial software and the script aimed to meet five thresholds:

> *"(a) Appear in records from at least 3 years; (b) Appear in at least 7 records; (c) The ratio of records containing the term in the active period to those in the base period must be at least 2:1; (d) The term cannot appear in 15% or more of the base period records; (e) Terms are also required to have more than one author that doesn't share the same record set. Authors asserted that thresholds (a) and (b) aimed to assure the level of persistence; (c) and (d) for demonstrating Novelty and Growth; and (e) for assuring multiple authors not all within one research group have engaged the topic."*

Script's defaults were at least 7 total records containing the term for 3 years and with at least 1 record but these values can be changed by users. They selected an additive model by considering different algorithms and incorporated three of four available component trends: active period trend for comparing the change from the most recent 3 years of the active period; Recent Trend for comparing the change from the most recent 2 years to the 2 years prior; Slope from the mid-year of the active period to the most recent year. By the way, they used the algorithm in Eq.(1) for calculating the emergence score (ESc) for one year and then aggregated it with Eq.(2) under the assumptions of mentioned thresholds:

$$\mathbf{ESc_t = \frac{TermArticle_t}{\sqrt{TotalArticles_t}}} \qquad (1)$$

$$\mathbf{\sum_{t=1}^{n} ESc_t} \qquad (2)$$

where TermArticle refers to the number of terms in articles for specified time frame and TotalArticles refers to total number of articles in specified time frame. Then, they settled a threshold for ESc of 1.77 (square root of □) to distinguish the emergence terms. This algorithm may be considered as automatic process and again linguistic expressions of expert opinions were not modelled in the proposed algorithm.

Another mostly applied algorithm for emergence topic detection is Kleinberg's Burst Detection Algorithm. Kleinberg (2003) developed this algorithm for tracking the topics in a document stream (especially in the emails) and asserted that the model was created by drawing an analogy with models from queueing theory for bursty network traffic in the literature. C. M. Chen (2006) adapted the Kleinberg (2003)'s burst-detection algorithm to identify research-front concepts in his study. He reviewed different emerging trend detection models by classifying these studies as visualization-based and statistically enhanced (C. M. Chen, 2006). He explained Kleinberg's model by assuming it as a probability of observing a temporal gap t between the arrival times of two consecutive messages following an exponential distribution as in Eq. (3):

$$\mathbf{f(t) = \alpha e^{-\alpha t}} \qquad (3)$$

The expected gap value is $(\boldsymbol{\alpha^{-1}})$; hence, α may be called the rate of message arrivals. The burst detection is formulated as a Markov source model that can reveal messages at certain arrival rates, and the change of arrival rates can be modeled as a state transition. C. Chen (2006) exemplified this as before the beginning of a burst period, the messages could be seen as revealed from a low state with a rate α; a burst could be defined as a sequence of messages that were emitted at a higher arrival rates $\boldsymbol{s_\alpha (s > 1)}$. He generalized the model to represent states that correspond to arbitrarily small gaps with rates increased by a factor of s and asserted that Kleinberg proved the model could be reduced to a finite-state system because the maximum likelihood state sequence involved only k stats, where k was bounded by a combined factor of the length of the time window, the minimum gap, and the acceleration rates. C. Chen (2006) asserted that the major advantage of Kleinberg's approach was handling multiple levels of bursts. He stressed on detecting abrupt changes with the least number of false alarms and filtering out noises from the original data as certain characteristics of algorithms for producing improved and exact information visualization.

Shibata, Kajikawa, Takeda, Sakata, and Matsushima (2011) proposed a citation network analysis by dividing the citation networks into clusters using the topological clustering method and tracking the positions of the papers in each cluster, and visualize citation networks with characteristic terms for each cluster. They applied a seven-step methodology. After retrieving data, they constructed the citation network and used only the data of the largest graph component. After extracting the largest connected component, they divided this component to clusters by using topological clustering method. They determined the role of each paper by using its within-cluster degree and its participation coefficient for identifying the node's position in its own cluster and between clusters. They assumed that nodes with identical roles should be in similar topological positions. The within-cluster degree $\boldsymbol{z_i}$measures how well connected node i is to other nodes in the cluster and is defined as:

$$z_i = \frac{K_i - \overline{K_{s_i}}}{\sigma_{K_{s_i}}}$$

where $\boldsymbol{K_i}$ is the number of links of node i linked to other nodes in its cluster $\boldsymbol{s_i}$, $\overline{\boldsymbol{K_{s_i}}}$is the average of K overall nodes in $\boldsymbol{\sigma_{K_{s_i}}}$is the standard deviation of $\mathbf{K}$ in $\mathbf{s_i}$. $\mathbf{z_i}$ is high if the within-cluster degree is high and vice versa. The participation coefficient $\mathbf{P_i}$ measures how 'well distributed' the links of node **i** are among different clusters and defined as:

$$\mathbf{P_i = 1 - \sum_{s=1}^{N_M} \left(\frac{K_{is}}{k_i}\right)^2}$$

where $\mathbf{K_{is}}$ is the number of links from node $\mathbf{i}$ to other nodes in cluster $\mathbf{s}$, and $\mathbf{k_i}$ is the total degree of node $\mathbf{i}$ (the number of links connected to node $\mathbf{i}$). The participation coefficient $\mathbf{P_i}$ is close to 1 if its links are uniformly distributed among all clusters and 0 if all its links are within its own cluster. The interpretation of within-cluster degree ad participation coefficient based on Guimera and Amaral (2005) is for $\mathbf{z \geq 2.5}$ as hub nodes and $\mathbf{z < 2.5}$ as non-hub nodes. Hub-nodes are divided to three roles with provincial hubs ($\mathbf{P \leq 0.30}$), connector hubs ($\mathbf{0.30 < P \leq 0.75}$), and kinless hubs ($\mathbf{P > 0.75}$); similarly, non-hub nodes are divided into four different roles as ultra-peripheral nodes ($\mathbf{P \leq 0.05}$), peripheral nodes ($\mathbf{0.05 < P \leq 0.62}$), non-hub connector nodes ($\mathbf{0.62 < P \leq 0.80}$), non-hub kinless nodes ($\mathbf{P > 0.80}$). Then, they used the tf-idf for term extraction. Finally, they found that analyzing cluster results with the average published year and parent-child relationship of each cluster can be helpful in detecting emergence. Furthermore, they emphasized the tracking of topological measures, within-cluster degree and participation coefficient, with their role of determining whether there were any emerging knowledge clusters.

Another algorithm was developed by Tu and Seng (2012) by calculating novelty indices. Their model could be abstracted as dimensional perspective. They used novelty and published volume indices to create a contradicting trade-off and by intersecting the indices aimed to identify detection point and emerging time. They applied their methodology on a scientific domain by using different datasets as conference paper dataset and article data set. Novelty index (NI) is calculated as in Eq. (4);

$$\boldsymbol{NI_k = \frac{1}{k - D_F + 1}} \qquad (4)$$

where k represents starting year and $\boldsymbol{D_F}$ is the first potential development year[1] in documents for a research topic. The other index was used in the study for trade-off was published volume index and it was formulated as in Eq. (5);

$$\boldsymbol{PVI_i(Topic) = \frac{Sum_i}{Sum_D}} \qquad (5)$$

where $\boldsymbol{Sum_i}$ is the accumulated number of papers from the first year to the *i*th year for the document and $\boldsymbol{Sum_D}$ is the accumulated number of documents from $\boldsymbol{D_F}$ to the *k*th year. After computing these indices, authors have prepared a trade-off curve on which new topic lacks the volume needed to be a hot topic and when a hot topic exists for a period of time, it loses novelty. Finally, intersection of these curves accepted as emergence score and the date of intersection is accepted as emergence date.

When probabilistic models reviewed Ding and Chen (2014)'s model might be considered. They focused dynamic topic detection and tracking by comparing Hierarchical Dirichlet Process (HDP), co-word and co-citation models in their study. HDP is a probabilistic model based on a Dirichlet process. They explained the model by applying analogy of Chinese restaurant problem and they assumed documents as restaurant and each words as customers. Customers would arrive at the restaurant one by one and each of them would choose a table which is here representing a topic. They operated the distribution process as follows:

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[1] The potential development year (PDY) is defined by the authors as the period from the first year to the current year when a topic becomes a research topic that does not include any year with zero papers in the following years. Hence, it can be asserted that before studying researcher should have adequate information on key trends in focused research domain.

"1. The first customer always chooses the first table to sit down,

2. The nth customer chooses an unoccupied table with probability of $\frac{\boldsymbol{\alpha}}{\boldsymbol{n-1+\alpha}}$ and chooses an occupied table with the probability of $\frac{\boldsymbol{c}}{\boldsymbol{n-1+\alpha}}$, where c represents the number of people who have already chosen that table, and $\boldsymbol{\alpha}$ is the parameter to control the table assignment.

They constructed a successive conditional distribution with one-by-one arrival of documents of the nth word $\boldsymbol{\theta_n|\theta_1,\theta_2,\ldots\theta_{n-1}}$. Then they got the $\boldsymbol{\theta_n}$ from the formula in Eq. (6).

$$\boldsymbol{\theta_n}\left|\boldsymbol{\theta_1,\theta_2,\ldots\theta_{n-1},\alpha,G}\sim\sum_{l=1}^{n-1}\frac{c_l}{n-1+\alpha}\boldsymbol{\delta_1}+\frac{\alpha}{n-1+\alpha}*\boldsymbol{G}\right. \qquad (6)$$

Where $\boldsymbol{c_l}$ represents the number of customers at that table, and $\boldsymbol{\delta_1}$is the distribution of a topic which this table belongs to, and G is a probability used to generate a topic for the new table. Then, for controlling the two choices of topic assignment, which one is choosing from existing topics or generating a totally new topic as another, they added another distribution over the Eq. (6) and the topic assignment was described as in Eq. (7):

$$\boldsymbol{\psi_n}\left|\boldsymbol{\psi_1,\psi_2,\ldots\psi_{n-1},\gamma,H}\sim\sum_{k=1}^{K}\frac{m_k}{m-1+\gamma}\boldsymbol{\delta_k}+\frac{\gamma}{n-1+\gamma}*\boldsymbol{H}\right. \qquad (7)$$

Where m represents how many tables have been assigned and $\boldsymbol{m_k}$ represents how many tables have been assigned to topic k, and $\boldsymbol{\delta_k}$ is the word distribution on the topic. $\boldsymbol{H}$ is the baseline distribution to generate new topics."

There are semantic approaches in literature to find latent topics. One of them is Latent Semantic Analysis (LSA) which allows one to compute whether two documents are topically similar, even if the two documents do not have any words in common. This approach extended by Newman and Block (2006) for topic discovery with Probabilistic Latent Semantic Analysis (pLSA) which was first introduced by Hofmann (1999) as a way to provide a sound statistical foundation to LSA. A recent development for latent semantic approaches was Latent Dirichlet Allocation (LDA) model similar to pLSA. The topic distribution is assumed to have a Dirichlet prior in LDA and this differentiates LDA from pLSA. Blei, Ng, and Jordan (2003) proposed this model based on Bayesian nonparametric approach for overcoming the shortcomings of pLSA.

Ding and Chen (2014) found that HDP performed better than other two methods in terms of sensitivity and persistence. In addition, they asserted that in topic detection co-citation method performed better than co-word method and in topic tracking co-word method performed better than co-citation method.

When methodological perspective changed from term level to document level Iwami, Mori, Sakata, and Kajikawa (2014)'s model was found in the literature. They applied a detection method for finding emerging leading papers by focusing network measures (Iwami et al., 2014). They used in-degree centrality, betweenness centrality and closeness centrality for comparison and found that in-degree centrality was more useful measure for detecting emerging leading papers in a time transition.

Dernis, Squicciarini, and de Pinho (2016) proposed a holistic perspective and applied Detecting the Emergence of Technologies and the Evolution and Co-Development Trajectories (DETECT) methodology which was based on Kleinberg (2003)'s burst algorithm. They joined the emergence topic discussion with diffusion of innovation perspective by analyzing Bass model and they emphasized the discontinuous and substitutive characteristics of emerging topics. Combining emergence topics with a distribution might enhance the further policy and strategy issues but some of the immeasurable attributes were not considered in these distributions. Therefore, it can be emphasized that modeling linguistic judgments of experts for evaluating immeasurable attributes is a significant issue.

Finally, it can be seen that there were linear, iterative, citation-based, semantic-based, term-based, and document-based approaches in the reviewed literature. It is found in this review that the literature gap is on modeling the linguistic judgments of experts. By modeling this process and adding it to the emergence topic detection procedure, it is thought that more objective compromised solution can be reached. Moreover, applying fuzzy modeling is preferred for overcoming the ambiguous nature of linguistic decisions.

2. CONCEPTUAL FRAMEWORK OF METHODOLOGY

The methodology is handled with a conceptual framework perspective. Therefore, MCDM methodologies are not mentioned with their titles but applicable ones can be applied in this methodological process. It is deemed to apply five steps as illustrated in Figure 1.

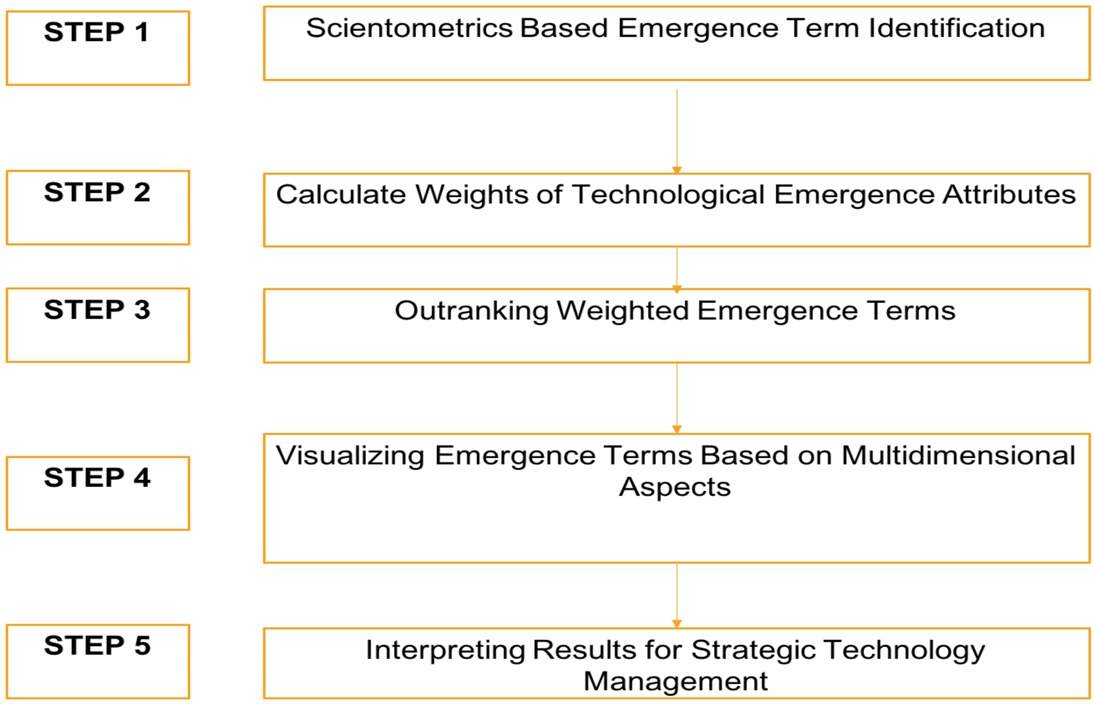

Figure 1 The Steps of Conceptual Framework of Methodology

In step 1, emergence term detection process is performed based on Garner et al. (2017)'s steps which is explained in literature review. With this process emergence terms are identified and verified qualitatively by two field experts. Then, Rotolo et al. (2015)'s technological emergence attributes are weighted based on linguistic judgments of domain experts in the second step. Weighting is applied by using MCDM procedure. In the third step, emergence terms are evaluated by domain experts by using MCDM procedure. By multiplying attribute matrix and weighted matrix emergence topics are outranked. In step 4, emergence topics visualized based on five dimensions of emerging technologies. Therefore, multidimensional attributes of the emergence topics can be evaluated and may be used in strategy or policy development processes based on diamond model as demonstrated in Figure 2.

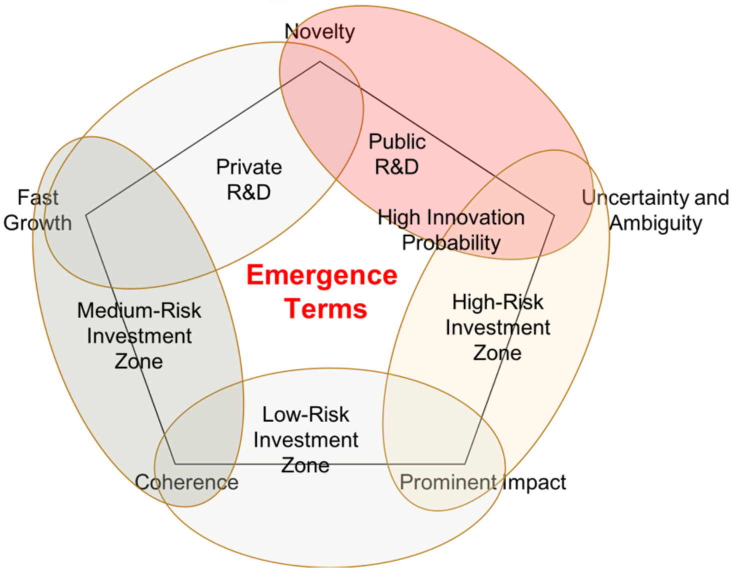

Figure 2 Proposed Diamond Model for Evaluation

As illustrated in Figure 2, multidimensional perspective of technology emergence model may give us insight about emergence terms in detail. We named intersection zones as Private R&D, Public R&D, High-Risk Investment Zone, Low-Risk Investment Zone, Medium-Risk Investment Zone. In Private R&D zone, we assumed that fast growing and novel terms may impact competitiveness of private firms and they may concentrate on these terms for short-term investments. In Public R&D zone, we assumed that uncertain but novel terms may be funded by public resources because of their risky nature and we think that it is compatible with the market failure perspective. High-risk investment zone may be accepted as risky for all parties and low-risk investment zone may be understood as not highly profitable. Medium Risk Investment Zone may be applied for government funded private company projects. So that, risk can be shared between public and private parties.

3. CONCLUSION

Forecasting technology emergence and understanding its nature may give competitive advantages to firms in micro level and countries in macro level. Finding the emergence terms is main subject of text mining and so called tech mining studies in the literature. There were many models proposed for finding it. However, there is no consensus on a model for finding technology emergence terms. Because of this, we propose a conceptual model by handling technology emergence from a multidimensional perspective. We call it Technology Emergence Evaluation Diamond and intersections of dimensions we proposed some strategy and policy solutions. In further studies, we think the model can be applied and based on findings applicability and reliability of the model can be tested.

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