

Unveiling the Knowledge Structure of Technological Forecasting and Social Change (1969-2020) through an NMF-based Hierarchical Topic Model

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Abstract: This article examines the knowledge structure of the journal *Technology Forecasting and Social Change* (TFSC) from its inception in 1969 until 2020. In this paper we argue that the structure of knowledge in the field of technological forecasting is more complex than a topic model -- a bag of words -- can in fact effectively reveal. Therefore we propose and demonstrate a hierarchical model that selectively combines topics at varying levels of generality. The resultant analysis, which is based on non-negative matrix factorization, reveals four distinct branches of technology forecasting work, composed of seven distinct topics. Each topic and branch are examined individually through a detailed examination of terms and keywords. Representative works and authors in each of the branches are also identified. The method enables the examination of the complex structure of knowledge in a scientific journal in a succinct representation. The resultant analysis can assist future researchers, enabling them to better position their work, and to better identify the key references across the various subject silos.

1. Introduction

Identifying key research topics, and highlighting promising emerging areas, is indispensable for multiple reasons of management and policy. In the previous literature on technological forecasting (TF), attempts have been made to review the development of this field as a scientific domain or discipline, to systematize the technology forecasting methods that are developed therein, to forecast technological change and to better understand its impact on public and private organizations' activities, and to build new guidelines to be followed by this field of study (Albright 2002, Martino 2003, Miles 2010, Miller and Swinehart 2010, Kang, Jang et al. 2013). Indeed, technological forecasting as a field continues to evolve even as the output of scientific work increases. It is common for scholars to periodically seek to make sense of the knowledge produced and accumulated, to identify new important contributions and works, detect trends and research traditions, understand which research topics are addressed, the methods and applications employed, delve into the knowledge structure of the discipline and its intellectual bases.

Our work begins with the concept that the future advancement of a field builds upon existing scholarship. As a result, we draw upon all research articles published in the journal of *Technology Forecasting and Social Change* (TFSC) during the last fifty years. This journal is regarded as the one of the most influential journals when it comes to the publication of research about technology forecasting. Such an approach neglects a vast literature of publication in books, as well as publication in white papers or reports – the so-called grey literature of science. This approach also neglects other influential journals for forecasting and scenario analysis. Despite these omissions the data which is collected and analyzed is suitable for the purposes of this article. These purposes are to reflect upon the history of the journal as a whole, to provide a comprehensive overview of the content of the journal, to help authors in deriving strategies for developing new research contributions, and to assist editors in understanding the structure and value of individual publications. Where possible given the data we also draw conclusions about opportunities and direction of change for the journal as a whole. This effort should thereby be of help to scholars in automatically discovering the intellectual bases of the field, in developing useful conceptual frameworks for the field, and in identifying the various streams of knowledge in TF. We further hope that this study can also be of assistance to journal editors, research scholars, and other private or public sector organizations to better assess the current and anticipate the future state of knowledge in TF.

The primary methodological challenge of this article is to succinctly and accurately reveal the structure of scientific knowledge in the journal. This paper makes two claims regarding the development of such structures. The first claim is that the content of the article itself is an effective measure of scientific knowledge. This claim is contested for instance by those that regard the primary means of encoding knowledge and structure is through a web of citations. The second claim is that knowledge structures are usefully and primarily structured in a hierarchical fashion. This claim is less contested than it is side-stepped. Many researchers build statistical models which implicitly assume the structure of knowledge is flat, or is contained in individual silos. We return to these issues of what needs to be mapped, and the structures onto which it is to be mapped, in the approach and methodology section.

The remainder of this paper is organized as follows. The literature review in section 2 presents a brief introduction of the research history of TF field and TFSC journal. Section 3 discusses prior work in the area of text and topic modeling. Section 4 introduces the methodological approach. Section 5 describes discuss the data and features of our NMF-based hierarchical topic model. In section 6 we discuss the results for detailed analysis. Section 7 provides results and recommendations, and the section contains our main conclusions and implications for future research.

2. A Historical Review

A brief look back at the trajectory of the TF field and TFSC makes clear why it is interesting to track the structure of knowledge in this journal. The following review is structured by decade. TF research was begun under the aegis of U.S. government in the 1950s (Kaplan, Skogstad et al. 1950, Helmer and Rescher 1959), the foundational era of the development of TF was from 1950s-1970s. It responded to requests by government for building the capability of

using foresight as a tool in designing policies and strategies that exploit emerging and critical technologies for the benefit of country development. All the principal methods of tech forecasting were introduced during this time, and can be fit into the main families: expert opinion, design methodologies and morphological analysis, creativity methods, monitoring, reasoning by analogy, scenarios, simulation, tech mining and other archival methods, case-based methods, and trend analysis (Porter 2010).

TF research developed further in the 70s and 80s, the application of TF methods crossed sectors from government to different areas. 1970's studies emphasized TF on building infrastructure and on the then emerging areas of computers and communication. Also some studies were related to the "lifestyle", showing the thinking of the time that technology could have influence on living standards and societal impact (Moore and Pomrehn 1971, Goodwill 1972, Kaufmann 1973, Huber 1979, Mcglen, Milbrath et al. 1979). By the 1980s, TF research focused mainly on engineering capabilities, associated with innovation in generic technologies including new materials, microelectronics, biotechnology, electronics, and information technologies. (Henize 1981, Ahmad 1986, Coates 1986, Ranta 1989), in addition, it expanding further into various topics such as business, education, political risk, market-opportunity and energy futures. (Bowonder 1981, Lee and Bereano 1981, Martino 1982, Hastedt, Ascher et al. 1985, Mitchell and Vraets 1988).

TF research grew further in the 90s and 00s, the further application of TF techniques brought foresight to science, technology and innovation policy-making, contributing insight into the technology base of new industrial sectors in the market such as the automobile sector and the energy sector. (Lehtila, Silvennoinen et al. 1990, Miyazaki and Kijima 2000, Jorgensen 2005, Steenhof and Fulton 2007). The TF research provided suitable methodologies to promote innovative development, fostering economic and social benefits. Its outcomes are policies that deal with innovation, industrial growth and competitiveness. In these two decades, TF methods were expanded - old methods retain value but being supplemented by new methods that exploit large information resources and deal with complex systems. For instance, network methods were used with TF activities in some degree, such as social networks (Lendaris 1990, Agami, Atiya et al. 2009), knowledge networks (Fernandez-Arroyabe and Arranz 2002), innovation networks (Rycroft 2007), R&D networks (Arranz and de Arroyabe 2007), etc.

TF research gained maturity as a field after 2000s. It is applied to a wide variety of new topics and technology during this time. By the beginning of the 2010s, technology forecasting activities were across a broad spectrum of technologies and application industrial sectors - nanotechnology, dye-sensitized solar cell technology and other high-tech industries (Joe, Tsai et al. 2014, Munari and Toschi 2014, Li, Zhou et al. 2015). In this era TF activities takes more responsibility for environmental protection and more concern for climate change and sustainable transition. More new topics are integrated to explore the application of TF methods, such as open innovation, urban sustainability, smart city, risk identification, energy transition, renewable economy, social commerce, etc. (Eames and Egmore 2011, Alexander and Martin 2013, Hajli, Shanmugam et al. 2015, Grimaldi and Fernandez 2017). Furthermore, though there are hundreds of TF methods were introduced, traditional TF methods are constantly being improved, and new methods are emerging for enriching TF methods in each family, such as context sensitive data fusion (Staphorst, Pretorius et al. 2016), complex adaptive system modeling (Kuhmonen 2017), and socio-technical energy transition (STET) models (Fernandez-Duran 2014).

From the foregoing overview, the development of TF research incorporated multiple research methods, applied across multiple topics, which are utilized in multiple domains. These developments have all been reflected by papers published in TFSC journal. As a field, TF is interesting because of its complex and extensive history. An attempt at exploring the structures of technological forecasting knowledge would be more interesting base on the TFSC journal.

3. Previous Work

As stated in the introduction to the paper our approach is two-fold. The paper evaluates the knowledge contained in papers using words and phrases. This knowledge is then mapped onto a hierarchical structure providing a succinct and accurate representation of knowledge in the field. Even though many studies have applied content analysis techniques to bibliometric analysis, there are still various questions which warrant further attention. How may we extract rich and useful information from text data efficiently? How can we show the associations among major research topics in a field or journal (i.e., how can detailed subject areas be categorized into a hierarchical relationship)? How to reveal the complex structure of scientific knowledge (i.e., words, documents and research topics) in a succinct representation?

Co-word and co-occurrence analyses are examples of fundamental methods for exploring concepts and the relationships between them by means of word relations in documents, which enables the identification of a scientific intellectual structure (Liu, Hu et al. 2011, Ronda - Pupo and Guerras - Martin 2012, Hu, Hu et al. 2013, Hu and Zhang 2015, Xie 2015). This work builds strongly upon this tradition of work. Co-word and other co-occurrence data have the potential of being analyzed using a variety of different techniques to reveal the implicit structures within the research (Kim and Lee 2008, Song and Kim 2013).

Citation and co-citation analyses, co-word analysis, keywords co-occurrence document co-citation analysis, authorship analysis, journal analysis, and social networks analysis are tools for investigating the knowledge structure of a field of inquiry or a journal (Ramos-Rodríguez and Ruíz-Navarro 2004, Charvet, Cooper et al. 2008, Durisin, Calabretta et al. 2010, Ravikumar, Agrahari et al. 2015, Uddin, Khan et al. 2015, García-Lillo, Úbeda-García et al. 2016, Khasseh, Soheili et al. 2017, Vargas-Quesada, Chinchilla-Rodríguez et al. 2017, García-Lillo, Claver-Cortés et al. 2018, Kabongo 2019). In addition, the intellectual structure of scientific domains can be examined as a cluster via clustering techniques (Cho 2014, Yan, Lee et al. 2015).

The early work in information retrieval involved indexing a corpus of data with keywords (Salton and McGill 1983) . Retrieving the relevant work entails evaluating matches between the user query and available records in the database. Cosine measures are used to quantify the degree of overlap, and frequency weighted measures such as tf-idf can be used to ensure that rarer terms in the query are given appropriate weighting when evaluating suitable matches. Unfortunately this technique has been proven to be brittle, and tends to be unduly concerned with the specific words used in the query rather than the general meaning of the words selected. A remedy was subsequently proposed whereby the words and documents are embedded in a lower dimensional space (Deerwester, Dumais et al. 1990). This lower dimensional space is useful for capturing general meaning, and removing over-dependence on rare words or singular occurrences in the data. The embedding procedures are linear, and are based on the L2 norm.

Previous reviews of knowledge structure of journal focused mostly on author and journal citations analyses, this study attempts to explore the knowledge structure of the articles of the TFSC journal via text classification and clustering and document representation. Such models succinctly and robustly represent the documents in a corpus, and as a consequence return summary vectors of the model vocabulary -- these are variously called factors, dimensions, or topics. There are multiple potential methodological approaches here, so we outline and justify the choices that are made in this study. The first choice is whether to use a deterministic or a stochastic algorithm. Deterministic algorithms, of which the chief example is singular value decomposition (SVD), perform a matrix reduction on the data. The data reduction technique returns column and row eigenvectors, which may be interpreted as dimensions of content, and document loadings. A wide variety of techniques are ultimately derived from SVD, including principal components analysis, correspondence analysis and multidimensional scaling (Cunningham 1996). A famous example of SVD applied especially to indexed documents, and purposed for information retrieval, is known as latent semantic analysis (Deerwester, Dumais et al. 1990).

Parallel efforts to develop statistical modelling techniques also progressed in the social and biosciences. Techniques such as principle component analysis, and factor analysis, were independently proposed and developed. A family of techniques for modeling and visualizing structural patterns of co-occurrence, known as correspondence analyses, were formalized and thereby demonstrated to share a common mathematical framework with principle components, factor analysis, and even latent semantic indexing. Still newer efforts in machine learning demonstrated how a language of probabilities and graphs could represent these older models, and specify heretofore unexplored models. These newer models are more explicit about the distributional characteristics of the data, and the expected structure of the underlying noise and residuals. A comprehensive survey of these various techniques is presented in Cunningham (1996).

Modern machine learning models emerged naturally out of this framework (Roweis and Ghahramani 1999). These models advance the state-of-the-art by specifying explicit distributions of the underlying data which can be confirmed or denied in light of the evidence. The non-negative matrix factorization approach offers techniques appropriate for count-like data, which cannot go negative (Lee and Seung 2001).. The underlying distributional assumption of the model is that it is being used to model Poisson distributed data at the level of individual words and documents. Another widespread and well-known machine learning and text modeling algorithms is topic modelling. Topic models assume that the data is drawn from a mixture of hidden distributions, hence the more formal name for the technique is latent Dirichlet analysis. In this technique hidden features in the data are discovered, extracted, and used to summarize and represent whole collections of text documents. The suitability of these two competing assumptions of document-word distributions, both Poisson and Dirichlet, is debated and continues to be empirically tested.

Probabilistic approaches defined hidden units as topics, which are represented by terms with a certain probability distribution, and assume that each document is mixed by topics. Such approaches include probabilistic principal components analysis, factor analysis, and probabilistic latent semantic analysis. Of these options the most mentioned in the literature is latent Dirichlet allocation (LDA), more popularly known as "topic modelling" (Blei 2012). Perceived failures of topic modelling have led to a number of expansions or extensions, including correlated topic models and nested hierarchical Dirichlet processes (Blei and Lafferty 2007, Paisley, Wang et al. 2015). Still other varieties of extended topic models include the Chinese restaurant process, and the pachinko allocation model (Blei, Griffiths et al. 2010). The chief difference between these models, beyond the distributional parameters, is the degree of mixing of topics permitted across different levels of the hierarchy. Most importantly the need for the hierarchical structure of these models also differs. Some models such as the correlated topic model afford a better representation of the data; other models such as the Chinese restaurant process allow better learning of a vocabulary which may be growing over time.

A regular hierarchy is based on a tree-like structure of nodes and arcs. The nodes are topics, or weighted bundles of associated keywords and phrases which have been indexed from the document set. The arcs are relationships between the various topics. The tree can be defined using two parameters. The first parameter is the number of levels in the tree, while the second parameter of interest is the number of children assigned to each parent. So for instance in this work we examine three-level trees, where each parent node has two children each. The tree is rooted in a single parent node. Each parent node then has a fixed number of children. The tree ends at the lowest level, with the leaves of the tree. The leaves themselves do not have any further children. The resultant hierarchy is regular, because it has the same structure at each node and level, aside from the parent and leaves. The resultant hierarchical topic model differs from a standard topic model because it constrains particular topics to be used in conjuncture with one another. This differs significantly from a regular topic model where all topics might be found together interchangeably.

While each node consists of a set of weighted bundles of keywords or topics, these topics may also be used to specify documents. In the topic models described in the following section, each document is modelled as a mixture of different topics. Thus we can use the topic models to identify relevant documents and to proportionally assign them to one or more nodes. Since the model is hierarchical, the weights for many of the topics are effectively constrained to zero. The mixtures are distributed down one branch of the tree, with the number of parameters of the mixture being equal to the depth of the tree. As we will see this assumption about constrained mixtures is a good fit given empirical evidence. Effectively then the model enables documents to vary from the most general topics, to specific and specialized topics, for which only certain documents qualify given their topical pre-commitments.

We propose a novel hierarchical topic modeling method using non-negative matrix factorization (NMF). The technique reveals various topics present in the data. It is not necessary that these topics be statistically independent or mutually exclusive of one another. In this method, the main difference from other hierarchical and probabilistic topic models is that we predefine a hierarchical topic model. Then the NMF model is constrained to fit within the hierarchical topic model by setting key quantities to zero. Using our method, we are able to identify the overlap between major research topics, share the valuable research branches, and present the documents in a concise form. Furthermore, by using the model we can produce a measure that shows how close the model conforms to, or departs from, hierarchical assumptions. Given evidence of this overlap, and using the method, we transform a flat structure of topics into a hierarchical topic tree structure.

The model proposed in this paper is based upon a well-known premise that science is structured like a tree. More specifically scientific knowledge is structured with overarching disciplines, fields or specialties, and research fronts. Individual authors will borrow from each of these languages when describing their own work. The highest-level language, associated with their discipline is likely to be shared by many others in their field. The language of research specialties is more unique, and is less likely to be used by others outside of their field. When authors use the language of a research front they have committed to a specific field of knowledge, and have identified themselves as members of this specialized community. This indicates that other specialized vocabularies will not be used or be useful when communicating their work. Although commonly discussed this hierarchical structure of scientific knowledge is rarely questioned or explored. A notable exception is the work of Machlup (1982).

4. Methodological Framework

Figure 1 displays the process used for the analysis. The analysis consists of five stages, with constituent steps. Many of these steps are common to and well documented in other text mining applications. We therefore provide extra details on the steps unique to this specific text mining methodology. The stages in the analysis are the collection of data, the modelling of the data, the reporting of the data, the validation of the model, and the formulation (or reformulation) of the hypotheses governing the data. The cycle is iterative, and can begin with stage 1 (the collection of the data), or with stage five (the formulation of the hypotheses).

Stage one begins with defining the question for investigation and defining the database and query used to collect the data. Once downloaded the data needs to be regularized, and the text divided into tokens for indexing. An appropriate vocabulary needs to be selected for the analysis. Certain common words, known as stop words, are disregarded from further analysis. The text is then indexed, with the presence of vocabulary words across documents noted. Represent the total number of documents in the analysis with the variable d , and the total number of words contained in the vocabulary with w . The analysis may then proceed to stage 2, the modeling of the data.

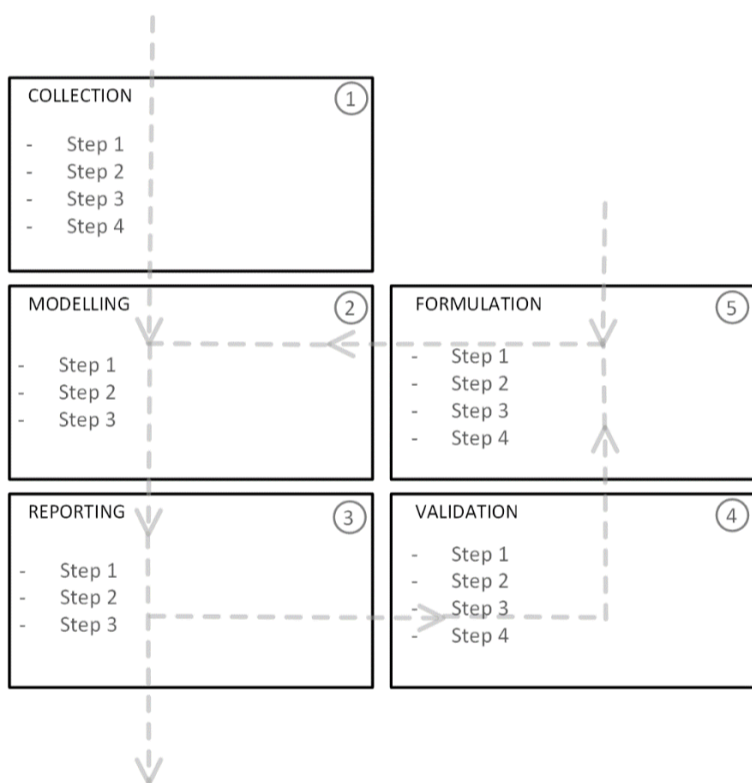


Figure 1. Analysis Flow Diagram

Stage two involves fitting a non-negative matrix factorization model to the data. Prior to the analysis the number of topics needs to be selected. A small, arbitrary number of topics can be selected to start the process. Let's call this quantity n . The total number of topics n will be revisited with evidence regarding the quality of the model in stage 5 of the modeling process. The analysis procedure returns a decomposed document matrix, called W . The matrix is sized d documents by n factors, and contains the weight or loading of each document on each factor. The analysis procedure also returns a topic matrix, sized n topics by w vocabulary words. This is represented by the variable H . This matrix shows the relative frequencies of words in each of the extracted topics. The extracted topics represent the main scientific specialties present in the data. Taken together the W and H matrix may be used to parsimoniously approximate the original data.

Another product based on the H matrix is useful for clarifying the structure of the matrix. This matrix (called D') is calculated by multiplying the H matrix by its transpose ($H^T H$). The matrix D' represents a co-occurrence matrix of the topics, and therefore consists of the overlap of topic terms taken in totality across all the documents in the data. There will not necessarily be a natural match between the topics of the extracted model and the topics of the design matrix. This is because there is no natural or predefined order in which the topics are extracted from the NMF algorithm. As a result it is also necessary to permute the data in order to enable the best possible match with the hypothesized design matrix D . The selection of this design matrix is discussed more fully in stage five. In absence of an explicitly selected design matrix, a flat model can be selected instead to initiate the process.

Stage three of the process involves reporting the results. Reporting the document matrix W requires that each document be assigned a particular branch of the classification tree, with different proportions of vocabulary across each of the nodes. Summary statistics regarding the number of documents located on each branch, and the percentage of vocabulary expressed at each node, is also useful to report. Reporting the topic matrix H consists of using word clouds to display the proportional content at each node. It is also useful to create a summary table of each topic vector, with highest loading vocabulary words, and a qualitative assessment of the overall content within the topic. Finally it is important to report on the overall structure of the model. The initial analysis may result in a flat “bag of words” model. However in step five a hierarchical structure may be formulated, and then tested in light of the model results. This process is described more fully in stage 5 of the process. The resultant diagram represents the structure of the topic tree, the relationship between the topics, and the assignment to overarching high level topics and specific topics positioned lower in the tree.

Stage four requires validating the data generation hypothesis. The first test is to determine the likelihood of the data under the flat model, whereby each document has an unconditional rate of word use across each of the extracted topics. A second test is to test the likelihood that each document contains an equal amount of topic content. The likelihood of the data under a hierarchical model can also be evaluated. This requires estimating the likelihood that specific topics are not used together in the data subject to the specified model hierarchy. In subsequent iterations the quality of fit of current and previous models can be compared, and a new hypothesis can be formulated. A final step in this validation process is to evaluate the parsimony and the interpretability of the model. An objective measure of parsimony is possible by calculating the total number of parameters required to specify the model. There is always a trade-off between more parsimonious and more accurate or more likely models. This trade-off can be captured using the Akaike Information Criteria (AIC) measure. The interpretability of the model cannot be solely reduced to numerical metrics, and depends on part of the audience and intended purpose of the model.

Stage five of the methodology involves formulating a new model in light of data and evidence. The principle model structure to be considered is a regular hierarchy. The regular hierarchy can be specified with two numbers m and n . The number m is the number of levels in the hierarchy beyond the root of the tree. The number n is the number of children of each node at non-terminating branches of the tree. The resultant tree structure can therefore be specified using the following notation $T(p,q)$. This is read as “a tree with p levels and q children at each node.” The total number of nodes in the tree can be calculated by summing the number of nodes at each level of the tree. Every tree has a single root node. A tree specified by $T(2,3)$ contains one node at the root of the tree, three nodes at the first level of the tree, and three children of each of the three parents at the first level of tree, for nine nodes at the second level. The total number of nodes in the tree is therefore 13. It can be helpful to draw out this tree, as well as to represent this tree in matrix format. The matrix format of the tree is known as D , the design matrix, and is used for model fitting purposes in subsequent iterations of the model. A variety of design matrices are presented in figure 2. The design matrix approach can be used to represent a range of structures including standard flat topic models, regular and irregular hierarchies, and lattice structures. This is discussed further in the future research section, where a specific design matrix and its principle spanning vectors are discussed.

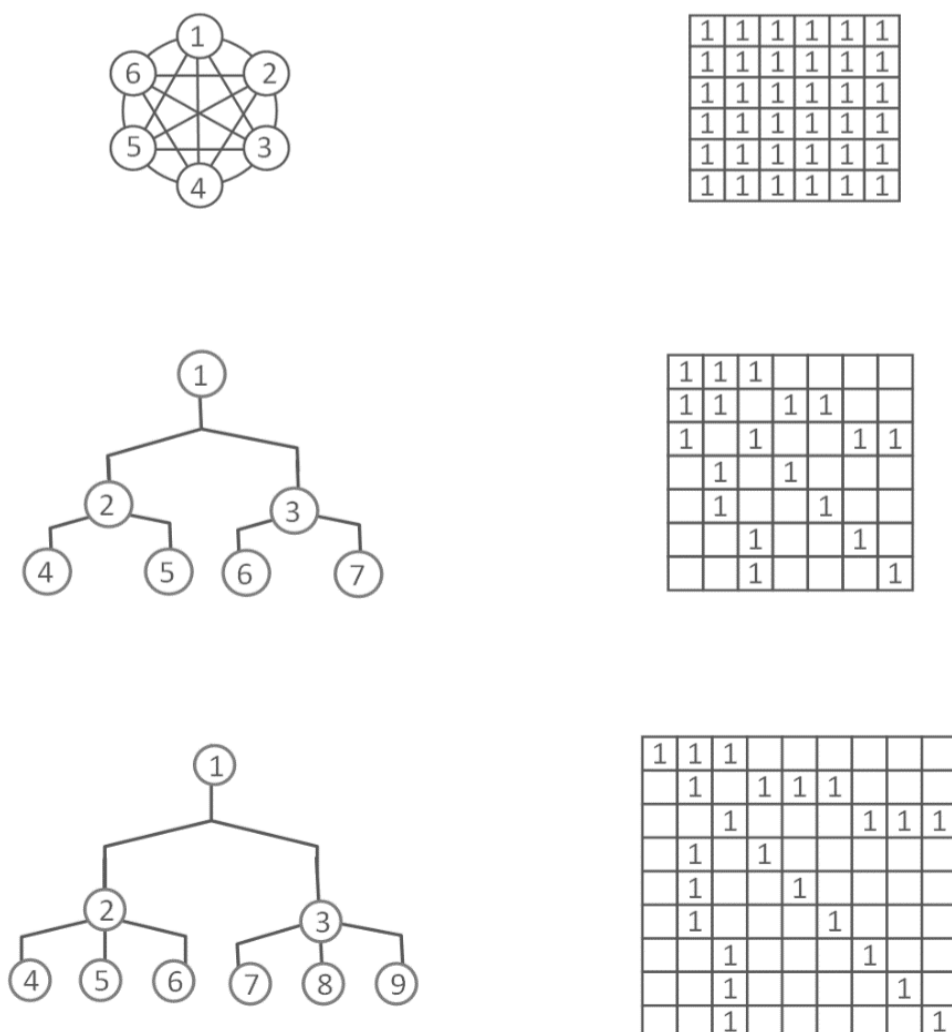


Figure 2. Example Design Matrices

A number of example design matrices are provided in figure 2. These consist of an undirected graph on the left of the figure, and a matrix representation of the graph on the right of the figure. Three graphs are presented. The topmost is a fully connected graph. As seen in the design matrix all nodes are connected to all nodes. The middle example is a regular tree $T(2,2)$. Most topics in the tree are unconnected to each other. This disconnection is an important assumption concerning the data, which can be empirically investigated. The bottom-most graph represents an irregular hierarchy with one, two and six nodes at each level of the tree. This structure implies an even greater amount of sparsity in the topic to topic relationships. A summary of the modeling steps discussed above is presented in table 1 below.

Table 1. Detailed Summary of Modeling Steps

| Stage | Name | Steps |
|---------|-------------|---|
| Stage 1 | Collection | Step 1. Define problem Step 2. Define query Step 3. Regularize the data Step 4. Index the data |
| Stage 2 | Modelling | Step 1. Analyze the data using NNMF Step 2. Extract the W and H matrices Step 3. Permute the output matrices to match structure |
| Stage 3 | Reporting | Step 1. Report and summarize the W matrix Step 2. Report and summarize the H matrix Step 3. Report and visualize the model structure |
| Stage 4 | Validation | Step 1. Evaluate the correctness of model assumptions Step 2. Evaluate the likelihood of the data under the model Step 3. Evaluate the parsimony of the model Step 4. Evaluate the interpretability of the model |
| Stage 5 | Formulation | Step 1. Formulate a new model in light of evidence Step 2. Specify the level and children of the new model Step 3. Create the design matrix associated with the model Step 4. Determine the appropriate parameters for the model |

5. Data and Analysis

In this section we discuss the choice of data, and the parsimony, quality of the NMF solution. We describe matrices include terms and documents, terms and topics, topics and documents involving the modeling regular hierarchical structure. The analysis involves all 5514 articles indexed in Web of Science under the source *Technological Forecasting and Social Change* as of 18 May 2020. For each of these articles the titles, the author keywords, the keywords plus, and the full abstract are extracted for further analysis. Some full abstracts are not available from before 1991. Therefore, we try to solve this problem during data processing. We sort all articles into abstracted set (3606 articles) and non-abstracted set (1908 articles), indexing the abstracted and non-abstracted set using only titles, and convert these into a full, non-sparse matrix, perform NMF to ensure robust comparison. We find the most similar abstracted article for each non-abstracted article by calculating the distance between the non-abstracted and abstracted set. Note that we lose some of the non-abstracted titles because we can't find index words, there are 1377 articles are lost due to lack the content, and 4137 articles can be used for indexing and content analysis.

It has been widely observed that singular value decomposition is inappropriate for count-like inputs since it may result in negative loadings in the row or column dimensions, and the low-dimensional approximation which results may also contain negative quantities. This inhibits the ready interpretation of these quantities as controlled vocabularies and as document loadings. As a consequence more recently another deterministic alternative is proposed. The non-negative matrix factorization (NMF) technique decomposes the document term matrix into a document by topic matrix, and a term by topic matrix (Lee and Seung 2001). By convention, the document by factor matrix is represented by the symbol W , and the term by factor matrix is represented by the symbol H . The technique is suitable for often dramatic reductions in the space of features. The methodological review turns to probabilistic implementations of these algorithms, before proposing a hierarchical, deterministic model that is described in the next section.

Indexing and analyses are performed in Python 3.3. Indexing is performed using the scikit-learn package `feature_extraction.text`. Stopwords (as provided by the package) are removed. The various forms of copyright used by Elsevier are removed as well. Words are reduced to lower case and punctuation is removed. No lemmatization or stemming is used. As will be shown, lemmatization or stemming does not materially change the output. Using plain text eases further interpretation. The top 5000 words by total count are used to index the articles. This number of features is sufficient to produce a rich description of journal content, and to effectively place individual articles within a taxonomy of content. After indexing the documents with the 5000 terms a dense document-term matrix is produced.

Seven major feature vectors, or topics, are extracted from the document, using Non-Negative Matrix factorization. This technique is implemented in scikit-learn. Seven feature vectors permit the creation of a topic hierarchy, which offers a richer structure for understanding the relationships between the topics. The fitting and exploration of this hierarchy is described more fully below.

5.1 Parsimony and Quality of Fit

The following section describes the quality of the NMF solution. In summary, the NMF solution reduces the dimensionality of the articles more than 300 times. The resultant summary reproduces a fifth of the total variance in the original matrix. The content in the document term matrix is highly varied. Unsurprisingly a seven-dimensional solution only duplicates a small portion of the full matrix. This can be seen through an analysis of variance in table 2, where

a seven factor solution explains 18% of the variance in the document-term matrix. The average explained variance per abstract is about 27%, indicating that about five explained words can be added to every document. Although the reproduction of the articles is quite limited, a full prediction of content is not necessary for the purposes of this article. In fact to accomplish the aims of this article in producing a readily interpretable model, we should err towards producing a smaller if less accurate model, than a larger and less interpretable one.

Table 2. Quality of Fit

| | |
|---------------------------|----------------|
| Explained Variance | 135,373 |
| Residual Variance | 625,527 |
| Total Variance | 760,900 |
| R² | 17.8% |

Although the explained variance is low, this is a highly succinct summary of the indexed articles. As shown in table 3, there are 4137 documents with vocabulary size 5000, resulting in over 15 million data points. By applying the proposed NMF algorithm to factorize document term matrix into two matrices, W Matrix of size 4137×7, and H Matrix of size 7×5000, and setting topic number is 7, where have been summarized in 56 thousand parameters, each row in W Matrix represent 4137 documents distribution over 7 topics and each column represents a topic, while each row in H Matrix represents 5000 terms distribution over 7 topics and each column stands for one topic. Thus, this is nearly a 323-fold reduction in the space of parameters.

Table 3. Dimensionality Reduction

| | Parameters | Dimension |
|---------------------------------|------------------------------|-------------|
| Document Term Matrix | 20,685,000 | 4137 x 5000 |
| W Matrix | 28,959 | 4137 x 7 |
| H Matrix | 35,000 | 7 x 5000 |
| W and H Matrix | 63,959 | |
| Dimensionality Reduction | 323 = 20,685,000 / 63,959 | |

Alternative numbers of topics are extracted, tested and interpreted. Alternative structures are examined for the data including regular and irregular hierarchies, two and three level graphs, and flat topic models. Alternative indexing schemes are also used and their impacts evaluated. The structure is robust with a few caveats. Increasing numbers of topics reveal a greater likelihood of artefactual topics related to the abstract structure of the raw text. Increasing numbers of topics often reveal an embedded character of topics, providing successive detail and resolution to major themes of the document corps. Frequently occurring terms serve as anchoring points for the overall structure of the data. Removing these commonly occurring terms results in dramatic differences in the topic structure extracted. As a result a very conservative stop list is used to ensure replicability. A more conservative stop word removal process also enables higher interpretability of the resultant factors, even given the lack of context for the common words introduced into the topic structure.

5.2 Documents

The total number of terms indexed from the text varied widely. For many documents from 100 to 150 total words could be indexed. For others this varied upwards to 350. The earliest records do not provide a full abstract, so these documents are naturally indexed much less richly than the rest. A smaller number of documents are indexed to fewer than a few dozen terms. The NMF replaces a string of terms with, in this case, a seven-dimensional vector. The vector may be sparse; many documents do not use the full vocabulary of the journal. The vector therefore contains rational numbers and zeros. Figure 1 shows the relationship between terms and the factorized vector. Each point is a single abstract.

A few observations of the articles and their factorization is in order. The longer the indexed abstract the richer the term usage. Abstracts over 150 words use an increasingly more varied vocabulary, as measured by the NMF algorithm. In contrast, the shorter abstracts tend to draw upon a much more limited sample of vocabulary (figure 3, left). The scaling of the factorized matrix is somewhat arbitrary. Since both the term and the document matrices are needed for reconstruction, either can be used in reproducing the full details of the factorized document. The documents are factorized into vectors ranging in sum from 0.5 to 1.5 (figure 3, right). Thus, each unit of the factorized matrix in this instance represents the placement of about 150 words.

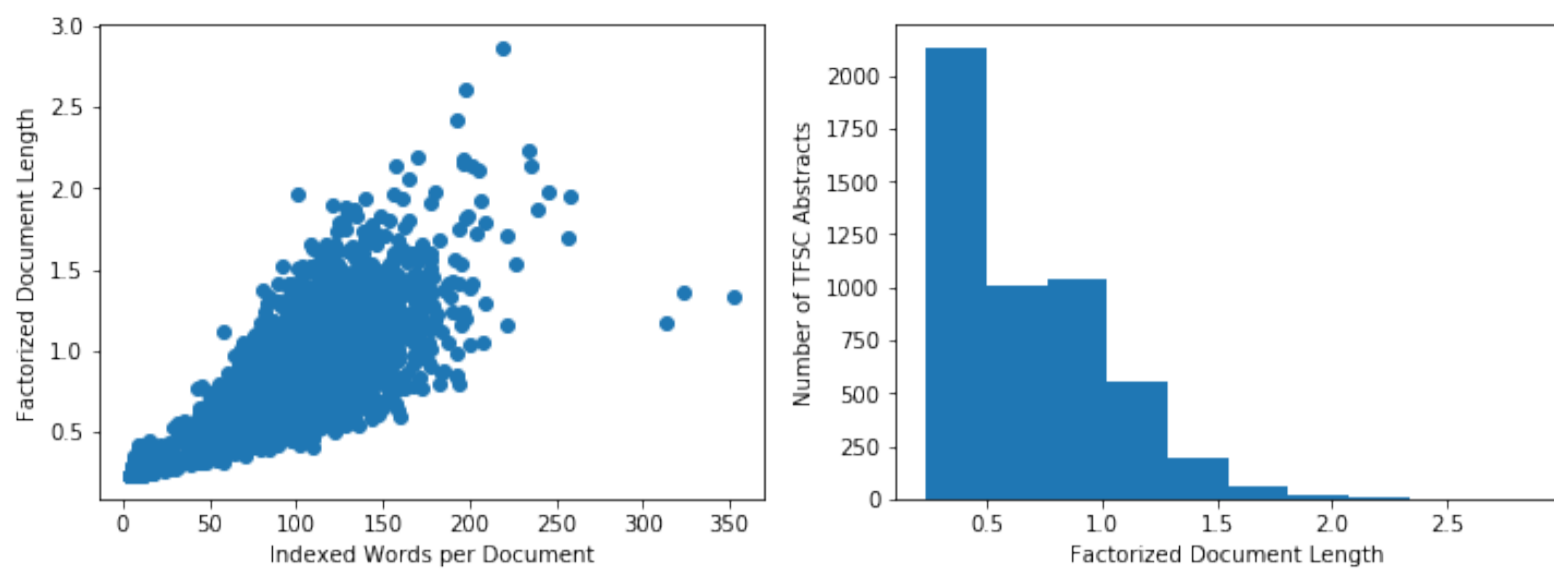


Figure 3. Indexed Documents and their Factorized Length

5.3 Terms and Topics

All 5000 indexed terms in the abstracts are factorized into seven topics using the NMF procedure. The technique is therefore an unsupervised learning procedure. The term factorization is encoded in the H matrix, which shows the respective weight and contribution of each term to a resultant topic. Terms which are explicable load highly on one or more of the topics. Terms which correlate poorly across all seven vectors are underweighted and thereby automatically drop out of the analysis.

Each of the seven topics is discussed briefly, and then in greater detail in the results section. In short, the various topics represent aspects of technological forecasting and social change. The term social requiring special detailing into two distinct topics, topics five and seven detail the *social* content of the journal, these topics involves social media, social change, social capital, social network, social theory, as well as market, commerce, business, economy with diffusion or bass models. The *technological* content of the journal is represented by topics one and four. Topic four represents technology development, while topic one involves *innovation*, more specifically innovation policy or open innovation. The *forecasting* content of the journal is subsumed in topic six, more specifically this topic includes foresight, futures, and scenario analysis approaches. The *change* content of the journal is embodied in topics two and three. Topic two involves climate/energy change, the other topic three involves *transition*, particularly socio-technical transition and sustainability transition, are discussed here.

5.4 Correlated Topics and Documents

A feature of the NMF model is that the derived documents and topics may be correlated. This stems naturally from the fact that no negative entries are allowed in the factorization matrices. As a result of the non-negativity constraint the dot product between any two documents or term vectors can be, at best, zero. The presence of non-negative dot products between term or document vectors indicates non-independent, or correlated factors.

Therefore, in practice there can be considerable overlaps between topics, created by shared usage of words. This is very different from other statistical techniques, such as SVD, which ensures linear independence between the extracted factors. As will be shown, these correlations between topics are meaningful, and provide useful additional insight into the structuring of topics within the journal.

In this work we investigate the presence of a sparse structure in the H1 matrix which is indicative of topic hierarchies. A regular hierarchy with seven topic nodes, three levels, and four branches is indicated by a particular structure of sparsity in the H1 matrix. Figure 4 (left) shows such a regular hierarchy, while on the right the equivalent matrix structure is presented.

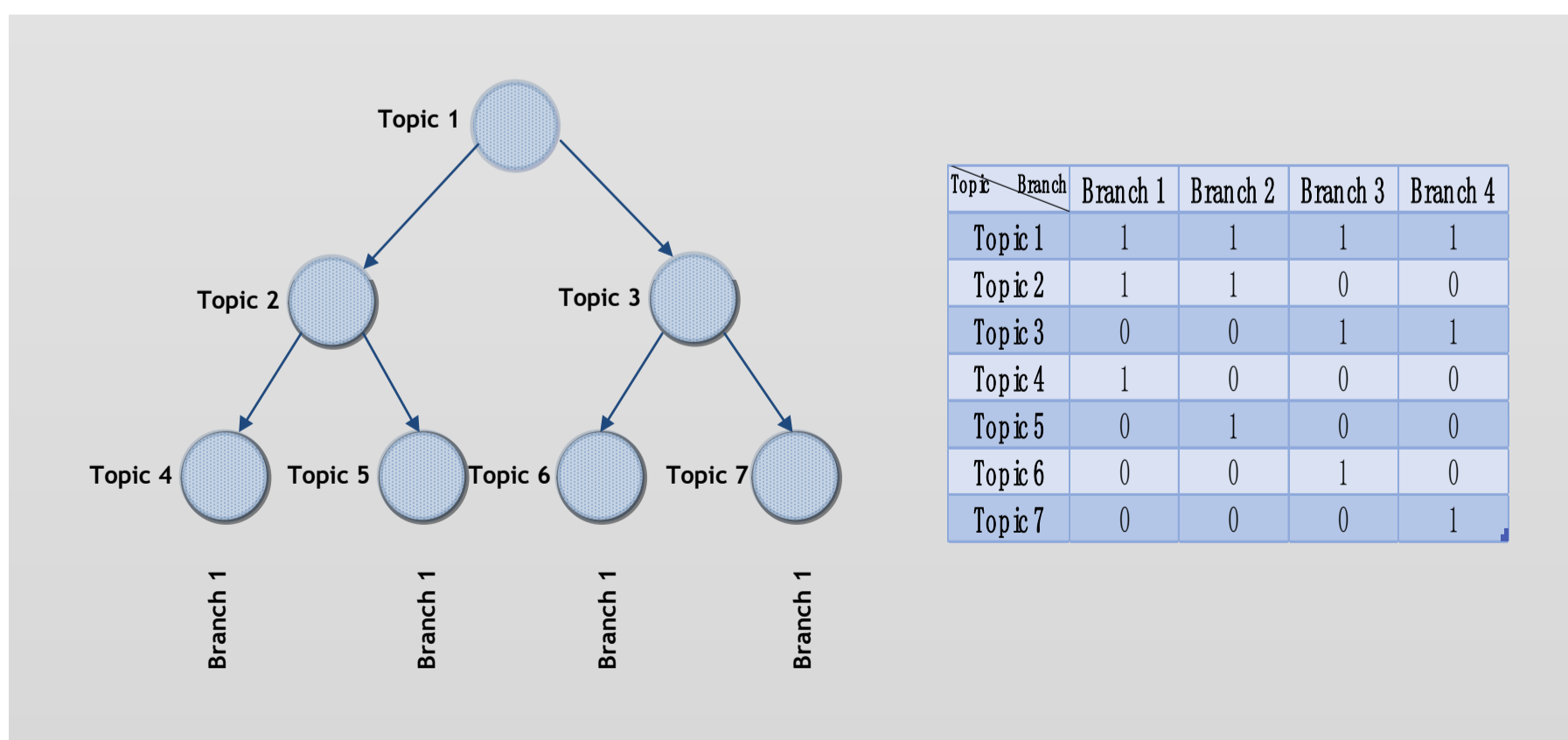


Figure 4. Regular Hierarchies and their Matrix Representation

Empirically a very similar structure is seen in the data for TFSC. The material shown in table 3 is based on the H matrix output from the NMF procedure. The objective is to find a series of small weights which can be set to zero and thereby regularized in order to best reveal the hypothesized hierarchical structure in the data. Recall that given this structure each branch of the tree must contain three, and only three topics. Furthermore, one topic must load on all four branches, two topics must load on two branches, and the remaining topics must load on one and only one branch. Table 4 demonstrates the sparse structure of the W matrix, demonstrating that any given document is restricted in its sampling of vocabulary across the four topics. Table 4 provides an indication of the fit of the empirical data to the design structure as specified in figure 4. The table numbers each of the topics, provides a summary name for each topic, and identifies each of the major branches of literature with a letter ranging from A to D. The summary name of the topic is introduced here, but will be later justified through an introspection of topic word clouds. This material is presented later as figure 5. The matrix is derived by finding the principle spanning vectors of the W matrix, demonstrating which topics are used in which combination. The quantities in the table are unitless and unstandardized but could be rescaled to sum to one and thereby be interpretable as probabilities.

Table 4. Topic Co-Occurrences

| Number | Name | Branch A | Branch B | Branch C | Branch D |
|----------------|---------------|----------|----------|----------|----------|
| Topic 1 | Innovation | 0.216 | 0.483 | 0.000 | (0.006) |
| Topic 2 | Change | 0.000 | 0.000 | 0.653 | 0.000 |
| Topic 3 | Transition | 0.373 | (0.058) | (0.045) | 0.000 |
| Topic 4 | Technological | 0.000 | (0.061) | 0.000 | 0.298 |
| Topic 5 | Social | 0.084 | 0.094 | 0.095 | 0.111 |
| Topic 6 | Forecasting | (0.014) | 0.000 | 0.095 | 0.245 |
| Topic 7 | Market | (0.063) | 0.132 | 0.000 | 0.000 |

A hierarchical pattern is revealed through comparison to the design matrix. Three caveats are in order in deriving this structure. First, the rows and columns may be reordered without any loss of generality. Second, there are small positive quantities which disrupt the perfect structure of the hierarchy. These elements are shown in parentheses. A third caveat is that in this hierarchy the topics are not equally weighted. Topics lower in the tree are drawn more frequently than higher level concepts.

Another generic way to assess the relationships among topics is their similarity (Cronbach and Gleser 1953). In order to check whether co-occurrences of topics play a role in the correlation among them, we performed cosine similarities. According to the results presented in table 4, relationships between each topic and cosine similarities exhibit high-frequency term co-occurrence in topics that are highly associated with similarity among topics.

Table 5. Topic Cosine Similarities

| | Topic 1 | Topic 2 | Topic 3 | Topic 4 | Topic 5 | Topic 6 | Topic 7 |
|----------------|---------|---------|---------|---------|---------|---------|---------|
| Topic 1 | 1 | 0.283 | 0.469 | 0.267 | 0.359 | 0.333 | 0.473 |
| Topic 2 | 0.283 | 1 | 0.339 | 0.312 | 0.445 | 0.435 | 0.254 |
| Topic 3 | 0.469 | 0.339 | 1 | 0.318 | 0.462 | 0.450 | 0.302 |
| Topic 4 | 0.267 | 0.312 | 0.318 | 1 | 0.336 | 0.518 | 0.317 |
| Topic 5 | 0.359 | 0.445 | 0.462 | 0.336 | 1 | 0.486 | 0.382 |
| Topic 6 | 0.333 | 0.435 | 0.450 | 0.518 | 0.486 | 1 | 0.370 |
| Topic 7 | 0.473 | 0.254 | 0.302 | 0.317 | 0.382 | 0.370 | 1 |

Table 4 and 5 reveal contrasting information about the topical structure. Table 4 shows that the model parameters are sparse across documents while table 5 shows that seven topics overlap to a degree, sharing some of the same core words and concepts. The two perspectives of the data are compatible because one reflects the structure of documents, while the other reflects the structure of words. The underlying NMF procedure demands the extraction of overlapping topics given the fact that there is a constraint to produce non-negative factor loadings. The hierarchical approach shown here demonstrates that it is possible to find independent topic structures conditioned on their being separate branches of a topic tree. Other linear, non-hierarchical models are insufficiently expressive to capture this dependency in structured.

The finding of a simple, higher-order structure in the data has multiple implications. The finding of such a structure ensures a greater degree of robustness in the findings. Strict assumptions lead to fewer parameters which need to be identified in the resultant model. This ensures that future incoming articles can be

maximally fit to the current structure. Such a model does not however enhance the quality of the fit on the existing data. Detuning the matrix, by replacing selected elements with zero, may actually degrade the quality of the fit. Nonetheless it is possible to re-estimate the W and the H matrix to make an optimal fit to the assumed structure of the data. This can subtly alter the balance of terms associated with each topic. On the positive side, a hierarchical structure greatly eases the interpretation of the final results, and may enhance the conclusions which can be drawn from the model.

The following section interprets the results using a two-level strategy. First the major branches of the tree are discussed. Then a more detailed discussion of each of the topics is presented. Each topic is accompanied by evidence including word clouds and key citations. The preponderance and citation patterns for each of the topics is given. The dynamics of each of the topics, and their relative growth over time is discussed.

6. Results

In this section, we first discuss some key metrics for measuring the basic information of each topic. Following this, from the overall seven topics, we present the general introductions for per topic, by terms-based word cloud and keywords analysis. Third, we discuss the hierarchical knowledge structure from the four knowledge branches and four research components of the TFSC journal, and summarize the detailed research interests and representative authors from the literatures in each research component based on document content analysis, respectively. Finally, the knowledge dynamics of TFSC research over the years are analyzed.

While the data, method and model parameters are all reproducible interpretation of the topics and branches is always going to be somewhat subjective. The interpretation presented below hinges on the name of the journal, and on its core mission -- consequently there are topics for technology, forecasting, society, and change. There are actually two distinct technology topics -- one for *technological*, and another for *innovation*, this categorical basis is innovation is the process that create that technology, technology is a driver of both the evolution and proliferation of innovation. There are two distinct societal-facing topics -- one topic is *social*, and the other is named *market*. This breakdown of the social content is based on the modern concept of societal that argues the “social” came from the market, economic forces, social was thus not the product of innate human nature, but of the underlying form of economic organization in a given society, implying that social changes in response to improvements in the evolving market forces and relations of production. There are two distinct change topics – one for *change*, and another for *transition*. This classification of change content is due to the fact that the transition is the process we go through in response to change.

One side of the hierarchical knowledge structure tree represents the journal's mission, while the other side represents emergent content of innovation, transition, and market. There are actually two distinct branches of right side of the tree – one for social systems, and the other for technological systems. Branch C represents forecasting social change, and branch D represents forecasting technological change. The left side of the tree represents emergent content of innovation. There are also two distinct branches A and B -- one for transitions, and the other for market.

Using these insights, we can return back to the interpreting the overall structure of the tree. The structure of the regular hierarchy has *social* at the top of the tree. The second order branches are *innovation*, and *forecasting*. At the foot of the tree, under the *innovation* branch, are *transition*, and *market*. At the foot of the tree, under the *forecasting* branch, are the nodes for *technological* and for *change*. The most general topic of *social* is seen in all the documents. Topic *innovation* is a large topic, representing about 24% of the content of the journal. The tree is bottom-heavy, with 50% of the content words in the actual documents and abstracts.

6.1 Topic Metrics

The seven topics vary widely across key metrics of average age and average citation. Each article is assigned to its maximally scoring topic; other content categories in the article are ignored. The largest category is the *forecasting* category, which includes 792 articles. The smallest category is dedicated to *change* with only 382 articles. The *transition* topic is also the oldest topic in the journal. These articles date on average to 2008. The newest topics in the journal is the innovation topic, followed closely by the topic of social.

Also shown are the average citations for each of the topics. These citation distributions are highly skewed -- most articles receive zero citations, and only a very few articles receive a hundred or more cites. To give a better indicator of this complex distribution both the mean as well as the standard deviation of citations are provided in table 6. The *forecasting* articles receive on average the highest number of cites. The *transition* articles in contrast receive the fewest. The *innovation* topic receives the highest variation in cites; the topic as a whole receives a moderate amount of citation. The *transition* topic has the lowest standard deviation of citation, with the topic in general receiving relatively few cites.

Table 6. Key Metrics by Topic

| Topic | Theme | Number of articles | Year | Citation (S.D.) |
|---------|---------------|--------------------|--------|-----------------|
| Topic 1 | Innovation | 579 | 2014.0 | 22.5 (47.5) |
| Topic 2 | Change | 382 | 2009.9 | 21.2 (42.3) |
| Topic 3 | Transition | 653 | 2008.7 | 8.4 (19.6) |
| Topic 4 | Technological | 633 | 2010.9 | 23.3 (40.0) |
| Topic 5 | Social | 386 | 2013.5 | 17.3 (35.4) |
| Topic 6 | Forecasting | 792 | 2011.5 | 23.7 (41.2) |
| Topic 7 | Market | 693 | 2010.3 | 20.0 (33.1) |

We argue that despite there being a large number of articles in *transition* topic, the average age of these articles is much older -- on average these articles are 1 years to 6 years older than articles from the other category. This makes the lack of citation of these articles all the more remarkable. It's possible that articles on socio-technical transition or sustainability transition appeared relatively early. An alternative interpretation could be that the *transition* topic is some sort of residual or super-topic, such topic is quite common topic analysis, and tend to mixed with other research objects and factors in the articles while still not offering much specific and differentiating detail, resulting in a comparatively lower contribution. Of course, both explanations are possible.

In addition, the number of articles related to forecasting topic is the largest, and the average citation of these articles is the highest, it is possible that the comparative advantage of specific journals means that some worthy articles on forecasting for technological, social, economic and environmental change that may have come to the adjacent journals in economics or management, have instead been submitted and published in TFSC journal.

6.2 Overall Research Topics

This section details the content of the seven topics. To accomplish this, we studied the terms extracting in the publications' titles and abstracts, the correlation of terms across the topics are weighted using NMF, the terms for each topic are shown in Word Clouds in the figure 5. In addition, the additional source of information of context for topics, is supplemented by the author provided keywords, which are also used in this analysis besides title and abstract terms to reveal more information per topic. To help demonstrate the content of topics in more detail, table 7 provides a detailed summary list of the high frequency keywords for each topic. Terms and keywords, complement each other. The terms provide a concise overview of the core theme of each of the seven topics. The keywords supply more detailed and more concrete description of the themes. In the following sections we survey the leading key terms and keywords in order to provide a succinct, easily interpretable measure of contents for the seven topics.

6.2.3 Transition topic

The most common terms in the *transition* topic are *firms, industry, R&D, performance, value, interaction, transition, innovations* and *universities*. There are phrases that do not appear in the list of terms but appear in the list of keywords, such as *R&D investment, patents, productivity, environmental performance, sustainability transitions, collaboration, socio-technical transition* and *triple helix*. The transition studies include multi-level perspective on socio-technical transitions, the transition management and innovation systems. Research in socio-technical transitions and innovation system aims at understanding social and technological change by analyzing the causes that enable or inhibit such long term, system level processes. Specifically, sustainability transitions are involved in socio-technical transitions studies related to environmental issues. The discussion of science, technological, and market transitions in universities, firms and industry administrations have always been of interest to researchers, these transitions difficult to manage, and R&D with its collaborations can be viewed as either resources or constraints in systems. Most of the scholars working in the co-evolutionary agree that R&D alliance intent co-evolved with changes in social, technological and relevant knowledge bases.

6.2.4 Technological topic

In the *technological* topic, the information displayed in terms and keywords are similar. This topic revolves around the terms such as *technology, development, patent, science, transfer, roadmapping, adoption, convergence, evolution* and *emerging*. The new phrases appear in the keywords such as *technology assessment* and *technological forecasting* and *technology intelligence*, and new words such as *bibliometrics* and *text mining*. More broadly, this topic encompasses the field of technometrics. Since, technology often needs to migrate from its place and culture of origin to other places through *technology transfer, technological adoption, technology diffusion* and *integration*. Driven by the conceptualization that these all represent different aspects of the study of technology, these keywords become even more compelling. Various fields of technology have attracted more attention from a wider range of researchers, such as *nanotechnology, information technology, emerging technologies, disruptive technologies, electric mobility, 3D printing, and digital technology*.

6.2.5 Social topic

The social topic is characterized by terms such as *social, media, capital, online, commerce, theory, networks, influences* and *intention*. The specific content of this topic is shown by the keywords *social media, social capital, social change, social entrepreneurship, social network, sharing economy, social innovation and social commerce*. The *social* topic is widely visible on others topics, the social studies address some social capital/social media/social networks/social intelligence on innovation and market, in addition, the discussion of social media marketing, social entrepreneurship, social innovation in economies have always been of interest to researchers and therefore they are presented and discussed. Social topic is also broad in transition, energy and climate change, technology and foresight. Such as, many studies discuss the social influence, social feasibility, social structures in socio-tech transition, sustainable change/transition; some works related to the application of forecasting methods to social commerce, social policy, and many works discuss the technological and social change.

6.2.6 Forecasting topic

The most common terms in the *forecasting* topic are *foresight, future, scenario, analysis, research, knowledge, methodology, approach, decision, delphi, policy* and *planning*. There are more phrases that do not appear in the list of terms but appear in the list of keywords, such as *strategic foresight, corporate foresight, technology foresight uncertainty, text mining, literature-based discovery and evaluation*. Foresight is a process by which one comes to a fuller understanding of the long-term future, which should be taken into account in policy formulation, planning and decision making. The *future* studies with linking forecasting and foresight activities; that includes qualitative and quantitative means for monitoring clues of evolving trends and developments. A range of most popular forecasting methods can be applied for *forecasting* studies include scenarios, delphi, correlation analysis, technology evaluation and bibliometrics. This has been the most impactful work in the journal, if citations can be accepted as a proxy for this.

6.2.7 Market topic

The *markets* topic is connected to terms such as *models, diffusion, market, product, adoption, data, business, consumer, demand, growth* and *dynamics*. The *markets* terms have been explained with detailed phrases in keywords, such as *Bass model, Agent-based model and Lotka-Volterra model*. New words reveal other research content like *innovation diffusion, system dynamics, competition, cellular automata* and *simulation*. It is clear that submissions in this topic have been strongly quantitative as well as methodological in emphasis. *Market* studies try to shed light upon the magnitude, timing, adoption, competence, intensity, diffusion, and substitution of relevant technological innovation developments. These can be opportunities or threats and might have a potential impact either on enterprises or on supply chains, industry, or consumer markets. In addition, companies combine numerous different technological innovation methods of with market analysis methods, such as innovation diffusion, new product diffusion, business model, market agent model, bench-marking and competition analysis. This topic is broad in various industries, for example, *electric vehicles* and *social media*. These industries are market-driven industry where market development and technological innovation are closely integrated. This is reflected by the importance of *emerging markets, consumer innovativeness, behavioral intention* and *decision support systems*.

Table 7. High frequency keywords per topic

| Topic | Theme | Keywords in the Topic |
|-------|------------|--|
| 1 | Innovation | Innovation policy; Open innovation; Innovation ecosystem; Disruptive innovation; Innovation performance; Innovation systems; Technological innovation; National innovation system; Absorptive capacity; Innovation management; India; Patents; Sustainability; Transition; Radical innovation; Networks; Foresight; Financing innovation; Innovation strategies; Environmental innovation; Governance; Triple Helix; Green |

| | | |
|---|---------------|---|
| | | innovation; Regional innovation system; User innovation; Collaborative innovation; Innovation capability; Innovation diffusion; Innovation efficiency; Innovation networks; Innovation pathways |
| 2 | Change | Climate change; Energy; Climate policy; Energy policy; Renewable energy; Scenarios; Energy efficiency; China; CO2 emissions; Sustainability; Carbon leakage; Energy modeling; Energy security; Mitigation; Rebound effect; Energy consumption; Greenhouse gas emissions; Integrated assessment; Technological change; Copenhagen pledges; Marine energy; Multi-level perspective |
| 3 | Transition | Innovation; R&D; Performance; R&D investment; Industry 4.0; Patents; Productivity; Industry; Firm; Environmental performance; Firm performance; Semiconductor industry; Sustainability transitions; Collaboration; Alliance; Interaction; Co-evolution; Socio-technical transitions; Employment; Fourth industrial revolution; Internationalization; Knowledge transfer; Eco-innovation; Universities; Triple helix; University-industry interactions; Academic entrepreneurship; Empirical evidence; Internet; Commercialization; Governance; Experience |
| 4 | Technological | Patent analysis; Technology assessment; Technology forecasting; Technology Road-mapping; Technology transfer; Text mining; Nanotechnology; Innovation; China; Information technology; Technology intelligence; Bibliometrics; Emerging technologies; Technology adoption; Technology development; Technology Integration; Electric mobility; Technological capabilities; Technology diffusion; 3D printing; Digital technology; Network analysis; Tech mining; Technology entrepreneurship; Patent citation; science and technology; Technology management; Technology progress; Absorptive capacity; Disruptive technology; Technology convergence; Technology life cycle; Technology strategy |
| 5 | Social | Social media; Social capital; Social change; Social entrepreneurship; Sharing economy; Social network; Sustainability; Global brain; Perceived value; Trust; Twitter; Performance; Acculturation; Crowdfunding; Knowledge sharing; social innovation; Online social networks; Sentiment analysis; Social commerce; Social support; Social theory; Collaborative consumption; Corporate social responsibility; New media; Online communities; Social learning; Social sustainability |
| 6 | Forecasting | Forecasting; Foresight; Scenario planning; Delphi; Strategic foresight; Uncertainty; Corporate foresight; Text mining; Literature-based discovery; Scenario development; Technology foresight; Bibliometrics; Evaluation; Futures studies; Intuitive Logics; Nanotechnology; Knowledge management; Organizational learning; Policy Delphi; Decision making; Strategic planning; Clustering; Citation analysis; Citation network analysis; Collaboration; Policy Delphi; |
| 7 | Market | Diffusion; Innovation diffusion; Bass model; System dynamics; Agent-based model; Business model; Grey forecasting model; Big data; Technology diffusion; Internet of things; Logistic growth; Simulation; Smart cities; Competition; Internet; Lotka-Volterra model; Cellular automata; Business cycles; Economic growth; Electric vehicles; Entrepreneurship; Mobile phones; Cellular automata; Globalization; Sharing economy; Demand; Behavioral intention; Consumer durables; Market penetration; Consumer innovativeness; Lead user method; Emerging markets |

6.3 The hierarchical knowledge structure

In the previous section, we built an overview of knowledge in TFSC journal with using terms and keywords of seven topics for demonstrating the content of TFSC literature. We now move on to provide a hierarchical knowledge structure within topics instead of the flat topics without a structure, in this paper, from figure 6 we have two observational perspectives here, four knowledge branches and four knowledge-based components.

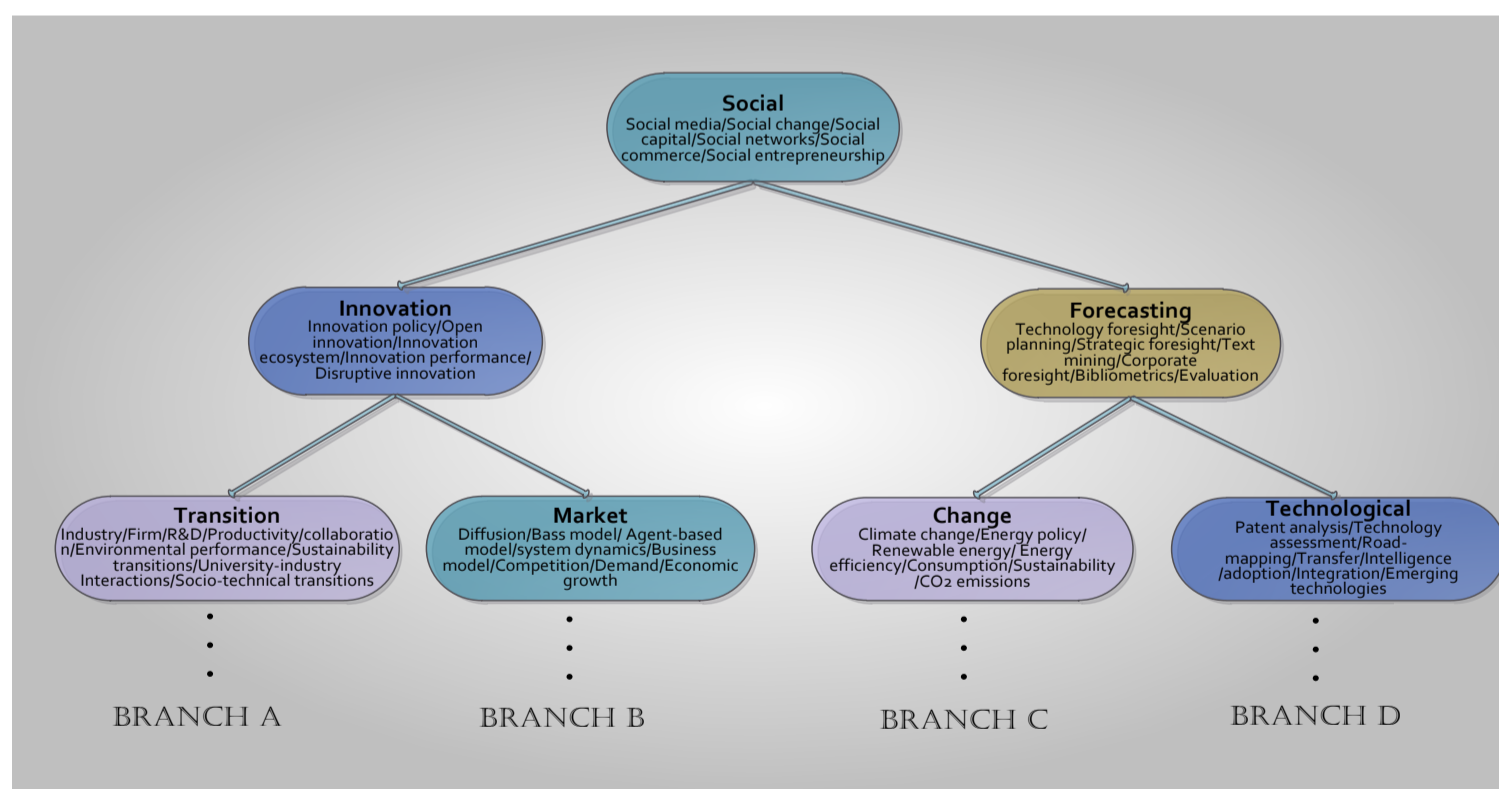


Figure 6. The hierarchical intellectual structure of journal research

(Green-Social component; Blue-Technological component; Yellow-Forecasting component; Purple-Change component)

6.3.1 Four Knowledge Branches

Based on the topic model the TFSC literature as a whole focus upon four branches or distinct strains of literature. As described earlier the topic model describes the recombination of various ideas into four branches. In this model an individual article may draw upon three topics, constrained by the tree structure, and in varying proportions. Each topic adds additional context to the root of the tree which involves social studies. The tree figure 4 exhibits the hierarchical structures among seven topics. In this figure each topic is represented by its typical keywords, with four branches encompassing following topic hierarchy:

Branch A. *Social→Innovation→Transition*. As one of the knowledge branches of the journal, social innovation and transition multi-level perspective is becoming a main knowledge stream for understanding and promoting social change. It took the social innovation theory as the basis of research and incorporated social, political, sustainable, technological factors into the journal's research, and it emphasized to promote the transition and innovation of the social-technical system or ecosystem between the macro, meso and micro levels.

Branch B. *Social→Innovation→Market*. Branch B is another main knowledge stream of journal, it reveals social innovation and market multi-level perspective. This branch is different from the branch A at the third level, it addresses market and innovation have their impact and role to serve socio-economic development. Social innovation is a support for marketing in the delivery of value and satisfaction to consumers and to a significant part of the society. It also independently affects bring the change of the society, owing to socialization, diffusion and aid in the more effective use of technological, managerial and marketing innovations.

Branch C. *Social→Forecasting→Change*. Journal's core mission integrated two other literature streams - Forecasting social change and forecasting technological change. Branch C with a specific focus on offer forecasting methods for social change, in particular, for climate and energy change. climate, energy, ecosystems, and societies interact over a range of temporal and spatial scales. Scholarly work on forecasting climate changes has tended to emphasize different question and variables depending on their interest. Forecasting climate, ecological, social change will affect domestic and international policies, trading patterns, resource use and the welfare of people. Studies of scenarios of long-term environmental development, scenarios for climate policy and climate change impacts are stressed in climate-ecosystem-society change perspective.

Branch D. *Social→Forecasting→Technological*. The overall understanding from branch D on forecasting technological change is that Technology has been the dominant force creating changes in people's lives, technological change has been at the center of social development. It's necessary to forecasting or projecting technological change and the resulting impact on managers in private and public organization's activities as well as the environment in general. Social influences for technological change are multiple, dynamic and interdependent, then forecasting tools are suitable for technologies change should not overlook the complexity of introducing social factors, such as social structures, social phenomenon, social capital and social resource.

These branches are mostly used to describe the relations within seven topics. It can be claimed that these themes are the first time to show the new established hierarchy relations in the content of TFSC and remain underdeveloped. As indicated in Fig.4, the topic of "Social" contains the most general terms or keywords, such as *social* and *social change*, the topics of "Innovation" and "Forecasting" are two comprehensive subject areas in TFSC. Since they are relatively more developed than other related topics, these topics permit richer interactions with other topics down the tree. For example, given the correlations of topics are revealed in Branch A, the most correlated terms of "Innovation" are keywords such as *innovation policy*, *system innovation*, *open innovation*, *innovation ecosystem* and *innovation performance*, these words are commonly used in R&D, university-industry interactions, sustainability or socio-technical transition to learn the processes and patterns in transitions, and develop transition pathways for social development and transformative policy making. Moreover, based on Branch B, the highly frequent keywords of "Social" and "Innovation" are also connected with the topic of market. It can be mentioned that keywords such as *social innovation*, *social capital*, *social networks*, *innovation networks*, *business model*, *demand*, *economic growth* are discussed in the content of social innovation and market economic development.

Another branch of the theme of "Social" is "Forecasting", further, they have been further developed in the two branches of "Forecasting". For instance, *social change/capital/networks/ structures*, *technology/strategic/corporate foresight*, *scenario*, and *delphi* are of keywords extracted from the themes of "Social" is "Forecasting", Branch C is a significant reflection of the correlation between the theme of "Forecasting" and "Change", "Changes" under this branch are mainly addressed climate and energy changes, including related structural changes, policy changes, and social changes in lifestyle. The changes of climate and energy have resulted in a shift from a system dominated by engineers to social-based system, moreover, foresight has contributed substantially to the "Change" of energy or environment systems. Furthermore, the Branch D indicates that these keywords related to a lot of content such as *technology assessment/transfer/adoption/ capabilities*, and *emerging technologies* in terms of the theme of "Technological". In this branch, foresight is put particular emphasis on technological change. it's important for policy makers to look into the future and know what changes are likely in technologies, through using forecasting tools to modeling and estimate technological change. Like any other forecasts, the purpose of technological forecasting simply to help evaluate the probability and significance of various possible future developments so that managers can make better decisions. Table 7 presents the sample articles that are the most relevant to the branch (including recent articles), we select these sample articles based on the average of the proportional content seen in documents assigned to each of the branches, and these articles can help readers better understand how different topics unfold in different knowledge branches.

Table 8. Sample articles in various branches

| Branch A Social→Innovation→Transition | | |
|---------------------------------------|---|-----------------------|
| From topic | Article's title | First Author |
| Topic 5 Social | Managing technological and social uncertainties of innovation: the evolution of Brazilian energy and agriculture (2011) | Jeremy Hall |
| Topic 5 Social | Transformative social innovation and (dis)empowerment (2019) | Flor Avelino |
| Topic 1 Innovation | Rotational symmetry and the transformation of innovation systems in a Triple Hix of university-industry-government relations (2014) | Inga A. Ivanova |
| Topic 1 Innovation | Understanding smart cities: innovation ecosystems, technological advancements, and societal challenges (2019) | Francesco Paolo Appio |

| | | |
|--|--|-----------------------------|
| Topic 3 Transition | Using the multi-level perspective on socio-technical transitions to assess innovation policy (2012) | Florian Kern |
| Topic 3 Transition | Experience in R&D collaborations, innovative performance and the moderating effect of different dimension of absorptive capacity (2020) | Marios Kafouros |
| Branch B Social→Innovation→Market. | | |
| From topic | Article's title | First Author |
| Topic 5 Social | Social innovation in emerging economies: A national systems of innovation based approach (2017) | Rekha Rao-Nicholson |
| Topic 5 Social | National innovation system, social entrepreneurship, and rural economic growth in china (2017) | Jie Wu |
| Topic 1 Innovation | The moderating role of innovation culture in the relationship between knowledge assets and product innovation (2013) | Gregorio Martin-de Castro |
| Topic 1 Innovation | Environmental pressures and performance: An analysis of the role of environmental innovation strategy and marketing capability (2016) | Wantao YU |
| Topic 7 Market | Modelling a dynamic market potential: A class of automata networks for diffusion of innovations (2009) | Renato Guseo |
| Topic 7 Market | Business model innovation for urban smartization (2019) | Francesco Schiavone |
| Branch C Social→Forecasting→Change | | |
| From topic | Article's title | First Author |
| Topic 5 Social | Can big data and predictive analytics improve social and environmental sustainability (2019) | Rameshwar Dubey |
| Topic 5 Social | Socio-technical scenarios as a methodological tool to explore social and political feasibility in low-carbon transitions: Bridging computer models and the multi-level perspective in UK electricity generation (2010-2050) (2020) | F.W. Geels |
| Topic 6 Forecasting | Long-term energy scenarios: Bridge the gap between socioeconomic storylines and energy modeling (2015) | Patrícia Fortes |
| Topic 6 Forecasting | Aligning integrated assessment modelling with socio-technical transition insights: An application to low-carbon energy scenario analysis in Europe (2020) | Mariësse A.E. van Sluisveld |
| Topic 2 Change | Making or breaking climate targets: The AMPERE study on staged accession scenarios for climate policy (2015) | Elmar Kriegler |
| Topic 2 Change | Economic and policy uncertainty in climate change mitigation: The London Smart city case scenario (2019) | Gabriela Contreras |
| Branch D Social→Forecasting→Technological | | |
| From topic | Article's title | First Author |
| Topic 5 Social | Transition in biofuel technologies: An appraisal of the social impacts of cellulosic ethanol using the Delphi method (2015) | Barbara E. Ribeiro |
| Topic 5 Social | Technology forecasting by analogy-based on social network analysis: The case of autonomous vehicles (2019) | Shuying Li |
| Topic 6 Forecasting | Strategic foresight in corporate organizations: Handling the effect and response uncertainty of technology and social drivers of change (2010) | Riccardo Vecchiato |
| Topic 6 Forecasting | Combining the scenario technique with bibliometrics for technology foresight: the case of personalized medicine (2015) | Birgit Stelzer |
| Topic 4 Technological | Monitoring the trends of technological changes based on the dynamic patent lattice: A modified formal concept analysis approach (2011) | Changyong Lee, J. Jeon |
| Topic 4 Technological | Forecasting the emerging technologies: A supervised learning approach through patent analysis (2017) | Moses Ntanda Kyebambe |

6.3.2 Four Knowledge-based components

When viewing the content of hierarchical structures among TFSC literature, we have presented descriptive analyses regarding the keywords-based knowledge branches. Following this, we move on to another hierarchical structure within topics of TFSC, based on an analysis of documents-based knowledge components. In this section, the main research interests and core publication in TFSC based on four knowledge components are introduced. In addition, how the content of each research component is related in knowledge branches will also be specifically demonstrated based on the document analysis.

Figure 4 exhibits another hierarchical structure among seven topics with various colors, the various colors of topics represent different components of *Technological Forecasting and Social Change*. The TFSC literature as a whole is focusing on four components:

1. Technological component - *Innovation* topic and *Technological* topic (Topic 1 and Topic 4)
2. Forecasting component - *Forecasting* topic (Topic 6)
3. Social component – *Social* topic and *Market* topic (Topic 5 and Topic 7)
4. Change component – *Transition* topic and *Change* topic (Topic 3 and Topic 2)

Each component is explained next in more detail, with illustrative examples of research within them. Many of the most-cited articles have developed or critically refined key issues that have inspired and shaped the whole research intellectual structure (Bragge, Kauppi et al. 2019), in addition, the highly cited articles in recent years can reflect the current hot issues. Tables 8–11 display the intellectual structure underlying published research into the four components. These tables provide an overview of the main subdomains of scholarly interest within TF&SC, as well as presenting the core articles (the most-cited articles, including recent articles) of these main subdomains from our sample. The tables also present information on how many citations they have received yearly, on average, and recent articles which are still being focused on by scholars. While our sample covers only a part of published research into these components, we can see several authors with a significant impact in the different fields of TF&SC through various representative publications relating to each component.

1. Technological component

Technological component including *Innovation* topic and *Technological* topic. In relation to the hierarchical knowledge structure showed in the knowledge tree, *Innovation* is one central bridge topic in branches A and B. It implies the possibility of association social theory with innovation to better promote social-technical transition or sustainable transformation, also, the possibility of association social innovation with market theory and business models to promote the

development of sustainable socio-economic. Studies of *Innovation* in journal describes the complex interactions between social, science, networks, market, technology and sustainable transition. There are four main subdomains of *Innovation* topic are presented in table 8.

Innovation is achieved in many ways, with much attention now given to scientific knowledge and networks for innovations. For instance, Caraca, Lundvall et al. (2009) give an overview of how the role of science in relation to innovation, and argue that science is only one of a plurality of other sources of knowledge that induce innovation-based growth, more attention should also be given to understanding markets and organizations. Musiolik, Markard et al. (2012) take a closer look at organizational and network resources, which are developed and deployed by networks to facilitate the building up of innovation systems.

In market business and in economics, innovation can become a catalyst for growth. Enterprises, firms and industries continuously look for better ways to improve their innovation performance, efficiency or capacity with advanced technologies and strategies (Rohrbeck and Gemünden 2011, Guerrero and Urbano 2016, Wang, Hang et al. 2016). Learning innovation enables businesses and industries to develop new business models with fewer resources by capturing customer needs and feedback. For example, Rayna and Striukova (2016) emphasis on 3D technologies bring product and process innovation, and have the potential to change the way business model innovation is carried out. Frank, Mendes et al. (2019) connect demand-pull and industry 4.0 from a business model innovation perspective.

Innovation is not only driven by scientific knowledge and market, it's also driven by technology, in the studies of innovation and technology subdomain, focus on the technological aspects of innovation or product, this provides a good means to combine technological absorptive capacity, technological diffusion, and technological transfer to produce a successful innovation process. This subdomain is developed within the scientific field of innovation studies which serves to explain the nature and rate of technological change. Song, Fisher et al. (2019) argue that the speed of technology-driven change is the main technological challenges for innovation. A prime example of this subdomain involved use innovation systems for analyzing technological change (Hekkert, Suurs et al. 2007); learn innovation pathways for technologies (Robinson, Huang et al. 2013); explore the technology absorptive capacity and innovation performance (Lau and Lo 2015); build technological innovation systems (Reichardt, Negro et al. 2016).

Some new types of innovation are called for a sustainable future, such as green innovation, environmental innovation, eco-innovation, sustainable innovation, these innovations that taking into account the environmental and social consequences of new innovations. This subdomain of innovation explores the relationship between innovation and the environment, including the potential to move toward a "green economy". Some prime examples of this subdomain's studies as follow, Oltra and Jean (2009) focus on environmental innovation, and apply sectoral systems of environmental innovation to industry; Polzin, von Flotow et al. (2016) address barriers to eco-innovation; Smith, Kern et al. (2014) explore the roles of niche spaces in the strategic management of sustainable innovations; Uyarra, Shapira et al. (2016) discuss the low carbon innovation and enterprise growth, and Popa, Soto-Acosta et al. (2017) study the outcomes of innovation climate and open innovation.

Table 9. Intellectual structure of *Technological* component research

| Technological component | | | |
|-------------------------|---|---|--|
| Topic | Subdomain | Brief Description | Core Articles (Cites per year) |
| Topic 1. Innovation | Innovation across science, knowledge and networks | This subdomain researches address the role of science in innovation process; knowledge management for innovation; knowledge transfer for innovation; knowledge assets and innovation; innovation dynamics/systems in networks; university-industry collaboration for innovation. | Caraca et al.,2009 (14.5); Musiolik, Jrg et al., 2012 (17.1); Martín-de Castro et al.,2013 (15); Santoro, Gabriele et al.,2018 (9); Vaccaro, Antonino et al.,2010 (15.5); Alexander, Allen T. and Martin, Dominique Philippe,2013 (9.4); Musiolik, Jrg et al.,2012 (17.3); Huang and Chen,2017 (6) |
| | Innovation in Market business and economics | This subdomain focus on innovation capacity of firm; product innovation; innovation performance/efficiency in enterprises/firms/industries/emerging economy. This also contains exploring the impact of economic crisis on innovation; developing business model innovation. | Rohrbeck and Gemünden, 2011 (24.7); Lau, Antonio K. W. and Lo, William, 2015 (9); Wang et al., 2016 (27.8); Guerrero and Urbano, 2016 (6.5); Yu et al., 2016 (7.8); Archibugi et al., 2013 (14.3); Frank et al., 2019 (7) |
| | Innovation and technology | This subdomain includes the works of technology and innovation policy; innovation pathways for technologies; innovation systems for analysing technological change. Also includes technological innovation systems; technology absorptive capacity and innovation performance, as well as technological challenges of innovation. | Hekkert. et al., 2007 (29.4); Hekkert and Negro, 2009 (32.7); Gupta et al., 2016 (7.8); Robinson et al., 2013 (11.4); Reichardt et al., 2016 (9.5); Stefan and Jakob, 2003 (8.5); Tigabu et al., 2015 (9) |
| | Innovation and Sustainable development | This subdomain brings research together the innovation with sustainable development, such as green innovation; environmental innovation; eco-innovation; sustainable innovation; low carbon innovation, as well as innovation climate and open innovation. | Abdul-Nasser et al., 2019 (6); Oltra, Vanessa and Jean, Maieder Saint, 2009 (24.5); Smith, Adrian et al., 2014 (14.7); Popa, Simona et al., 2017 (4.7); Augusto et al., 2016 (13); Ghisetti, 2017 (7) |
| Topic 4. Technological | Technological change | This subdomain focuses on modeling technological change and monitoring trends of technological change, involves emphasis on technological progress function; technology roadmap process; technological revolution; environment-biased technical progress. | Baumers et al., 2016 (10.6); Fuenfchilling and Truffer, 2016 (13.3); Koh and Magee, 2006 (4.3); Chang et al., 2009 (18.5); Daim and Oliver, 2008 (5.4); Lee and Park, 2011 (9); Koh and Magee, 2006 (4.3); Guo et al., 2016 (4.5); Robert et al., 2004 (54) |
| | Technology forecasting | This subdomain tends to use technology futures analysis attempt to predict the future of technology based on the high technology, such as forecasting emerging technologies; trend analysis in nanotechnology; forecasting disruptive technology ; technology roadmapping of robotics technology. | Daim et al., 2006 (55.7); Walsh, 2004 (19.1); Bengisu and Nekhili, 2006 (20.4); No and Park, 2010 (13.9); Kim and Bae, 2017 (13); Joung and Kim, 2017 (12); Momeni and Rost, 2016 (7); Ju and Sohn, 2015 (5.4); Kyebambe et al., 2017 (11.3); Daim et al., 2018 (8) |
| | Technological methods | These articles focus on methods, such as technology roadmapping; technology assessment; technology diffusion; technology opportunity analysis; technology transfer; technological intelligence; technology life-cycles analysis; patent portfolio value analysis, patent network analysis, etc. | Carvalho et al., 2013 (14.2); Kostoff et al., 2004 (27.1); Phaal et al., 2004 (10.2); Schot and Rip, 1997 (13.3); Tran and Daim,2008 (9.7); Park and Yoon, 2005 (9.1); Lee et al.,2015 (9.3); Zhang et al., 2014 (8.8); Zhu and Porter, 2002 (6.7) |

Technological is the other topic in Technological component, from the hierarchical knowledge structure, it's distributed in knowledge branch D and at the lowest level, meaning it's more specific and relatively independent research topic, and the research content is targeted, less general associations with other topics. There are three main subdomains of *Technological* topic are presented in table 9.

Classifying technological change into a subdomain stems from the idea that technological change is seen as a social process involving social capital, political institutions and marketing. This subdomain discusses how society, politics and market affect technological change, and how these, in turn, affect society, politics and market. Several articles concern about the impact of technology in social development. For example, Baumers, Dickens et al. (2016) discuss how technology-push impacts the productivity, economies of scale. Fuenfchilling and Truffer (2016) study the interplay of institutions, actors and technologies in socio-technical systems. Several articles discuss technological progress, Koh and Magee (2006) apply a functional approach for studying technological progress, new technical changes made are embodied in this progress. Chang, Lai et al. (2009) explore technology diffusion as a phase of technological progress, that pertains to the spread of technology throughout a society or market.

Another one important subdomain of *Technological* studies focuses on technological-related methods such as technology roadmapping (Kostoff, Boylan et al. 2004, Phaal, Farrukh et al. 2004, Carvalho, Fleury et al. 2013), technology assessment (Schot and Rip 1997, Tran and Daim 2008), technology life-cycles analysis (Huenteler, Schmidt et al. 2016). Some studies focus on technology opportunity analysis, for example, Yoon and Park (2005) propose a systematic approach for identifying technology opportunities, and Lee, Kang et al. (2015) use patent mapping for technology opportunity analysis. Particularly, scholars argue that technology intelligence is able to identify the technological opportunities (Zhu and Porter 2002, Zhang, Porter et al. 2014).

A subdomain with TFSC journal characteristics is formed under *Technological* topic, which is technology forecasting, but many studies of this subdomain focus on high technologies, for example, emerging technologies, internet of things technology, robotics technology, and disruptive technologies, etc. All of these technologies combining technology futures analysis (such as, trend analysis, technology intelligence, roadmapping, technological assessment, and forecasting) with bibliometric and patent analysis. For instance, Daim, Rueda et al. (2006) and Kyebambe, Cheng et al. (2017) use bibliometrics and patent analysis for forecasting emerging technologies. (2002) use technological intelligence for technological forecasting. (2018) combined use technology assessment and roadmapping for robotics technologies. This subdomain has since been studied extensively, also within our sample, see e.g. (Walsh 2004, Bengisu and Nekhili 2006, No and Park 2010, Ju and Sohn 2015, Momeni and Rost 2016, Joung and Kim 2017, Kim and Bae 2017)

2. Forecasting component

The Forecasting component only contains the *Forecasting* topic, this topic plays a bridge role in knowledge branches C and D, we extend two different knowledge streams from it. One is forecasting social change, indicating it probably better combines forecasting methods with climate change studies for strategic planning and providing climate policy, the other is forecasting technological change, indicating it probably strengthens the correlation between social studies and technological change studies. According to the literature in this component, show the *Forecasting* of TFSC journal supplements traditional forecasts to provide a view of the complete social, economic, technological, political and sustainable environmental. Forecasting studies is based upon an understanding in depth of the fundamental factors which are shaping the future, those factors, be they social, political, economic, technological or sustainable. In table 10, we summarize the forecasting articles of journal into four subdomains.

The first subdomain of *Forecasting* topic is forecasting for technology, more commonly referred to as foresight studies, and introduce the major forecasting methods for technological predictions, critically assess future technological impact and the impact of technology on foresight process (Robinson 2009, Martin 2010, Miles 2010, Lee, Cho et al. 2012, Haegeman, Marinelli et al. 2013, Keller and von der Gracht 2014). Track emerging technologies also be discussed, with an increasing emphasis on forecasting technical roadmap for sustainable energy (Kajikawa, Yoshikawa et al. 2008, Stelzer, Meyer-Br?Tz et al. 2015, Andreani, Kalchschmidt et al. 2018).

Forecasting studies not only encompass methods and techniques for technological predictions, but also the focus on social and economic changes, social and economic are changing rapidly, forecasting techniques can capture the dynamics of changes, and affect the socio-economic processes by forecasting the socio-economic development. A forecast of the social-economic development incorporates corporate forecasting representing the future of different spheres of the companies/firms and the comprehensive economic forecast representing the development of the economy and the social sphere of the country or region in the generalized form. These core topics are discussed in this subdomain include: the evaluation of national foresight activities, estimate demographic situation and economic change in the country (Luke, Georghiou et al. 2006, Gr?bler, O'Neill et al. 2007, Jiang, Kleer et al. 2017), socio-economic scenarios for estimate the dynamics of demand for economy (Hejazi, Edmonds et al. 2014, Vishnevskiy, Karasev et al. 2015). In recent years corporate forecasting has become more professional and popular, such studies typically use corporate foresight to identify emerging business fields and increase their innovation capacity. Articles typical examples of scholars applying corporate foresight practices include: Battistella, Cinzia et al. (2015), Vishnevskiy, Karasev et al. (2015), Rohrbeck, Rene et al. (2018).

The third subdomain presents the content for socio-political forecasting, which shows to use formal planning for strategic decision making, references to socio-political forecasting in this subdomain mean formal strategic planning and forecasting. Description of forecasting methods are then provided, suggestions are made on which forecasting methods to use when developing plans for national or individual. Studies in this subdomain are interested in applying scenarios to strategic management (Godet 2000, Postma and Liebl 2005, Raford 2015). Particularly, these studies address strategic forecasting for corporate organizations, companies and smart city development (Vecchiato and Roveda 2010, Rohrbeck and Schwarz 2013, Iden, Methlie et al. 2017, Mora, Deakin et al. 2018). Several studies discuss how scenarios or Delphi can be purposefully designed in order to support public policy (Tapio 2003, Volkery and Ribeiro 2009, De Loe, Melnychuk et al. 2016).

Finally, the fourth subdomain looks at sustainable forecasting studies, this subdomain provides valuable information about the expected changes in the climate, energy, water resources, or smart cities in the future. These articles describe development of forecasting methods that integrated econometric models, energy modeling, strategies, public policies, and companies' projected intentions. Some forecasting studies in this subdomain address climate change and energy issues (Hughes 2013, Varho and Tapio 2013, Fortes, b et al. 2015, Van Sluisveld, Hof et al. 2018). The other important set of studies in this subdomain provide detailed information on the most recent scientific articles focusing on smart cities and sustainability issues (John, Robinson et al. 2011, Andreani, Kalchschmidt et al. 2018, Calabrese, Costa et al. 2019, Kummitha and Crutzen 2019).

Table 10. Intellectual structure of *Forecasting* component research

| Forecasting component | | | |
|-----------------------|--|---|--|
| Topic | Subdomain | Brief Description | Core Articles |
| Topic 6. Forecasting | Forecasting for technology | These articles encompass forecasting methods and techniques for technological predictions, study the development of technologies over time, track emerging technologies, assess future technological impact. Also, study the impact of technology on foresight process. | Miles, 2010 (13.5); Martin, 2010 (13.6); Robinson, 2009 (10.8); Haegeman et al., 2013 (11.2); Lee et al., 2012 (9.3); Keller and Gracht, 2014 (11.3); Stelzer et al., 2015 (5.8); Lu et al., 2017 (6.7); Andreani et al., 2018 (5) |
| | Forecasting for social and economic changes | This subdomain focus on the forecasting of the socio-economic development. Following aspects include scenarios of demographic and economic change; forecasting methods on economic and social implications; corporate foresight for companies/firms; the future and social impact in economic. | Grübler et al., 2007 (22.5); Luke et al., 2006 (11.6); Jiang et al., 2017 (8.3); Hejazi, Mohamad et al., 2014 (11.7); Battistella et al., 2015 (8); Vishnevskiy, Konstantin et al., 2015 (8.6); Gracht, 2013 (7); Rossmann et al., 2018 (5); Rohrbeck et al., 2018 (6) |
| | socio-political forecasting | This subdomain address forecasting and planning, and it has been used by business, government and organizations. These articles include strategic foresight in corporate organizations/ companies/smart city development; scenario for public policy; policy delphi practice; collaborate foresight for strategic planning. | Michel and Godet, 2000 (17.7); Postma and Liebl, 2005 (22.9); Volkery and Ribeiro, 2009 (9.3); Vecchiato and Roveda, 2010 (11); Rohrbeck and Schwarz, 2013 (14); Eriksson and Weber, 2008 (10.7); Vecchiato, 2012 (9.9); De Loe et al., 2016 (8); Weigand et al., 2014 (6.3) |
| | Forecasting for environmental sustainability | These works use forecasting approaches for sustainability research, such as climate change, energy, water, waste management, smart city or sustainable urban development. | John et al., 2011 (18.8); Patricia et al., 2015 (11); Hughes, 2013 (7.4); Varho and Tapio, 2013 (7.1); Calabrese et al., 2019 (7.5); Mora et al., 2018 (5.5); Van Sluisveld et al., 2018 (9); Kummitha and Crutzen, 2019 (6) |

3. Social component

Social component contains *Social* topic and *Market* topic. First, we discuss *Social* topic, it plays a fundamental role in each knowledge branch, also is the root of distinct research streams of TFSC, and various topics can be extended from it. The four main subdomain of *social* topic summarized in table 11, highlight that within the fragmented and multi-disciplinary social research area, a limited number of core subdomains (social and innovation system; social sustainability; social forecasting; social commerce and economy) function as hubs, bridging research addressing some issues of relevant social, market and economic, within academic, industrialists and policy makers.

Research on social and innovation has gained momentum, specifically by the growing interest in social issues related to entrepreneurship and public management. Social innovation is widely studied, for example, Cajasanta (2014) argues that social innovation as a driver of social change. Rao-Nicholson, Vorley et al. (2017) study social innovation in emerging economies. Yoon, Yun et al. (2015) study social entrepreneurship in innovation systems, both social entrepreneurship and social enterprise are important contribution to social innovation by creating social value. Also, various studies for social and innovation, such as innovation approaches to explore social uncertainties, these social uncertainties can act as leverage by providing socio-political legitimacy (Hall, Matos et al. 2011); exploring how social capital facilitates innovation or innovation networks (Landry, Amara et al. 2002, Rutten and Boekema 2007, Camps and Marques 2014); exploring social media capability in innovation management (Scuotto, Del Giudice et al. 2017, Bhimani, Mention et al. 2019).

The subdomain of social commerce and economy is also a widely studied interest of *social* topic research. This subdomain involves social support, social capital, social media or social networks that support social interaction, then contribute to assist commerce and economy development by buying and selling of products and services (Steinfeld, Scupola et al. 2010, Blazquez and Domenech 2018). Several articles argue that social factors influence social commerce intention, social interaction produce different values for business (Hajli 2014, Huang and Benyoucef 2015), some new works focus on social media marketing, address theories from marketing need to be investigated with a view to application in social media (Laurell and Sandstrom 2016, Bashir, Naheed et al. 2017, Chen and Lin 2019).

Furthermore, concern for the issues of social sustainability is also at the core of *social* topic, these studies of this subdomain present a slightly broader understanding of social sustainability incorporating social and economic aspects as well as environmental. Several studies in this subdomain discuss the social aspects of sustainability are intertwined with the environmental and economic aspects such as social sustainability in economy (Parguel, B et al. 2017), sustainable social relationship in business (Chen and Lin 2015). Some studies focus on social and environmental sustainability (Sheikh, Nasir et al. 2016, Dubey, Gunasekaran et al. 2017). Despite recognition of these economic or environmental elements are usually be discussed, the social side of sustainability has often been investigated, for example, social structures for sustainable development, social wellbeing of sustainability, sustainability within social media, sustainable social networks (Wangel 2011, Munzel, Meyer-Waarden et al. 2018, Vismara 2018, Laurell, Sandstrom et al. 2019).

In addition, social forecasting is another subdomain of concern in *social* topic, it developed social forecasting including political, economic and technological factors in addition to social, with applying forecasting techniques. Forecasting the future trend for each factor, these will affect social attitudes which, will feed back upon the political, economic and technological factors. The specific foci of interest in research are for example forecast social trends, forecast change in social attitudes, social forecasting for business planning, social networks for forecasting (Masini and Vasquez 2000, Cachia, Compaño et al. 2007, Yin, Liu et al. 2015, Leon, Rodríguez-Rodríguez et al. 2016). Particularly, forecasting methods to explored potential social impacts of tech/production, socio-technical scenarios to explore socio-political feasibility (Ribeiro and Quintanilla 2015, Geels, Mcmeekin et al. 2018).

For strategic design and policy analysis in market, these articles address strategic design and policy analysis involve three levels of scope, such as corporate strategy for company, business strategy for industries and functional decisions for particular functions and groups. These strategic decisions studies focus on market position to help the company sustain a competitive advantage on a long term in its industry, or aim at improving the efficiency of the overall business (Namdeo, Tiwary et al. 2014, Ghezzi, Cortimiglia et al. 2015, Gaurav and Indranil 2019). Particularly, policy analysis has been addressed by several articles, one of the main works for their policy analysis is the understanding of the competitive environment and the interpretation of the effects of the competition in a business (Spyridoula, Lakka et al. 2013, Rixen and Weigand 2014, Wolinetz and Axsen 2016). In addition, some works perform policy mixes analysis by measuring the demand and supply (Safarzynska and Bergh 2010, Harrison and Thiel 2016).

In addition, social market and market strategy, the other two subdomains are market forecasting, as well as market, innovation and technology. Actually, market forecasting can be seen as an important process for the marketing strategy, here we discuss it separately. This subdomain is primarily concerned with the potential market, forecast market values and market share, forecasts of revenue and cost of sales (Modis 1999, Yang 2003, Yang and Williams 2009, Eggers 2011, Orbach and Fruchter 2011, Shafiei, Thorkelsson et al. 2012). Market studies provide a number of models for studying how markets, competitors and prices behave, these models provide a useful toolbox for the market forecasting (Frank 2004, Lee, Lee et al. 2005, Shin and Kim 2008). For example, the product and industry life cycle and its use in market forecasting are discussed (Sousa and Wallace 2006, Huang and Tzeng 2008, Penna and Geels 2012), the bass model and diffusion model are commonly used for demand forecasting, describe how a new product or service is adopted by population (Kim, Lee et al. 2005, Lee, Cho et al. 2006, Hyeonju, B et al. 2012, Hakyoon, B et al. 2014).

The last subdomain under *Market* topic analyzes the convergence of technology, innovation, business practices, and market for improving business performance, it pursues innovation in market and business, and discussed in some studies that how business model innovation describes the process in which an organization adjust its business strategy, and this innovation reflects a fundamental change in how a company delivers value to its customers (Bogers, Hadar et al. 2016, Ehrenhard, Wijnhoven et al. 2016, Rayna and Striukova 2016, Boons and Bocken 2018, Schiavone, Paolone et al. 2018). In addition to business model innovation, innovation diffusion theory has sparked considerable research among consumer behavior and marketing management scholars, these scholars have been concerned with developing normative guidelines for how an innovation diffuses in a social system (Vijay, Mahajan et al. 1996, Centrone, Goia et al. 2007, Cantono and Silverberg 2009). Furthermore, research on the modeling the diffusion of innovation in marketing has studied in an extensive article, such as agent-based modeling of the diffusion of innovation, new product diffusion model (Schwarz and Ernst 2009, Lee, Kim et al. 2010, Rixen and Weigand 2014, Palmer, Sorda et al. 2015). These researches aim to explain the rate at which new product acceptance and diffusion spread, that helps marketers to understanding the characteristics of each segment that will either facilitate or hinder the adoption of an innovation.

4. Change component

Change component including *change* topic and *transition* topic, they are located at the bottom of branch C and branch A, respectively. In the first place table 11 shows the main subdomains of *change* topic, this topic discusses the first subdomain - the social dimensions of climate change from a range of perspectives, emphasizes social, environmental and economic interactions. An important set of studies in this subdomain discuss the main social drivers of climate change, highlighting how they play out in different processes, including consumption and production. For instance, some articles study long-term linkages between economic growth and energy consumption, between economic output and energy efficiency, and between market and carbon emission (Ramanathan 2006, Saunders 2013, Luukkanen, Panula-Ontto et al. 2014, Bauer, Bosetti et al. 2015, Fei and Lin 2016), these relationships provide an understanding of the social structures that drive climate change, or provide an understanding of social infrastructures and how their interaction contributes to climate change. Tacking climate change requires understanding of how societies and the activities drive climate change in different ways, while societies interact with the environment and reshape it in response to their evolving patterns of production and consumption (Bolton and Foxon 2015, Guenther, Edeltraud et al. 2015). The other important set of studies discuss the impacts of climate change on societies and economies (Fischer, Tubiello et al. 2007, Rokityanskiy, Benítez et al. 2007, Tubiello and Fischer 2007, Schwanitz, Longden et al. 2014, Lu, Bai et al. 2019), these scholars conduct their impact assessments and evaluations to environments and infrastructure impacts, they argue that climate change affects a much wider range of environmental developments issues such as urban/cities development, agriculture, water resources, land use, deforestation, transport, electrification, etc.

The second subdomain of *change* topic is focus on policy and strategic management in climate change. These studies discuss the long-term or neat-term climate change policies, including mitigation strategies and adaption support systems, some of which are being applied globally, like financing and technology transfer mechanisms, others of which are provided nationally, such as energy industry or agricultural extension (Chi, Nuttall et al. 2009, Bauer, Bosetti et al. 2015, Bertram, Johnson et al. 2015, Johnson, Krey et al. 2015). Also various practices for making decisions or policy choices on effective investment in emerging technologies and deploy energy and low-carbon technologies (Norberg-Bohm 2000, Kajikawa, Yoshikawa et al. 2008, Weiss, Junginger et al. 2010, Masini and Menichetti 2013, Iyer, Hultman et al. 2015). These studies discuss the long-term or neat-term energy policy, climate policy, and draw lessons for the design of future policies to promote innovation in sustainable technologies.

The third subdomain in this topic deals with forecasting methods in climate change, energy, climate policy or energy policy. A forecasting of climate change provides an understanding of climate variability or trends for better resource such as energy or water management (Hejazi, Edmonds et al. 2014, Schaeffer, Gohar et al. 2015). Some studies focus within climate field on the forecasting of emissions and impact on the environment, compounded by the late entry of social organizations into climate change work, as well as late attention to adaptations as a priority in policy (Kriegler, Riahi et al. 2015, Sascha, Samadi et al. 2017, Contreras and Platania 2019). In the specific topic of the studies in energy forecasting are for example forecast energy production, distribution and consumption, particularly predict future energy needs to achieve demand and supply equilibrium (Wei, Liang et al. 2006, Paravantis and Georgakellos 2007, Riahi, Grübler et al. 2007, Alizadeh, Lund et al. 2016).

Table 12. Intellectual structure of *Change* component research

| Change component | | | |
|------------------------|---|---|--|
| Topic | Subdomain | Brief Description | Core Articles |
| Topic 2. Change | Social dimensions of climate change | This subdomain discusses the social dimensions of climate change from a range of perspectives, emphasizes social, environmental and economic interactions, some studies discuss social drivers of climate change, such as social structures, social infrastructures, also discuss the impacts of climate change on societies and economies, studies such as climate change impact on urban/cities development, agriculture, water resources, land use, deforestation, transport, electrification. | Ramanathan, 2006 (25.9); Saunders, 2013 (14.7); Fei and Lin, 2016 (5.8); Fischer et al., 2007 (38.8); Tubiello and Fischer, 2007 (25.2); Luukkanen et al., 2014 (12.7); Guenther et al., 2015 (6.6); Schwanitz et al., 2014 (4.6); Lu et al., 2019 (4); Bolton and Foxon, 2015 (12); Rokityanskiy et al., 2007 (13.4) |
| | Policy and strategic management in climate change | These articles explore the political implications for climate change, such as learn from energy policy, climate policy; also articles focus on Long-term climate goals and short-term climate targets; energy policy analysis; investment decisions in energy. | Chi et al., 2009 (9.2); Johnson, Nils et al., 2015 (12); Bertram et al., 2015 (23.8); Bauer et al., 2015 (9.2); Iyer et al., 2015 (13.8); Norberg-Bohm, V., 2000 (10.7); Kajikawa et al., 2008 (15.7); Masini and Menichetti, 2013 (11.2); Weiss et al., 2010 (15.9) |
| | Climate/energy Forecasting | This subdomain is mainly to conduct research on energy and climate with forecasting methods, such works as: scenario analysis of climate/energy change; forecast technological change in energy; forecast trends in energy consumption and carbon emissions. | Schaeffer et al., 2015 (7.2); Hejazi et al., 2014 (11.7); Contreras and Platania, 2019 (6); Kriegler et al., 2015 (36.6); Sascha et al., 2017 (5.7); Alizadeh et al., 2016 (6.8); Riahi, Keywan et al., 2007 (68.5); Wei et al., 2006 (8.8); Paravantis and Georgakellos, 2007 (9.5) |
| Topic 3. Transition | Socio-technical transition | This subdomain addresses transition in society, which is influenced by knowledge, science, market, industry and technology. Including such works as: socio-technical transition in industry; technology transition pathways; knowledge in tech-market transition; transition pathways in cities; politically accelerated transition; transition policy in socio-technical systems. | Bos and Brown, 2012 (10.6); Marletto, 2018 (6.5); Pereira et al., 2016 (7.5); Chau et al., 2017 (6.3); Meng et al., 2019 (4); Sandstrom et al., 2016 (8.5); Kern, Florian, 2012 (7.8); Van Welie et al., 2018 (6.5); Roberts and Geels, 2018 (5.5); Rogge et al., 2018 (6.5); Rotmans, 2011 (16.3); Kern, F., 2012 (8.1) |
| | Sustainability or energy transition | Sustainability transition and energy transition studies that explore these transitions in electricity sector, eco-city, national development; also studies of sustainability transition through system innovation; complementarities analysis for energy transition; instrument mix for energy transition. | Elzen and Wieczorek, 2005 (24.1); Farla et al., 2012 (27.9); Berkhout et al., 2009 (4.7); Foxon et al., 2010 (24.4); Kerkhof and Wieczorek, 2005 (15.8); Ren, J. et al., 2017 (8); Murphy, 2001 (8.1); Li, Francis G.N et al., 2015 (10.2); Falcone et al., 2019 (5); Markard and Hoffmann, 2016 (13) |
| | Innovation and R&D in transition | This subdomain focuses on apply innovation activities and R&D to operate and assist transition management, involves following topics: public subsidies/support on R&D investment in transition process; specific transition of organization from R&D to operations; university-industry interaction; entrepreneurial university; R&D collaborations/networks, innovation performance/system for transition economy; learn transition strategic from R&D to operational or production environment. | Geels, Frank W, 2005 (35.4); Dai and Cheng, 2015 (5.8); Ganotakis et al., 2019 (5); Carboni, 2016 (9.3); Huergo et al., 2016 (5.8); Young et al., 2016 (7); Suh and Oh, 2015 (4); Jung et al., 2018 (4.5); Sa and De Pinho, 2019 (6) |

Table 12 shows the main subdomains of *transition* topic, first, research on socio-technical transition subdomain aims at understanding technological and social change, the socio-technical transition which is influenced by policy, knowledge, science, market, industry and technology, offers an integrative view on transitions, ranging from science, technology to sector-level regimes and broader societal contexts, related some social groups of actors such as technology, policy, industry, science, and market groups (Bos and Brown 2012, Pereira, Tiago et al. 2016, Sandstrom, Christian et al. 2016, Chau, Gilman et al. 2017, Marletto 2018, Meng, Li et al. 2019). These articles discuss social-technical transition with regard to: politics and power, multiple transition pathways, incumbent industry or firm reorientation, tech-market transition, policy analysis (Rotmans 2011, Kern 2012, Roberts and Geels 2018, Rogge, Pfluger et al. 2018, Van Welie, Cherunya et al. 2018).

Furthermore, most of these social-technical transition towards more growth, production of innovations and consumption of resources, at present transitions cover a broad range of issues, including urgent ones like sustainability. Sustainability transition are being investigated as a new research subdomain, which focuses on multidimensional struggles between “green” innovations and entrenched systems (Elzen and Wieczorek 2005). Some articles study sustainability transitions in electricity sector, eco-city, national development sustainability transitions (Kerkhof and Wieczorek 2005, Berkhout, Angel et al. 2009, Foxon, Hammond et al. 2010, Farla, Markard et al. 2012, Ren, Liang et al. 2017), sustainability transition continues to increase in attention of researchers as investors prioritize environmental, social and governance factors. In the sustainability transition process, energy transition can contribute to accelerating the transition towards a climate neutral economy (Murphy 2001, Li, Trutnevyte et al. 2015, Markard and Hoffmann 2016, Falcone, Lopolito et al. 2019), these articles address renewable energy technologies, energy efficiency, market design, R&D, policy formulation and finance instruments with the aim of fostering the development of systemic innovation.

The third subdomain presents and explains social change from innovation itself levels, it involves multi-dimensional struggles between niche-innovation and incumbent systems, which must adapt to these social change developments and innovate itself, building upon strengths such as a culture of cross-border

cooperation between industry, universities, and research institutes (Geels 2005, Dai and Cheng 2015, Huergo, Trenado et al. 2016, Young, Hoon et al. 2016, Ganotakis, Kafouros et al. 2019). This subdomain focuses on the process of innovation activities and R&D to operate transition management, and implement transition strategic. R&D and innovation support the industrial transition. bridging the gap between basic research and social economic (Suh and Oh 2015, Carboni 2016, Jung, Hwang et al. 2018, Sa and De Pinho 2019).

6.4 Knowledge Dynamics

To monitor the developments in different areas in TFSC over time is meaningful for the technology forecasting field, scholars, editors and organizations, it useful in understanding the trend and direction of development of TFSC journal and the field. In this section, we will first present a brief general description regarding the temporal development of TFSC research topics. Furthermore, we provide a more detailed analysis of the evolvement of topics over four periods. Finally, we present a clear visualization for the evolvement of four knowledge-based components in TFSC over the years, based on analysis of the keywords.

Although there are a few articles dated to 1969 these are excluded from the analysis, due to the long time and the relatively small number of articles per year, they will not have a great effect on our understanding of the research content of journals. It wasn't until 1991 that the Web of Science produced fully indexed abstracts for covered journals. Therefore, this section analyzes our observation period from 1995 to 2020, and the data information is enough to gain a general picture about the dynamic trends in TFSC content.

Figure.5 shows the trends in each topic's publications during the time period of 1995-2020. We can see an overall increasing trend, with a particularly significant increase in the number of publications during the last five years. Overall, the number of publications in the journal appears to have tripled during the period covered in this analysis. In 2015, we can particularly note an obvious increase in the number of articles for each topic. During 2016-2018, there also is a significant increase in the number of publications in the *Innovation* topic. In 2019, there has been a substantial increase in the literature both under *Social* and *Forecasting* topics. Although we only download the data for 2020 until May, it can be seen that, with the exception of *Social* topic and *Technological* topic, the number of articles under each topic exceeds half of the number of articles under each topic of 2019.

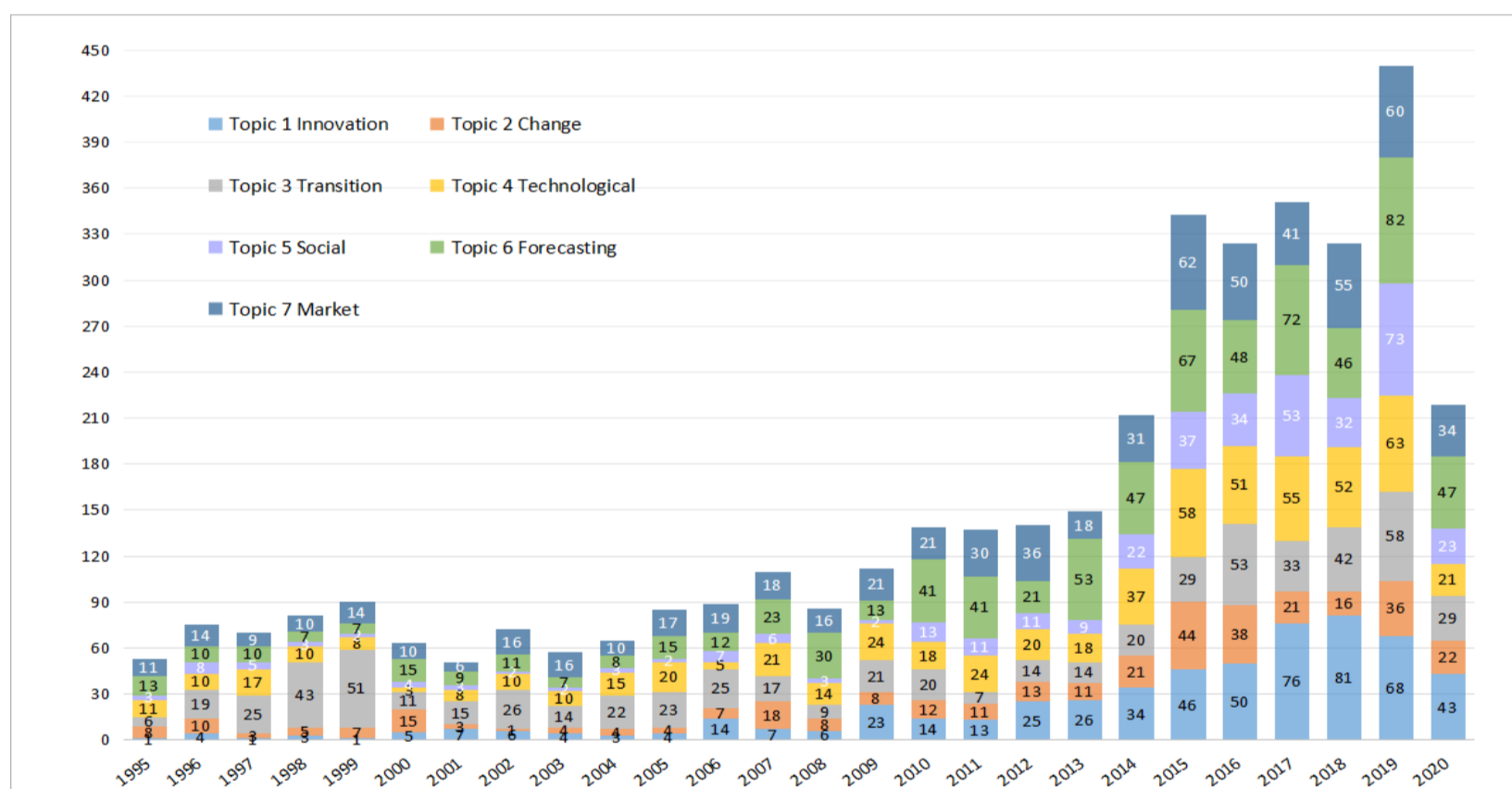


Figure 7. Yearly quantity of TFSC publications per topic in the sample

We now move from the analysis of the evolvement of topics over time to portray evolvement of four knowledge-based components in TFSC over the years. Figure 8 presents a bubble chart of the components with their newer and high frequency keywords in the sample throughout the 2002-2020 timespan. We select respective 10-15 keywords of each topic that belong to the component, this chart demonstrates their frequency year-by-year (the larger the bubble, the more frequently).

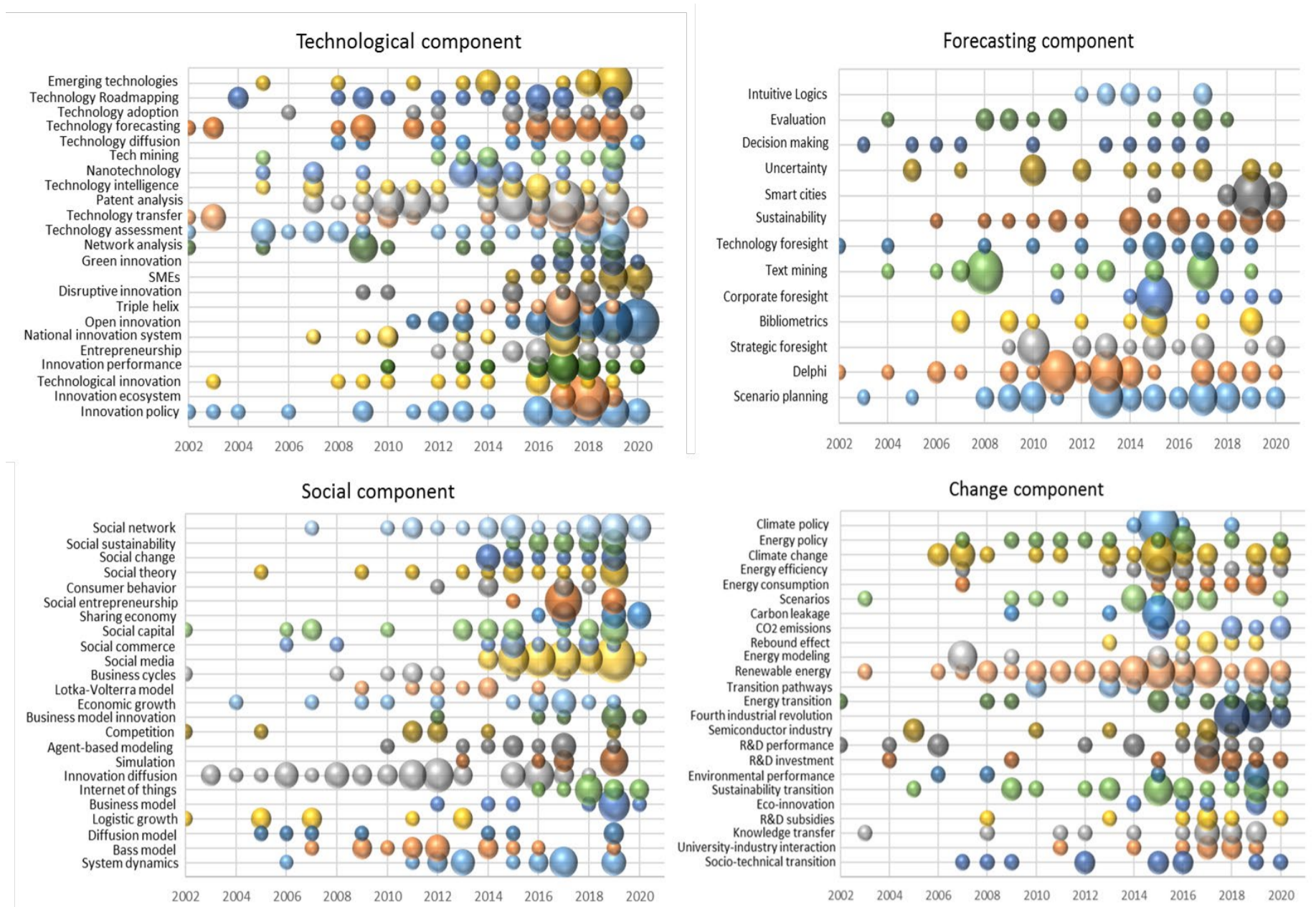


Figure 8. Bubble chart of keywords in different components

Technological component rapidly evolving, especially research relate to the *Innovation* topic, as demonstrated by appearance in increasing no. of keywords in the publication. Research keywords related to the *Technological* component in 2016-2019 shows a research trend focusing on *Innovation policy* (occurred in 32 publication's author keywords), *Open innovation* (39), *Technology transfer* (23), *Patent analysis* (47), *Technology forecasting* (24), *Emerging technologies* (19). Some research keywords which do not have good frequency like *Green innovation* (6), *Disruptive innovation* (10), *Innovation ecosystem* (12) and *SMEs* (12) but get popularity in 2015-2020.

In the studies of Forecasting component, research keywords mostly focus on forecasting methods such as *Scenario planning* (38), *Delphi* (36), *Strategic foresight* (21), *Bibliometrics* (18), *Text mining* (26) have been commonly used. So far, *Scenario planning*, *Delphi* and *Strategic foresight* are still widely used, while *Corporate foresight* (13) is a relatively new method emerging in the past decade. It can also be found from the figure 6 that forecasting methods pay more attention to *sustainability* (22) issues, especially in the period of 2018-2020, forecasting approach are lately employed in *Smart Cities* (15).

In the Social component, research keywords relate to *social* topics are obviously newer than the research keywords on *market* topics. With the recommendation of *Social Theory* (15), other research keywords *Social media* (37), *Social change* (11), *Social entrepreneurship* (11), *Social sustainability* (10) are being given increasing amount of attention in year 2014-2019. And can be seen from the research keywords on market topic, many research keywords showing some of the core, mainstream market approach models such as *Bass model* (14), *Diffusion model* (8), *Business model* (10), *Agent-based model* (10), *Lotka-Volterra model* (7). The keywords *Innovation diffusion* (37) has long been a focus in the market-related research during the sample timespan. In addition, *Sharing economy* (10), *Internet of things* (10), *System dynamics* (18), *Social capital* (18), *Social network* (23), *Social commerce* (11), *Economic growth* (13) are also the concerned research keywords of this component.

Based on the new visual angle for demonstrating the evolvement of Change components, we detect some research keywords that raises a large amount of attention by scholars, such as *Renewable energy* (36), *Climate change* (25) and *Sustainability transition* (19). The figure shows, *Climate policy*'s appearance frequency in 2015 reached 8 times, correspondingly, *Climate change*, *Carbon leakage*, *Renewable energy* and *Sustainability transition*, their frequency reached the highest in the same year. Also some research keywords which follow with interest in 2015-2019 such as *R&D investment* (10), *Energy transition* (9), *Fourth industrial revolution* (12), *Energy consumption* (7) and *Energy efficiency* (12).

7. Conclusions and Recommendation

As the *Technological Forecasting and Social Change* marched forward to become a premier forecast journal, it is worth taking a look at the past, the present and the future. In this work, the hierarchical knowledge structure of TFSC, its main research topics, research branches, research components, and dynamics development of knowledge in journal are studies by means of hierarchical topic model method with non-negative matrix factorization technique and bibliometric methods. By employing our methods, one can determine its major topics in a field or journal, in addition to examine the hierarchical knowledge structure and evolution over the time. This methodology provides researchers with a suitable instrument for identification of various correlated topics in research,

building an overview of studies, in other words, there are collections of topics in a scientific journal that build its knowledge structure, these topics are expressed as terms that are made for describing and naming them. It additionally explores exploring the correlation among various topics, which led to the formation of various knowledge branches and components that examine some complex relationships and depict the hierarchical structure of knowledge in a field or journal. Studying the hierarchical structure can be fruitful for managers, journal editors, and individual scholars.

From the knowledge branches of the journal, we can conclude that *innovation* and *forecasting* studies should be considered significant areas of research and scholarly interest, and we expect these fields to garner emphasis in the future orientation of TF&SC: (1) *innovation* studies should be considered a significant area in socio-technical-sustainability transition and socio-economic development, and can act as a bridge between *social*, *transition*, and *market* studies; (2) *forecasting* studies is another significant area, function as a bridge between *social* studies, *change* studies, and *technological* studies. We are more convinced than ever of the importance of the links among these research topics, and both current and upcoming TF&SC research may enable tighter integration of these topics. Our research results can be considered major references, as a researcher who recognizes the magnitude of the social, environmental, and economic issues we are facing can adopt a social innovation view, whether it takes the form of an object or process, and can focus on the transition towards a sustainable development, or on building new markets and strengthening supply chains. Furthermore, our research can be a major reference for those wishing to deal directly with the methodology and practice of forecasting and future studies as planning tools, as they interrelate social, environmental, and technological factors.

Within the seemingly fragmented research areas of TF&SC which cross different disciplines: management science, decision sciences, development studies, economics, business management, engineering, information & computer science, environmental sciences, our hierarchical knowledge structure analysis revealed four components of TF&SC research, each component united by a common thematic area: *Technological* component focusing on innovation and technology; *Forecasting* component focusing on future studies and application of the forecast method; *Social* component focusing on develop and integrate marketing & social theories and methodologies with other approaches to social change; *Change* component focusing on climate change, energy and sustainable development, social-technical and sustainability transition.

The division of TF&SC literature into four components helps managers, editors, and scholars to understand the different dimensions that are important research content in TF&SC. Our knowledge components suggest that we can expect future emphasis in TF&SC on the following orientations: (1) From the perspective of the *technological* component, focusing on the relationships among innovation, science, society and markets; catering to future sustainable demand and supporting technological innovation with sustainable development, especially certain new types of innovation such as green innovation, eco-innovation, sustainable innovation, etc.; encouraging future research into the methods used for technology forecasting and into certain specific related technologies such as emerging technologies, disruptive technologies, the internet of things, robotics, etc.; (2) from the perspective of the *forecasting* component, forecasting is not only used for technology but also encouraged to be applied to socio-economic, socio-political, and sustainable development; promoting the diversity of forecasting methods and their wide application in various fields (for example, applying forecasting methods in developing cities, urban, regional and national infrastructure, industry, and environmental management); (3) from the perspective of the *social* component, it reminds scholars of TF&SC that socio-economic-technical development should aim to influence behaviors that benefit individuals and communities, that achieve social good, and that provide competition-sensitive social change strategies that are efficient and sustainable. Social and innovation systems, social sustainability, and social forecasting can be expected to see further research based on socio-economic-technological environments; (4) from the perspective of the *change* component, future research can be expected into how to consolidate and leverage the social and innovation system, technology and forecasting means in energy, and carbon emissions and climate change processes. It should also address environmental problems such as climate change requiring a shift to new kinds of energy, mobility, housing, and agro-food systems (i.e. socio-technical-sustainability transition). We expect the future “change” to include research into policies, infrastructures, cultural, business models, technology, and resource utilization.

TF&SC has clearly established itself as a discourse in its own right, and its seven core research themes are identified in this study. Considering the evolution of TF&SC discourse over time, we can see that the diversity of topics addressed by scholars has been increasing continuously over the analyzed time period, indicating that TF&SC, like many more established cross-disciplinary research themes such as innovation and social research, is continuing to attract new authors who are bringing fresh perspectives to the research. In addition, we can identify certain research topics that have continued to attract a high number of contributions in recent years. These core topics focus on innovation policy, open innovation, social media, social change, energy, and sustainability transition. Thus, it would appear that TF&SC is gradually establishing itself as a recognized discourse, and that these core topics are acting as hubs that provide researchers with methodologies and areas of application to which new research application areas can be anchored. TF&SC would expect the future to present more abundant methodologies, such as technology road mapping, patent analysis, triple helix, technology/corporate/strategic foresight, social network analysis, business model innovation, agent-based models, system dynamics and innovation/technology diffusion, transition pathways, etc. More methods are expected to place multifaceted solutions on various complex problems. Some complex problems still need to be further explored in the future, such as disruptive innovation, green innovation, innovation ecosystems, social entrepreneurship, social sustainability, SME development, smart cities, the sharing economy, the internet of things, the Fourth Industrial Revolution, socio-technical transition, innovation transition, energy transition, etc.

Concerning limitations, the most important one related to the actual research design derives from the selection of a single journal – *Technological forecasting and social change*, in our case, to undertake the empirical study. Obviously, some significant changes might have occurred in the results as well as in the conclusions drawn if the range of journal had been expanded, for example, other foresight journals with a high impact level in the field of foresight, such as *Foresight*, *Futures*, *International Journal of Forecasting*, *International Journal of Foresight & Innovation Policy*. In any case, the high number of papers considered in our research allows us to confidently state that the literature reviewed in this study is sufficiently representative of the research developed around the technological forecasting discipline under study.

A keyword-based analysis would have enabled us to widen both journal intellectual base. However, our preliminary searches indicated that it would not fully demonstrate our research yet, since TF&SC is an interdisciplinary field journal that covers different discourse under different aspects. We found that our

article selection and analysis served better our purpose and interest to build an overarching view to studies in the field of technology forecasting across management disciplines. Our document analysis enabled us to know the contributions of articles and authors on different research topics in different knowledge structures of the TFSC research, however, limiting the study to the high year-average cited articles in the sample could have biased the insights concerning the more information of publication and authors to TFSC research topics contents.

As for possible future research avenues, we encourage researchers to reproduce our analyses with a broadened database with a wider variety of foresight or management journals. We be convinced that a comparison might be drawn between the results obtained in our research an those others which might derive from applying the traditional topic model or bibliometric analysis to the papers about the technological forecasting published during the same time period in the most important general foresight or management & business journals, such as *Long range planning*, *Research policy*, *Technology analysis & strategic management*, *Strategic management journal* or in any other journal belonging to this study field.

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