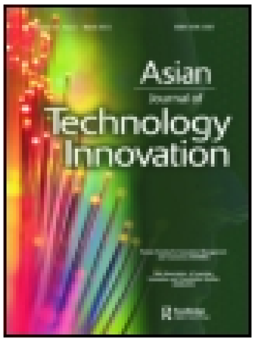

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Emerging industrial root technologies: a structural topic model- and topic matrix analysis-based approach

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ABSTRACT
This study aimed to identify emerging industrial root technologies from the unstructured text of journal papers, in order to establish a research and development (R&D) strategy. Hence, a structural topic model and topic matrix analysis were employed to evaluate the promising topics in Korean and international root technology papers, published from 2011 to 2019, from a domestic perspective. Subsequently, 75 topics in the main research domains of root technology were identified. Of these identified topics, five requiring leading R&D and five requiring follow-up R&D were selected based on priority: 'Corrosion', 'device current–voltage characteristics', 'electrode', 'carbide alloy', and 'titanium alloy' were determined to be the leading R&D topics, whereas 'material applications', 'photocatalytic activity', 'additive manufacturing', 'ductility', and 'high-entropy alloy' were determined to be the follow-up R&D topics. These results are significant because journal articles were used to determine emerging technologies according to the differences between the research published in Korean and international journals.

KEYWORDS
Root technology; topic modelling; structural topic model (STM); topic matrix; R&D strategy

1. Introduction

In South Korea, the term 'root technologies' is used to refer to fundamental technologies employed in key manufacturing processes that determine the quality and competitiveness of the manufacturing industry. Such processes include those that employ casting, moulding, forming, welding, surface treatment, and heat treatment technologies (KPIC, 2019). Root technologies have contributed significantly to the growth of major traditional industries in Korea, such as the automobile, machinery, and shipbuilding industries. Furthermore, the contribution of such technologies to emerging industries, such as the robotics and biotechnology industries, is expected to increase. The South Korean government has continuously promoted research and development (R&D) support policies for root technologies since the Root Industry Act was enacted in 2011. However, government-funded R&D projects for root technologies have been terminated due to changes in R&D policies. Hence, the demand for novel R&D project planning has increased. Moreover, the importance of an R&D management strategy in

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increasing the volume and efficiency of R&D investments has been emphasised (Cho et al., 2011; Lee & Cho, 2015). Government support must be sustained to secure competitiveness in manufacturing, pursue continued innovation, and surpass the perception that root technology is traditional.

Focused R&D investments are being performed, as strategic and efficient R&D investments have been emphasised in recent government R&D policies (MSIT, 2018). R&D policies have shifted from supporting diverse domains to focusing on those with the maximum potential for developing leading technology. Therefore, emerging vital processes include identifying the degree of interest in a technology, analysing technological trends, and identifying aspects that can lead to new frontiers in the corresponding field. However, these processes have previously employed subjective methods that rely heavily on experts in the field, and results have indicated that ensuring objectivity is difficult. Thus, leading R&D aspects must be identified through an objective analysis.

With the development of information and communications technology (ICT), data-based R&D planning and management is being employed to derive meaning from large sets of open data (Bibri & Krogstie, 2017). Typical achievements in science and technology include papers, patents, and technology transfers. Because most of these achievements entail large unstructured texts, conducting an objective, resourceful, and methodological analysis is difficult. Since research papers report on the emergence and extinction of new technologies, the basic text analysis of such papers can regularly reveal useful emerging technologies.

In this study, major R&D topics related to root technology in academia and industry were analysed. We derived emerging technologies from the perspectives of domestic journals through text analysis of research papers. Major R&D topics in the field of root technology were derived using topic modelling, and emerging topics in domestic root technology were derived through a topic matrix analysis, which was based on both promise and domestic superiority.

2. Background

2.1. Discovery methodology of emerging technologies

The phrase ‘emerging technologies’ is generally used to represent promising future technologies. Various studies have been conducted on emerging technologies, but no academic consensus has been reached on the concept (Rotolo et al., 2015). As the importance of technological innovation continues to grow, research is being conducted to identify emerging technologies and analyse their characteristics. Rotolo et al. (2015) analysed previous research on emerging technologies and identified five of its attributes: radical novelty, relatively fast growth, coherence, prominent impact, and uncertainty and ambiguity. In addition, empirical approaches for discovering emerging technologies were classified into five categories: indicators and trend analysis (Bengisu, 2003; Guo et al., 2011), citation analysis (Boyack et al., 2014; Iwami et al., 2014), co-word analysis (Lee, 2008; Zhang et al., 2014), overlay mapping (Leydesdorff et al., 2013; Rafols et al., 2010), and any combinations thereof (Chen, 2006; Yan, 2014).

Various methods related to emerging technologies have been studied, but the current research on developing emerging technologies has proven insufficient for the in-depth analysis of text content. It is essential to conduct a study to form a set of words and derive emerging technologies through changes in the relationships among the words with time, instead of only considering the co-occurrence relationships between words. Thus, we propose that emerging technologies should be derived based on topics through topic modelling, a recent method used to analyse unstructured text data.

2.2. Topic modelling

Topic modelling is a method for analysing text. With topic modelling, topics from a document can be deduced using a word distribution to cluster a set of words with similar meanings, and an algorithm that determines a topic from a large set of unstructured words can be created. The types of topic modelling range from the latent semantic index (LSI), which locates related words by reducing their dimensions, to latent Dirichlet allocation (LDA), which estimates the distributions of words and topics. These approaches have continued to expand and develop.

LDA, which is a typical and probabilistic method of topic modelling, assumes a Dirichlet distribution in topic and word distributions (Blei et al., 2003). Based on this distribution, the composition of topics and words that maximise the likelihood of the model can be estimated. Other complementary methods, such as the correlated topic model (CTM) (Blei & Lafferty, 2007), have been developed to complement the correlations between topics and the dynamic topic model (DTM) (Blei & Lafferty, 2006), which use time information for topic modelling. A Dirichlet multinomial progress (DMR) (Mimno & McCallum, 2008) reflects the characteristics of data in model's parameters, and the sparse additive generative model (SAGE) (Eisenstein et al., 2011) overlaps the distribution characteristics of various data in the context of probability parameters. Recently, a structural topic model (STM) was developed to reflect metadata in topic modelling, and it has been applied in research.

2.3. Structural topic model (STM)

Roberts et al. (2014) combined CTM, DMR, and SAGE based on LDA and proposed an STM that uses metadata for topic modelling. The CTM and DMR approaches were applied with the assumptions that the topic probability distribution was a logistic normal linear distribution rather than a Dirichlet distribution and that the characteristics of the data reflected the topic probability distribution. In applying SAGE, an exponential function was utilised in the word probability distribution to reflect the effect of a covariate on a set of topics.

STMs are designed to reflect metadata information on topic and word probability distributions based on LDAs. Thus, they can conduct topic modelling analyses based on metadata characteristics such as time. STMs are used for trend analysis according to the characteristics of data in various fields such as science, technology, policymaking, and media. STMs are easy to use because they can be implemented as packages in the open statistics program R (version 3.6.2).

2.4. LDA and STM application research

Various studies have been conducted to analyse technologies elucidated in papers using LDAs. Griffiths and Steyvers (2004) applied an LDA to papers from the National

Academy of Science to discover topics in science and technology. Song and Kim (2013) applied an LDA to papers published in 47 journals related to bioinformatics to explore the knowledge structures of bioinformatics. Xiong et al. (2019) applied an LDA to 43 journals related to manufacturing engineering to identify manufacturing-related research topics over time. Additionally, several other studies applied LDAs to unstructured data, such as patents (Kim et al., 2016), news articles (Savoy, 2013), reports (Dyer et al., 2017), reviews (Wang et al., 2018), and social network services (SNSs) (Du et al., 2020).

Recently, STMs have been used in various fields to conduct topic modelling analyses to reflect metadata information. Bohr and Dunlap (2017) used an STM to analyse the main topics in environmental sociology; three common core clusters were identified: environment and society, social theory, and natural resources. Das et al. (2017) used an STM to analyse trends in transport-related research fields, such as transportation and logistics, and consecutively obtained three clusters: traffic safety, traffic flow, and pavement. Clare and Hickey (2019) used an STM to analyse research trends in community forestry and identified four major research domains, including carbon sequestration and tenure. In addition, studies were conducted to apply STMs to news articles (Roberts et al., 2016), reports (Kuhn, 2018), reviews (Hu et al., 2019; Korfiatis et al., 2019), surveys (Roberts et al., 2014), and SNSs (Muthusami & Bharathi, 2019).

Thus, topic modelling methods such as STMs and LDAs have been actively applied to research papers to analyse technology, but the research has primarily focused on analysing changes in topic prevalence over time, resulting in insufficient research to derive emerging technologies. The 'prevalence' obtained from an STM corresponds to the probability of topic appearance, and the sum of the prevalences of all topics for each document is 1. To distinguish emerging technologies, the rates of change in prevalence and the perspective of domestic research must be considered by utilising the characteristics of metadata. Thus, this study reflected the characteristics of Korean and international journals via topic modelling and derived emerging technologies suitable for Korea.

3. Research method

3.1. Overall research framework

To discover emerging root technologies based on journal papers, we followed these steps. First, a set of Korean and international paper data related to root technologies was constructed. Second, the text of the constructed data was pre-processed. Third, an STM analysis was performed. Fourth, a topic matrix analysis, such as that based on a topic portfolio matrix (TPM) and topic competitiveness matrix (TCM), was performed. By combining the results of the two matrices, the leading Korean and international topics were classified. Based on the results, a domestic perspective-based R&D strategy was established. Figure 1 depicts the overall process of identifying emerging technologies.

3.2. Step 1: data building

Root technology is largely divided into six (sub) technologies, each having a local academic association. For the six major associations for root technology, we conducted an analysis of 2,221 online accessible research papers published between 2011 and

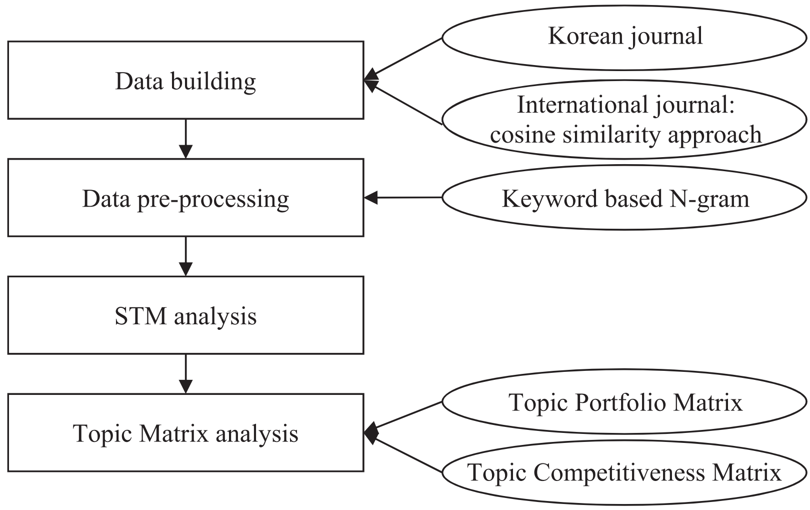

Figure 1. Overall research process.

2019. The starting period of 2011 was selected because that was when the concept of root technology originated. Major data, such as the abstract, keywords, title, and author information, were collected using databases of academic information such as DBpia. The detailed composition is shown in Table 1.

To select international papers focused on root technology, we conducted three stages of screening, considering the suitability of the field, representativeness of the journal, and relevance of the paper. First, based on the journal information corresponding to the papers published by root technology researchers, the most suitable root technology sectors were derived for the field of metallurgy and metallurgical engineering from 236 sectors of the Web of Science (as of 2018) classification. Second, the journal impact factor (JIF) was used to conduct a screening process for that field. The top-ten-JIF journals in the field of metallurgical engineering were classified, and the top five journals were selected based on the total number of citations and JIF indexes. Journals that were limited to certain topics were excluded. 51,836 papers published between 2011 and 2019 were selected, and major data such as the abstracts and keywords were collected from the ScienceDirect academic information database. A third screening process was conducted to distinguish papers that are highly relevant to root technology. The

Table 1. Number of research papers under Korean root technology (2011–2019).

Journal	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
KFS[a]	30	28	22	21	21	20	19	15	10	186
KSDME[b]	0	35	12	20	24	30	30	30	29	210
KSTP[c]	79	68	54	57	54	46	42	42	40	482
KWJS[d]	51	51	74	78	66	64	71	68	66	589
KISE[e]	44	43	45	59	58	88	77	60	53	527
KSHT[f]	30	23	24	24	24	24	25	29	24	227
Total	234	248	231	259	247	272	264	244	222	2,221

Notes: [a] Korea Foundry Society, [b] Korea Society of Die & Mold Engineering, [c] The Korean Society for Technology of Plasticity, [d] The Korean Welding and Joining Society, [e] The Korean Institute of Surface Engineering, [f] The Korean Society for Heat Treatment cosine similarity (Singhal, 2001; Tan et al., 2016) between the total word distribution of the Korean paper and the word distribution of the abstract of each international paper was calculated. Subsequently, 18,367 papers with high similarity (> 0.2, Korean paper average) were classified as international root technology papers. The detailed compositions are shown in Table 2.

3.3. Step 2: data pre-processing

The data of 2,221 and 18,367 Korean and international root technology papers, respectively, were integrated. Data consolidated in databases, such as text and Excel files, were integrated using the R program. The integrated data consisted of abstracts, keywords, journals, international journal variables, and time variables for each paper. The international journal variables were considered to be internal for Korean journal papers and external for international journal papers. The time variables were converted into numerical information equivalent to 108 months (0–107) corresponding to 9 years on a monthly basis, based on the volumes and issues of the papers.

The abstract and keyword formats from the papers of each journal were arranged identically. Text pre-processing, such as removing punctuation and special characters, was conducted on the abstract and keywords using the tm package of the R program. The data pre-processing was completed by converting words into a basic form using lemmatisation and removing stopwords. Owing to the efficiency of the STM analysis and limitations involved in the use of more than 10,000 words in STM packages, words appearing in less than nine papers were removed.

A keyword-based N-gram method was applied to supplement the limitations of the LDA-based methodology, which does not consider the word sequence. An N-gram represents a chain of adjacent N words that appear consecutively (Silge & Robinson, 2017). Through the application of the keyword-based N-gram, N consecutive words are considered as one word. In this study, a maximum of four adjacent words from more than ten papers were considered. If a word group appeared in the keywords in more than three papers, the spaces between the words were converted to underscores, thereby considering the word group as a single word.

3.4. Step 3: STM analysis

An STM assumes that the distribution of topics and words follows a logistic normal distribution and uses the covariates of the metadata variables for topic modelling. The

Table 2. Number of research papers under international root technology (2011–2019).

Journal	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
Acta [a]	236	239	236	245	261	290	282	263	268	2,320
JMST [b]	76	79	62	60	63	69	66	119	125	719
Scripta [c]	49	65	48	30	46	69	63	65	81	516
JAC [d]	555	448	654	846	989	989	1,440	1,209	1,520	8,650
MSEA [e]	594	587	693	690	603	742	773	713	767	6,162
Total	1,510	1,418	1,693	1,871	1,962	2,159	2,624	2,369	2,761	18,367

Notes: [a] Acta Materialia, [b] Journal of Mechanical Science and Technology, [c] Scripta Materialia, [d] Journal of Alloys and Compounds, [e] Materials Science and Engineering: A properties of metadata can be reflected in the topic prevalence and probability of topical content. In this study, the time and international journal variables were considered to be factors affecting topic prevalence. The changes in topic prevalence according to time and Korean/international classification were analysed. In contrast, we assumed that no variables affected the probability of topical content.

Similar to an LDA, an STM needs to specify the total number of topics while performing topic modelling. No established rule exists for determining the number of topics. Hence, the judgement of the researcher is required (Roberts et al., 2018). In this study, we used the anchor-based number estimation method proposed by Lee and Mimno (2014). This method constructs a network of words based on the number of co-occurrence words, calculates their relative position, and then estimates the number of topics from the convex hull. This method determines the number of topics by considering the meanings of the words based on co-occurrences rather than by the model characteristics.

The STM was employed using the STM package (Roberts et al., 2018) of the R program. Estimating the optimal model through an STM can lead to an indication of the topic prevalence corresponding to each document. Additionally, the words for each topic can be estimated. Words can be structured according to the probability order based on the frequency or according to the frequency and exclusivity (FREX) index order, which calculates the frequency and weight of exclusivity (Airoldi & Bischof, 2016; Bischof & Airoldi, 2012). For the topic name setting, the words were comprehensively considered according to frequency and the FREX index, and a topic name was set to represent the words.

The functions contained in the STM package were used to estimate the changes in topic prevalence over time. The topic prevalence was regressed over time to estimate the slope. A statistically significant slope value was used as the rate of change.

3.5. Step 4: topic matrix analysis

In this study, a TPM was proposed to distinguish emerging topics (Figure 2). The topic prevalence for the entire period was represented on the X-axis and the rate of prevalence change was represented on the Y-axis. The quadrant plane was constructed based on the median value of the prevalence and the zero value of the rate of change, including the promising, potential, declining, and mature groups.

In addition, the total period was divided into three sections on a three-year basis, and the matrix position change of each quadrant section was analysed by section. Using this technique, the matrix position change path of the topic can be estimated.

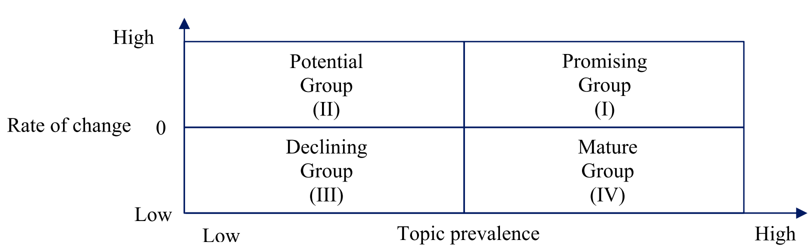

Figure 2. Topic portfolio matrix (TPM).

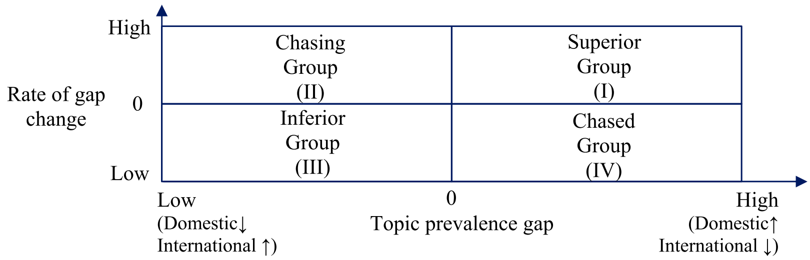

Figure 3. Topic competitiveness matrix (TCM).

In this study, a TCM was proposed to analyse the differences in emerging topics of Korean and international journals (Figure 3). The international journal variables were used as adjustment variables along with the time variable for topic modelling. In the figure, the difference in the gap of topic prevalence in the Korean and international journals for the entire period is represented on the X-axis and the rate of gap change is represented on the Y-axis. The quadrant plane was constructed in terms of the superior, chasing, inferior, and chased groups based on the zero value of the gap in topic prevalence and the zero value of the rate of gap change.

Based on the results of the TPM and TCM, emerging technologies were derived. R&D strategies were established to promote leading R&D for promising and active topics in Korean journals, and follow-up R&D was conducted for promising and active topics in international journals.

The four quadrants in each matrix of the TPM and TCM were divided into 16 domains; the promising (quadrant I) and potential (quadrant II) groups were considered as promising topics. Topics corresponding to promising domains, that is, the superior (quadrant I) and chasing (quadrant II) groups, were classified as leading R&D topics. Furthermore, topics corresponding to promising domains, that is, the inferior (quadrant III) and chased (quadrant IV) groups, were classified into follow-up R&D topics. Priority was determined based on the domain value multiplied by the prevalence value and rate of change.

4. Research results

4.1. Major research domains in root technology

The R&D topics were derived from Korean and international papers on root technology published between 2011 and 2019. The number of derived topics was estimated to be 76, but only 75 of them were utilised as one topic had no root technology characteristics and consisted only of general words. The top 20 prevalent topics and corresponding configurations of words were expressed as shown in Figure 4, and prevalence values per topic are listed in the Appendix.

The topics with the highest prevalence were related to 'content change' (0.033), followed by 'material application' (0.031) and 'ductility' (0.029). However, these results do not reflect the rate of change. Thus, there was a limit to distinguishing topics that have recently gained focus or interest. Accordingly, the topic prevalence was regressed over time for each topic.

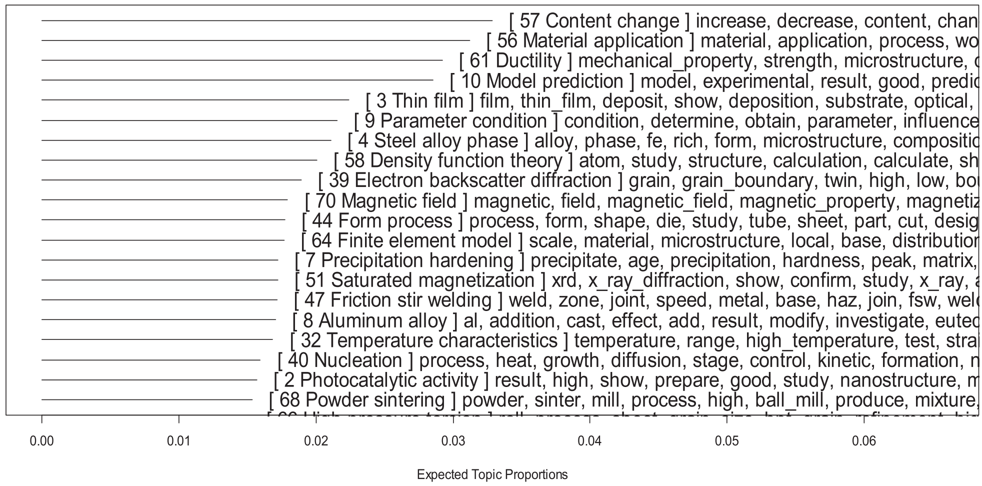

Figure 4. Topic prevalence and words (top 20 topics).

4.2. Change in topic prevalence over time and domestic perspective

The change in the topic prevalence over time was derived for each topic (Figure 5), and the rates of change per topic are listed in the Appendix. 'Content change' (topic 57) had the highest prevalence, but it decreased over time. Thus, distinguishing it as an emerging topic is difficult. Conversely, the prevalence of 'material application' (topic 56) was lower than that of 'content change', but it increased over time, making 'material application' a potential emerging topic. Topics with statistically significant changes in prevalence over time are indicated by green lines in the figure. Of the 75 total topics, 28 exhibited significant increases in prevalence over time, 38 exhibited significant decreases, and the remaining nine topics were not statistically significant.

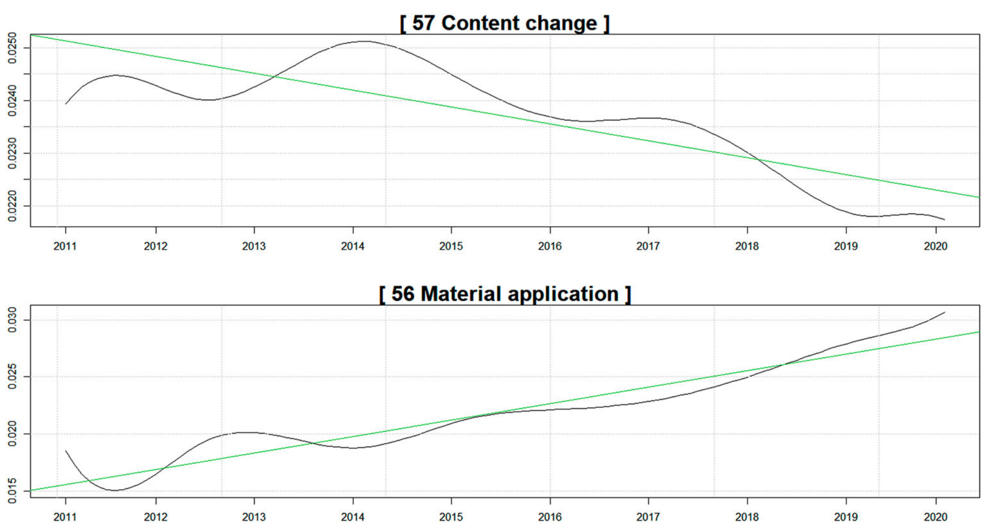

Figure 5. Topic prevalence change by time (topics 57 and 56 as examples).

The topic prevalence values according to the international journal variables and rates of change were derived as shown in Figure 6; the rates of gap change per topic are shown in the Appendix. For example, 'parameter condition' (topic 9) initially exhibited a higher prevalence in Korean journals, resulting in an increase in prevalence over time. However, its prevalence in international journals was lower, resulting in a decrease in prevalence over time. Thus, the rate of gap change was positive because of the high prevalence in Korean journals. This portrays the characteristics of the first quadrant. In addition, 'thin film' (topic 3) initially had a higher prevalence in Korean journals but decreased in prevalence over time. Moreover, the prevalence of this topic in international journals was lower than that in Korean journals. Thus, the rate of gap change in this case was negative. This indicates the characteristics of the fourth quadrant. The gaps between the prevalence values of the Korean and international journals were calculated, and the slope was estimated as the rate of change for every topic.

4.3. Topic matrix analysis result

The TPM was formed based on the prevalence and rate of change of prevalence for the topics. Considering the rate of change, nine statistically insignificant topics were excluded from the matrix configuration. The configuration ultimately consisted of 13 topics for the promising group (quadrant I), 15 for the potential group (quadrant II), 18 for the declining group (quadrant III), and 20 for the mature group (quadrant IV). The position of each topic was schematised and is shown in Figure 7 and Table 3. The domain values, multiplied by the topic prevalence and rate of change, were prioritised by topic.

The period between 2011 and 2019 was divided into three-year periods, and the results of the changes in location in the TPM were summarised (Table 4). In all three periods, 22 topics exhibited significant changes in the rate of change. An analysis of the changes in these 22 topics resulted in the movement of the declining group (quadrant III), potential

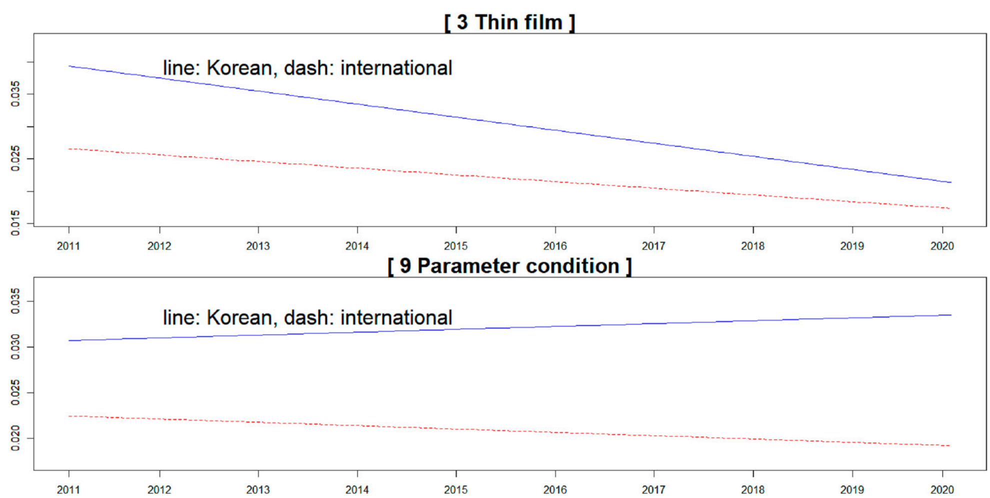

Figure 6. Change in prevalence according to Korean/international journals (topics 3 and 9 as examples)

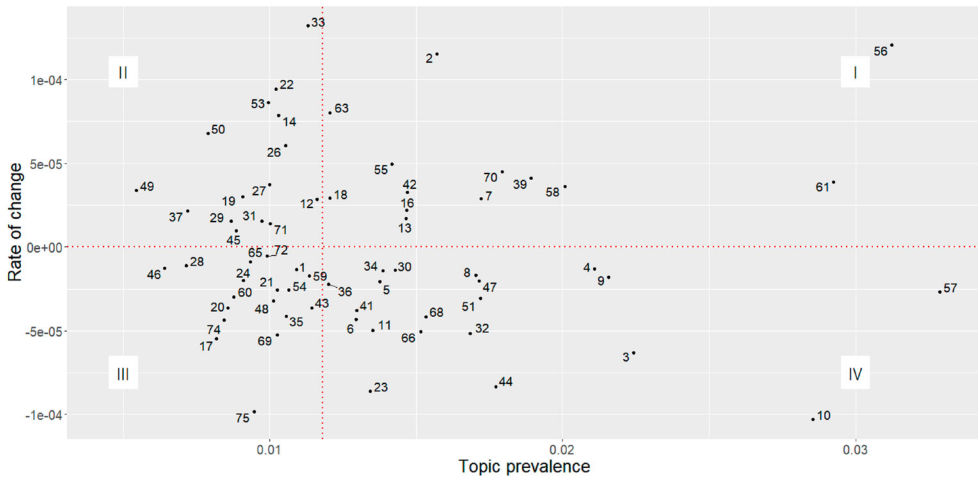

Figure 7. Topic distribution on the TPM.

group (quadrant II), promising group (quadrant I), and mature group (quadrant IV) (Figure 8).

The TCM was formed based on the prevalence gap between Korean and international journals and the rates of gap change among the 75 topics of root technology. It consisted of 14 topics for the superior group (quadrant I), 25 for the chasing group (quadrant II), 28 for the inferior group (quadrant III), and 8 for the chased group (quadrant IV). The positions of each topic were schematised as shown in Figure 9 and Table 5.

The R&D strategy map was derived by combining the TPM and TCM. The two matrices were applied together and divided into 16 domains, and the compositions of topics for each domain were analysed. These can be schematised as shown in Table 6. The promising group (I quadrant) consisted of 13 topics, divided into 2 for the superior group, 1 for the chasing group, 9 for the inferior group, and 1 for the chased group. Topics related to 'corrosion' (topic 63) and 'oxide layer' (topic 13) were active in Korean journals, whereas topics such as 'photocatalyst activity' (topic 2) and 'ductility' (topic 61) were active in international journals. The activeness of 'carbide alloy' (topic 18) was observed to increase in Korean journals, whereas that of 'material application' (topic 56) increased in international journals. Therefore, the follow-up R&D focusing on topics belonging to the inferior and chased groups, such as 'photocatalyst activity' (topic 2) and 'Material application' (topic 56), along with the leading R&D focusing

Table 3. Topic distribution by TPM position (top 5 topics).

Promising group (I quadrant)	Potential group (II quadrant)	Declining group (III quadrant)	Mature group (IV quadrant)
56 Material application	33 Additive manufacturing	75 Constitutive model	10 Model prediction
2 Photocatalytic activity	22 High entropy alloy	17 Equal Channel Angular Pressing	44 Form process
61 Ductility	53 Device current-voltage characteristics	69 Fatigue strength	3 Thin film
63 Corrosion	14 Electrochemical performance for batteries	74 Residual stress	23 Hot deformation process map
70 Magnetic field	26 Thermal conductivity	35 Injection mould	57 Content change

Table 4. TPM quadrant change.

Topic names	2011–2013	2014–2016	2017–2019	Topic names	2011–2013	2014–2016	2017–2019
57 Content change	1	4	4	13 Oxide layer	3	2	1
56 Material application	1	1	1	55 Phosphor	2	1	4
9 Parameter condition	4	1	4	33 Additive manufacturing	2	2	1
4 Steel alloy phase	1	4	1	38 Rolling	2	4	3
58 Density function theory	1	4	1	15 Accumulative roll bond	2	4	3
39 Electron backscatter diffraction	1	1	1	14 Electrochemical performance for batteries	2	2	1
51 Saturated magnetisation	1	4	4	22 High entropy alloy	2	2	1
8 Aluminium alloy	1	4	4	71 Sample susceptibility	2	2	3
32 Temperature characteristics	4	4	4	75 Constitutive model	4	3	3
66 High-pressure torsion	4	4	4	67 Thermal conductivity	3	2	2
16 Slip deformation	1	4	1	50 Electrode	3	2	2

on topics belonging to the superior and chasing groups, such as ‘corrosion’ (topic 63) and ‘carbide alloy’ (topic 18), must be promoted.

The potential group (quadrant II) consisted of 15 topics, divided into 4 for the superior group, 1 for the chasing group, 9 for the inferior group, and 1 for the chased group. Follow-up R&D focusing on topics belonging to the inferior and chased groups, such as ‘additive manufacturing’ (topic 33) and ‘coating’ (topic 12), and leading R&D focusing on topics belonging to the superior and chasing groups, such as ‘device current–voltage characteristics’ (topic 53) and ‘titanium alloy’ (topic 19), must be promoted.

The declining group (quadrant III) consisted of 18 topics, divided into 5 for the superior group, 10 for the potential group, and 3 for the chased group.

The mature group (quadrant IV) consisted of 20 topics, divided into 2 in the superior group, 11 in the chasing group, 4 in the inferior group, and 3 in the chased group.

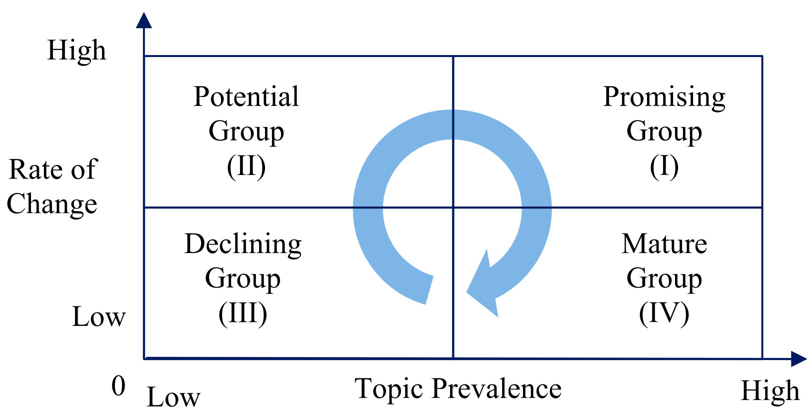

Figure 8. Path of the TPM location change.

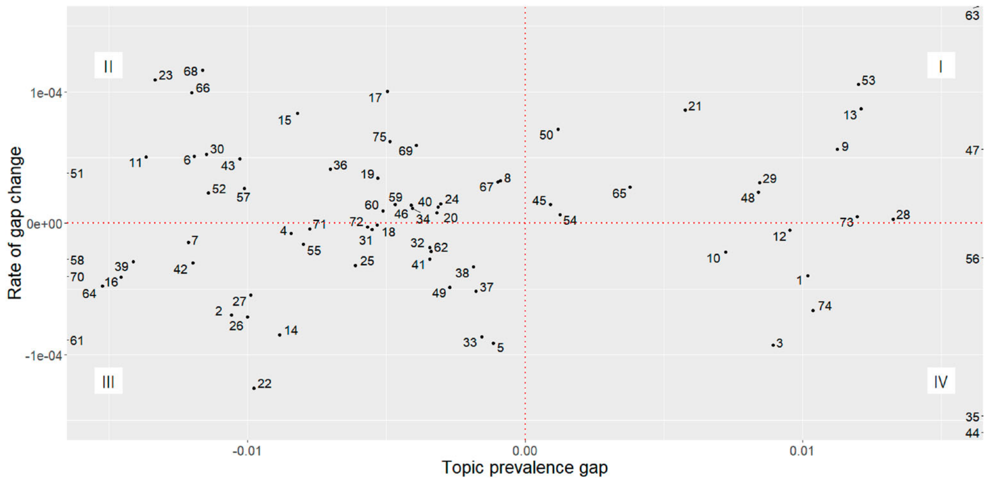

Figure 9. Topic distribution on the TCM.

Table 5. Topic distribution by TCM position (top 5 topics).

Superior group (I quadrant)	Chasing group (II quadrant)	Inferior group (III quadrant)	Chased group (IV quadrant)
63 Corrosion 47 Friction stir welding 53 Device current-voltage characteristics 13 Oxide layer 9 Parameter condition	23 Hot deformation process map 68 Powder sintering 66 High-pressure torsion 30 Nanoparticle synthesis 15 Accumulative roll bond	61 Ductility 22 High entropy alloy 2 Photocatalytic activity 70 Magnetic field 14 Electrochemical performance for batteries	44 Form process 35 Injection mould 56 Material application 3 Thin film 74 Residual stress

Based on these results, a topic-based R&D strategy was established. Among the topics derived from the promising and potential groups, those with domestic competitiveness were considered for leading R&D, and those that were promising but required support to secure domestic competitiveness were considered for follow-up R&D. For leading R&D, topics such as 'corrosion' (topic 63) were derived. These topics can be considered primarily as leading R&D targets. For follow-up R&D, topics such as 'material application' (topic 56) were derived. These topics can be considered primarily as follow-up R&D targets. The results are summarised in Table 7.

5. Discussion and conclusions

This study analysed emerging root technologies based on the text found in journal papers. A novel method of prioritising emerging technologies from a domestic perspective was established by applying an STM and the topic matrix method. Using a TPM, the promising and potential groups were classified by considering the prevalence and the rate of change simultaneously. Using a TCM, the emerging technology group was classified from a domestic perspective. Consequently, we categorised emerging technologies in root technology as leading and follow-up topics for domestic R&D.

Table 6. Topic distribution on R&D strategy map.

Potential group (II)		**Promising group (I)**	
Chasing group (II)	Superior group (I)	Chasing group (II)	Superior group (I)
19 Titanium alloy	53 Device current-voltage characteristics · 50 Electrode · 29 Gallium laser · 45 Oxygen concentration	· 18 Carbide alloy	· 63 Corrosion · 13 Oxide layer
Inferior group (III)	Chased group (IV)	Inferior group (III)	Chased group (IV)
33 Additive manufacturing · 22 High entropy alloy · 14 Electrochemical performance for batteries · 26 Thermal conductivity · 27 Ferroelectric · 49 Solar cell · 31 Copper alloy · 37 Irradiation · 71 Sample susceptibility	12 Coating	2 Photocatalytic activity · 61 Ductility · 70 Magnetic field · 39 Electron backscatter diffraction · 58 Density function theory · 55 Phosphor · 7 Precipitation hardening · 42 Carbon nanotube · 16 Slip deformation	56 Material application
Declining group (III)		**Mature group (IV)**	
Chasing group (II)	Superior group (I)	Chasing group (II)	Superior group (I)
72 Nanoparticle size · 46 Glass ceramic · 24 Porous structure · 59 Solidification · 60 Creep test · 20 Magnesium hydride · 43 Shape memory alloy · 17 Equal Channel Angular Pressing · 69 Fatigue strength · 75 Constitutive model	65 Cooling time · 28 Nickel silicon compounds · 21 Twip steel · 54 Indentation · 48 Specimen treatment	30 Nanoparticle synthesis · 34 Fatigue fracture · 36 Plastic deformation · 8 Aluminium alloy · 51 Saturated magnetisation · 6 AC conductivity according to frequency · 68 Powder sintering · 11 Amorphous alloy · 66 High-pressure torsion · 57 Content change · 23 Hot deformation process map	47 Friction stir welding · 9 Parameter condition
Inferior group (III)	Chased group (IV)	Inferior group (III)	Chased group (IV)
–	1 Soldering · 74 Residual stress · 35 Injection mould	4 Steel alloy phase · 5 Extrusion · 41 Tension direction · 32 Temperature characteristics	3 Thin film · 44 Form process · 10 Model prediction

In previous studies, only topic prevalence or rate of change was considered in the classification of emerging topics. In this paper, we proposed a method that considers both topic prevalence and rate of change using a TPM; moreover, the proposed

Table 7. Results for leading and follow-up R&D topics.

Leading R&D topics	Follow-up R&D topics
63 Corrosion	56 Material application
53 Device current-voltage characteristics	2 Photocatalytic activity
50 Electrode	33 Additive manufacturing
18 Carbide alloy	61 Ductility
19 Titanium alloy	22 High entropy alloy

method enables us to classify emerging topics with high prevalence as the prevalence increases over time. In addition, there have been insufficient prior attempts at classifying emerging topics from a domestic perspective by distinguishing between domestic and international topics. In this paper, a method of analysing the differences between domestic and international topics using a TCM was proposed. The proposed method allows us to distinguish among emerging topics based on the level of domestic or international prevalence.

The results obtained after analysing the emerging technologies were similar to the current R&D scenario with regard to root technologies. For example, 'additive manufacturing' was derived as a follow-up R&D topic, and currently, an active R&D program on this topic is being planned to reduce the technology gap via a 3D printing-related policy in Korea (MSIT, 2020). Regarding 'Material application', derived as a follow-up R&D topic, the focus is on the promotion of extensive R&D programs aimed at improving technological competitiveness through improving the materials, parts, and equipment policy employed (MOTIE, 2020). The technology related to 'titanium alloy', derived as a leading R&D topic, was selected as an excellent technology for public R&D (MSIT, 2019). Furthermore, 'device current–voltage characteristics', which was derived as a leading R&D topic, corresponds to a technology necessary for OLEDs, and it can be considered to possess technological capabilities considering Korea's excellent OLED industry competitiveness (MOTIE, 2017). The follow-up R&D topics correspond to technical fields in their infancy that reflect changes in industry. The leading R&D topics correspond to well-established technical fields in Korea. Based on these results, different R&D strategies are required according to the characteristics of the topic and purpose of R&D. Exceptional results are expected to be generated if R&D is performed regarding the leading R&D topics, and extensive R&D for technology acquisition are expected to be promoted for the follow-up topics.

This analysis provides new insights for objectively analysing the changing trend of root technologies. This study can contribute to policy making and R&D planning regarding emerging technologies.

First, concepts related to root technology that do not exist internationally are classified based on the technological field and word similarity. In previous studies that analysed emerging technologies, a method of searching for keywords or selecting a specific journal was used to consolidate data for a specific field. However, when analysing an overall field instead of a specific technology, consolidating data based on journals can be considered to be more effective in terms of representation.

Second, the limitation of topic modelling is partially compensated by applying the keyword-based N-gram method. Topic modelling considers only the number of appearances of words and does not consider the order of words, in accordance with the 'bag-of-words' model. The words combined using an N-gram can be employed as a single word to reduce confusion in interpreting the results of topic modelling.

Third, the topics were divided into four categories, namely, the promising, potential, declining, and mature groups, based on the topic prevalence and rate of change in prevalence over time. Further, the characteristics of each group were employed to determine the emerging technologies.

Fourth, the topics were also divided into four other categories, namely, the superior, chasing, inferior, and chased groups, based on the differences in the prevalence and rate of gap change over time. Moreover, the characteristics of each group were employed to determine the emerging technologies, as well as to categorise the associated topics as leading and follow-up R&D topics.

Fifth, based on the results of the two matrices, an R&D strategy for root technologies was established from a domestic perspective. For the emerging topics, a domestic R&D strategy was established to promote leading R&D for topics corresponding to a relatively high domestic prevalence and to pursue follow-up R&D for topics with a relatively low domestic prevalence.

However, this study also has several limitations. In particular, subjectivity is entailed in setting the name of a topic or setting a reference value for pre-processing. Moreover, even if the suggested research method is used, it may be difficult to classify a technology that has emerged rapidly in recent years as an emerging technology.

Further research is needed to consolidate and analyse data in the long term, to derive emerging topics based on industrial technologies using patent data in addition to research papers, and to identify the differences between the results obtained using the two types of data.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix. TPM: Topic portfolio matrix; TCM: Topic competitiveness matrix

Topic No	Topic name	Pre-valence	Rate of change ($\times10^3$)	Domain value ($\times10^5$)	TPM	Gap	Rate of gap change ($\times10^3$)	TCM
1	Soldering	0.011	−0.013	−0.015	3	0.01	−0.047	4
2	Photocatalytic activity	0.016	0.115	0.181	1	−0.011	−0.063	3
3	Thin film	0.022	−0.063	−0.141	4	0.008	−0.103	4
4	Steel alloy phase	0.021	−0.013	−0.027	4	−0.009	−0.01	3
5	Extrusion	0.014	−0.021	−0.028	4	−0.001	−0.095	3
6	AC conductivity according to frequency	0.013	−0.043	−0.056	4	−0.012	0.047	2
7	Precipitation hardening	0.017	0.029	0.05	1	−0.012	−0.007	3
8	Aluminium alloy	0.017	−0.017	−0.029	4	−0.001	0.035	2
9	Parameter condition	0.022	−0.018	−0.038	4	0.011	0.061	1
10	Model prediction	0.029	−0.103	−0.294	4	0.007	−0.025	4
11	Amorphous alloy	0.014	−0.05	−0.067	4	−0.013	0.055	2
12	Coating	0.012	0.028	0.033	2	0.01	−0.011	4
13	Oxide layer	0.015	0.017	0.025	1	0.012	0.09	1
14	Electrochemical performance for batteries	0.01	0.079	0.081	2	−0.009	−0.094	3
15	Accumulative roll bond	0.01	0	0	0	−0.008	0.084	2
16	Slip deformation	0.015	0.022	0.032	1	−0.014	−0.047	3
17	Equal Channel Angular Pressing	0.008	−0.055	−0.045	3	−0.005	0.103	2
18	Carbide alloy	0.012	0.029	0.035	1	−0.005	0.006	2
19	Titanium alloy	0.009	0.03	0.027	2	−0.005	0.036	2
20	Magnesium hydride	0.009	−0.036	−0.031	3	−0.003	0.013	2
21	Twip steel	0.01	−0.026	−0.026	3	0.006	0.095	1
22	High entropy alloy	0.01	0.094	0.096	2	−0.01	−0.132	3
23	Hot deformation process map	0.013	−0.086	−0.116	4	−0.013	0.124	2
24	Porous structure	0.009	−0.02	−0.018	3	−0.003	0.025	2
25	Hardness	0.01	0	0	0	−0.006	−0.024	3
26	Thermal conductivity	0.011	0.061	0.064	2	−0.01	−0.07	3
27	Ferroelectric	0.01	0.037	0.037	2	−0.01	−0.058	3
28	Nickel silicon compounds	0.007	−0.011	−0.008	3	0.013	0.005	1
29	Gallium laser	0.009	0.015	0.013	2	0.008	0.033	1
30	Nanoparticle synthesis	0.014	−0.014	−0.019	4	−0.012	0.064	2
31	Copper alloy	0.01	0.016	0.015	2	−0.006	−0.008	3
32	Temperature characteristics	0.017	−0.051	−0.087	4	−0.003	−0.023	3
33	Additive manufacturing	0.011	0.132	0.149	2	−0.002	−0.09	3
34	Fatigue fracture	0.014	−0.014	−0.019	4	−0.004	0.024	2
35	Injection mould	0.011	−0.041	−0.043	3	0.073	−0.262	4
36	Plastic deformation	0.012	−0.022	−0.026	4	−0.007	0.044	2
37	Irradiation	0.007	0.022	0.016	2	−0.002	−0.052	3
38	Rolling	0.011	0	0	0	−0.002	−0.037	3
39	Electron backscatter diffraction (EBSD)	0.019	0.041	0.077	1	−0.014	−0.032	3
40	Nucleation	0.016	0	0	0	−0.003	0.015	2
41	Tension direction	0.013	−0.038	−0.049	4	−0.004	−0.03	3
42	Carbon nanotube	0.015	0.033	0.048	1	−0.012	−0.04	3
43	Shape memory alloy	0.011	−0.036	−0.041	3	−0.01	0.044	2
44	Form process	0.018	−0.083	−0.147	4	0.114	−0.329	4
45	Oxygen concentration	0.009	0.01	0.009	2	0.001	0.013	1

(*Continued*)

Continued.

Topic No	Topic name	Pre-valence	Rate of change (×10^3)	Domain value (×10^5)	TPM	Gap	Rate of gap change (×10^3)	TCM
46	Glass ceramic	0.006	−0.012	−0.008	3	−0.004	0.011	2
47	Friction stir welding	0.017	−0.02	−0.035	4	0.047	0.072	1
48	Specimen treatment	0.01	−0.032	−0.032	3	0.008	0.027	1
49	Solar cell	0.005	0.034	0.018	2	−0.003	−0.047	3
50	Electrode	0.008	0.068	0.054	2	0.001	0.081	1
51	Saturated magnetisation	0.017	−0.03	−0.052	4	−0.019	0.035	2
52	Solid-state reaction	0.011	0	0	0	−0.011	0.034	2
53	Device current-voltage characteristics	0.01	0.086	0.086	2	0.012	0.115	1
54	Indentation	0.011	−0.026	−0.027	3	0.001	0.006	1
55	Phosphor	0.014	0.05	0.07	1	−0.008	−0.012	3
56	Material application	0.031	0.121	0.377	1	0.034	−0.032	4
57	Content change	0.033	−0.027	−0.088	4	−0.01	0.037	2
58	Density function theory (DFT)	0.02	0.036	0.073	1	−0.021	−0.031	3
59	Solidification	0.011	−0.017	−0.02	3	−0.005	0.005	2
60	Creep test	0.009	−0.03	−0.026	3	−0.005	0.009	2
61	Ductility	0.029	0.039	0.113	1	−0.018	−0.095	3
62	Retain austenite	0.011	0	0	0	−0.004	−0.032	3
63	Corrosion	0.012	0.08	0.096	1	0.025	0.243	1
64	Finite element model	0.018	0	0	0	−0.015	−0.044	3
65	Cooling time	0.009	−0.009	−0.008	3	0.004	0.03	1
66	High-pressure torsion	0.015	−0.05	−0.076	4	−0.012	0.109	2
67	Thermal conductivity	0.009	0	0	0	−0.001	0.029	2
68	Powder sintering	0.015	−0.042	−0.064	4	−0.012	0.13	2
69	Fatigue strength	0.01	−0.052	−0.054	3	−0.004	0.053	2
70	Magnetic field	0.018	0.045	0.08	1	−0.018	−0.039	3
71	Sample susceptibility	0.01	0.014	0.014	2	−0.008	−0.005	3
72	Nanoparticle size	0.01	−0.005	−0.005	3	−0.005	0.001	2
73	Defect rate	0.007	0	0	0	0.012	0.006	1
74	Residual stress	0.008	−0.043	−0.037	3	0.011	−0.076	4
75	Constitutive model	0.009	−0.098	−0.093	3	−0.005	0.072	2