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Strategies for sensing innovation opportunities in smart grids: In the perspective of interactive relationships between science, technology, and business

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ABSTRACT

In response to the many changes and uncertainties facing the future, sensing opportunities for innovation is an important agenda. Formulating strategies for sensing opportunities in innovation requires an ecosystem perspective that integrates the science, technology, and business (S-T-B) fields that shape the innovation ecosystem. This study was to identify potential in the innovation ecosystem focusing on a text mining technique and similarity-based analysis, which is the fundamental concept of Literature-Based Discovery, an approach to deriving hidden associations between two areas in bibliometric databases. The purpose of this study was sensing innovation opportunities through intelligent trends and interaction analysis in S-T-B fields in the value chain of smart grids, which is the research target area. Topic modeling, and cosine similarity measurements were carried out using scientific papers, patents, business publication data corresponding to the S-T-B ecosystem. Through multi-dimensional data sources corresponding to the S-T-B fields, the evolutionary path of the smart grid value chain and its potential as a strategic tool for future innovative challenges were identified. This study has practical and policy implications in that it identifies a niche in the innovation system and provides meaningful information that could contribute to the revitalization of participation in the private sector and consumers.

1. Introduction

Sensing opportunities that are considered seeds to grow into innovation deserves attention as a response to the many changes and uncertainties faced in the future (Teece, 2007, 2012; Terwiesch and Ulrich, 2009). Opportunities are “embryonic-type innovations, newly perceived needs, newly discovered technologies, or coarse agreements between needs and possible solutions” (Terwiesch and Ulrich, 2009). While some opportunities ultimately achieve innovation, others may not guarantee real progress, effective application of mechanisms to sense exceptional opportunities could increase the number of opportunities competing in innovation tournaments (Terwiesch and Ulrich, 2009). This also needs to be viewed from a strategic perspective: the ability to identify and integrate the value of new information and apply it commercially, namely, innovative capabilities (Cohen and Levinthal, 1990). Teece (2007) emphasized that dynamic capabilities are required to respond to changing environments and sensing opportunities, seizing those opportunities, and reconfiguration capabilities as key drivers. Of the key drivers, we focused on sensing opportunities. Opportunities are constantly in flux, and most new trajectories are difficult to identify (Teece, 2007). Sensing opportunities is considered an important activity for setting up an enterprise’s initiatives and requires constant exploration of technology and markets (Danneels, 2002). The scope of sensing activities includes technological orientation, customer demand, and industrial structure (Teece, 2007). Furthermore, potential opportunities for technological innovation vary depending on the sectoral or specific field (Klevorick et al., 1995; Olsson, 2005), which requires strategies to take into account ecological system characteristics accordingly.

The energy sector is facing an evolutionary response to climate change and the transition of efficient systems, as it considers the 3Ds (Digitalization, De-centralization, and De-carbonization) as three key driving forces (Di Silvestre et al., 2018; Gielen et al., 2019). However, since the energy sector is considered an area where new value creation is difficult due to structural legacy inertia (International Energy Agency, 2019; Unruh, 2000), well-managed strategy studies are needed to provide rich insights. Smart grids are an essential system in conjunction with the 3Ds in the energy sector (Dranka and Ferreira, 2020; Kuzlu et al., 2020; Wu et al., 2021). Identifying variable challenges and sensing

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opportunities for innovation are considered an attractive strategic research agenda. Smart grids are the next-generation power infrastructure system that incorporate information and digital communication technologies into existing power grid systems, enabling bidirectional communication and electrical flow that could improve security, reliability, and efficiency (Markovic et al., 2015; Moslehi and Kumar, 2010; Tuballa and Abundo, 2016; Yu et al., 2014; Zame et al., 2018).

A novel methodology needs to be explored based on information resources as a strategic approach to sensing innovation opportunities. Technology Future Analysis (TFA) is useful for sensing opportunities for innovation, including technology intelligence, forecasting, roadmapping, and quantitative TFA methods such as bibliometric analysis, social networking analysis, Analytic Hierarchy Process(AHP), and cross-impact analysis are widely used (Technology Futures Analysis Methods Working Group, 2004). In particular, approaches from the bibliometric perspective, such as database analysis, morphological analysis, and text mining have been useful in past studies to identify opportunities for innovation (Daim et al., 2006; Kostoff and Schaller, 2001; Ma et al., 2014; Yoon et al., 2014; Yoon and Park, 2005; Yoon and Kim, 2012). In the case of smart grid discipline, retrospective or prospective analysis was attempted by applying patent analysis and text mining based on bibliographic information (Park and Cho, 2017; Ree and Kim, 2019). However, it is limited to single-dimensional data sources or lacks integrated discussions. In order to improve the limitations of the one-dimensional source-based analysis, and for a richer discussion, the following research directions were established to sense smart grid innovation opportunities from the perspective of multi-dimensional source-based interactions in the innovation ecosystem:

✓ Seek available data sources to provide insight into sensing opportunities for innovation
✓ Analysis of intellectual evolution trends by value chain as a smart grid ecological system
✓ Derive the strategies for sensing innovation opportunities by analyzing intellectual interactions between knowledge and business fields of smart grid systems.

The findings of this study could lead to a comprehensive understanding of the innovation ecosystem of smart grids and contribute to the formulation of strategies for sensing potential innovation opportunities in specific sectors, including smart grid systems.

2. Theoretical background

2.1. Innovation ecosystem: approach of S-T-B ecosystem

The term "innovation ecosystem" and related attributes are being discussed in academic and industrial areas, but it is not defined as a strictly established concept (de Vasconcelos Gomes et al., 2018; Oh et al., 2016). Jackson (2011) defines an innovation ecosystem as the result of interactions between numerous individual elements, including industry, government, and academia, that are complex relationships that create value for innovation. From an advanced perspective, Granstrand and Holgersson (2020) more recently defined it as an "evolving set of actors, activities, and artifacts, and the institutions and relations, including complementary and substitute relations, that are important for the innovative performance of an actor or a population of actors". In a consistent context of various reviews and discussions on innovative ecosystems, it is divided into two fields: a research-driven knowledge economy and a market-oriented business economy (Jackson, 2011; Oh et al., 2016). The tension between these two fields is the driver behind the innovative ecosystem, and the linkage between innovative knowledge generation in the knowledge field and value capture in the business field is discussed as a fruitful research agenda (Clarysse et al., 2014; Oh et al., 2016). The knowledge field is evolving into interactions between two factors: the creation of scientific knowledge and the development of technical knowledge (Xu et al., 2018). Scientific knowledge research can be stimulated by innovations for technological development, and conversely, scientific progress requires the support of technology, i.e., science and technology are interdependent (Meyer, 2002; Petrescu, 2009). Also, exploring potential opportunities for scientific and technological development plays an important role in industrial innovation (Kostoff and Schaller, 2001; Leydesdorff et al., 1994; Ogawa and Kajikawa, 2015; Shibata et al., 2008). It is effectively used to uncover trends and potential opportunities in knowledge from the relationship between science and technology (Ogawa and Kajikawa, 2015; Shen et al., 2020; Shibata et al., 2010; Wang et al., 2015). Understanding the relationship between science and technology is recognized as a key challenge for R&D managers and policy makers focused on future innovation (Shibata et al., 2010; Wang et al., 2015).

Shibata et al. (2010), Wang et al. (2015) proposed three types of relationships (A, B, and C) between science and technology, as shown in Fig. 1, demonstrating potential opportunities for future scientific and technological developments. Scientific publications and patents are regarded as a result of scientific research and technological development, and are used as sources for strategic analysis (Martino, 2003). Comparisons between scientific papers and patents could provide insight into potential opportunities (Shen et al., 2020; Shibata et al., 2010; Wang et al., 2015).

✓ **Type A**: Areas where science and technology interact, and coevolution occurs
✓ **Type B**: Areas without scientific research corresponding to technological development
(The opportunities for scientific research development because it may require high scientific support)
✓ **Type C**: Areas without corresponding technological advances in scientific research

(The gaps between science and technology provides potential technology development or commercialization opportunities)

In the extended context of the relationship between science and technology in the knowledge field discussed above, to bridge the gap between knowledge and business fields for creating integrated value of the innovation ecosystem, it is necessary to approach the interaction or dynamics between the two distinct fields (Clarysse et al., 2014; Xu et al., 2018). In this regard, Xu et al. (2018) conceptualized the innovation ecosystem as shown in Fig. 2 as a complementary and interactive S-T-B ecosystem between knowledge (science and technology) and business fields.

Comparing specific features (e.g., value chains) from science, technology, and business fields that form an innovative ecosystem along with analyzing trends, helps to better evaluate the innovation ecosystem

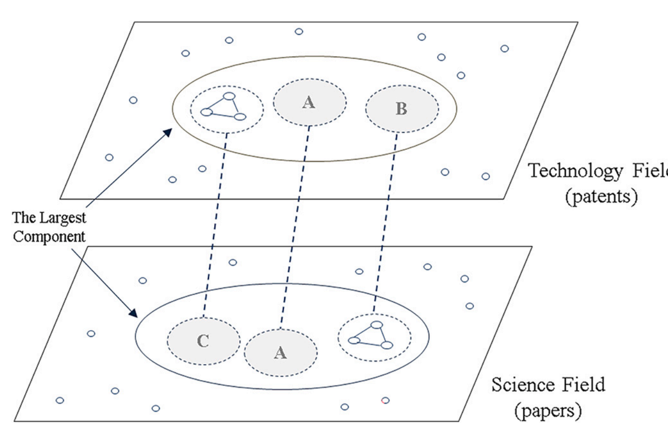

Fig. 1. Relationships between science and technology derived from Shen et al. (2020); Shibata et al. (2010); Wang et al. (2015).

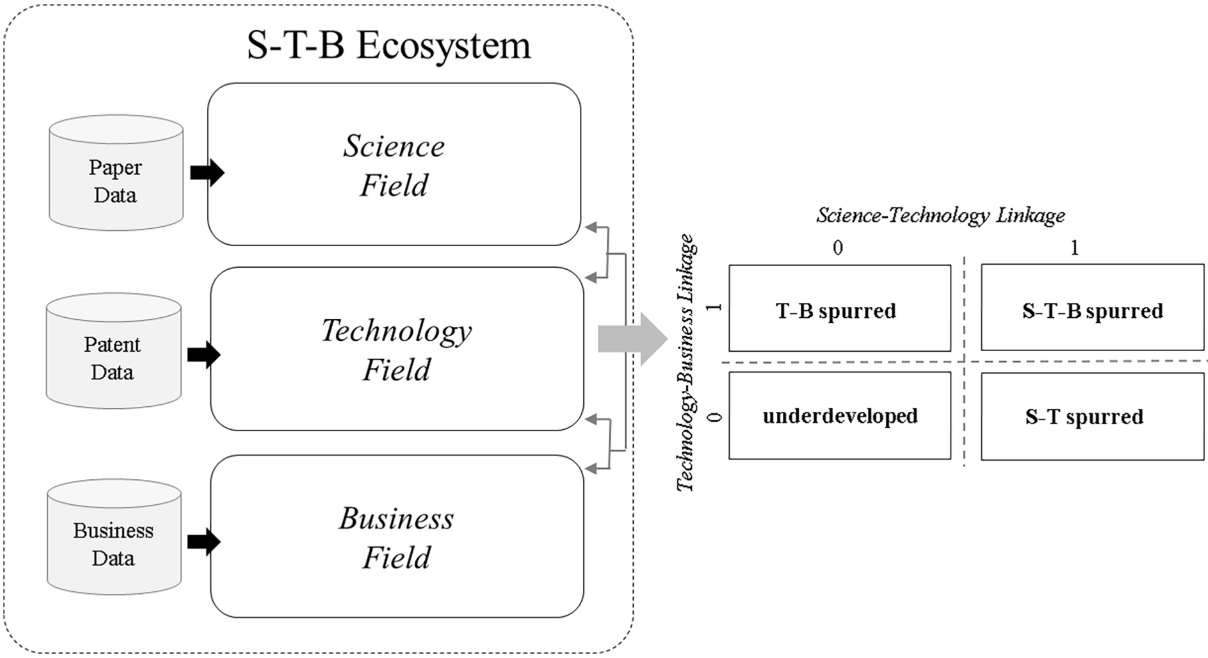

Fig. 2. Conceptual Framework of the S-T-B Ecosystem derived from Xu et al. (2018).

in a holistic view (Xu et al., 2018). "The relationships between science and technology" developed by Shibata et al. (2010) could also be effectively applied to analyze the linkage between scientific fields that produce scientific knowledge, technological fields that lead to technological advancement, and business fields aimed at value creation. Accordingly, it is possible to effectively sense the evolutionary trajectory and potential innovation opportunities for each value chain within a specific sector by classifying the types of interactions between the fields. The types of interaction included are underdeveloped, S-T spurred, T-B spurred, and S-T-B spurred quadrants (Xu et al., 2018).

- ✓ **Underdeveloped**: No linkage between the science, technology, and/or business fields
- ✓ **S-T spurred**: Well-established scientific and technological research but have not been commercialized
- ✓ **T-B spurred**: Market-oriented and have developed relevant industrial knowledge but lack the basic research
- ✓ **S-T-B spurred**: Linked on all three levels and have achieved a balanced operational state

As data sources that could provide insight for practical analysis of the conceptual framework of the S-T-B ecosystem, multi-dimensional data sources such as scientific publications, patents, and industrial business reports (related to technology investment/transaction, strategy, and demonstration) corresponding to each field are useful and enhance the reliability of research (Xu et al., 2018). In addition, it leaves ample room for research approaches and methodological improvements related to the S-T-B ecosystem, which is discussed in the next chapter.

2.2. Literature-based discovery (LBD)

As mentioned in the introduction, sensing potential opportunities can evolve into innovation. Combinations of concepts derived from attractive information to address challenges could lead to potential innovation (Kostoff, 2008). Principles and insights derived from a combination of homogeneous or heterogeneous disciplines could provide researchers and analysts with opportunities to challenge potential directions (Kostoff, 2006, 2008). However, as the number of research funds and researchers has increased over the decades, the number of scientific and technical literature has also increased significantly, and the resulting specialization acts as a barrier to knowledge transfer between disciplines and delays growth with discovery and innovation of potential opportunities (Kostoff, 2002). LBD is a comprehensive approach to systematically accelerate discovery and innovation, a concept of finding undiscovered public knowledge by finding hidden connections between two entities in bibliographic databases (Kostoff, 2008; Swanson, 1986). LBD is widely applied to uncover the association between technology and social problems in scientific and social science databases. It is effectively utilized to identify various sources using text mining, which extracts valuable information from large amounts of text (Ittipanuvat et al., 2014). As traditional approaches, limited to search with keywords or categories, are not sufficiently helpful for knowledge discovery, LBD enriches fruitful discussion as an approach to find new and potential relationships between literature that are not directly connected (Ittipanuvat et al., 2014). LBD devised by Swanson (1986) is divided into two types: "open-discovery systems (ODS) and closed-discovery systems (CDS)". It is applied in a variety of research areas.

Furthermore, new approaches are being attempted for methodological improvement. In general, it tends to be an approach based on similarity, such as a measure of the frequency of association (Kostoff, 2008). LBD is useful for analyzing the innovation ecosystem described above. Binz et al. (2014) explored components of the innovation system through bibliographic analysis and patent analysis. Ittipanuvat et al. (2014) analyzed the gap between knowledge and business ecosystems by integrating patent and enterprise-level survey data and uncovering the relevance between technology and social issues through the LBD approach. Xu et al. (2018) proposed a framework for integration into synergy across science, technology, and business ecosystems based on literature-based and qualitative interview data, and derived new development pathways for emerging technologies through collaborative network analysis among actors. However, these were not considered innovative ecosystem analysis based on intrinsic characteristic of LBD in terms of conceptual linkage among disparate literatures. Identifying the potential of innovative ecosystems, focusing on LBD's fundamental approach of text mining techniques and similarity-based analysis, was expected to be the core of meaningful research.

2.3. Smart grids value chain

Great expectations are placed on the development of smart grids to achieve transition in electricity markets and systems, such as improving energy efficiency, de-carbonization, and the integration of renewable energy sources (Erlinghagen and Markard, 2012; Lunde et al., 2016; Moura et al., 2013; Verbong et al., 2013). The reason is that smart grids are considered to be the solution to a number of interconnected problems (Verbong and Geels, 2010). Strategic power infrastructure and related detailed technologies are evolving to realize the potential of smart grids, but there are many challenges to upgrading from conventional grids to smart grids (Vineetha and Babu, 2014). In particular, the challenges of integration in conjunction with ICT: *standards-based interoperability, reliability and security, distributed and self-organizing grid architectures, and the formation of value chains*, are considered focal points (Mourshed et al., 2015). However, integrated smart grids are still closer to a vague vision than reality and could entail different strategic approaches and institutional setups (Foxon et al., 2013). As the boundaries of the energy system are also ambiguous, various structural ecosystems could be formed according to smart grid discourse, policy objectives, and strategies (Verbong and Geels, 2010). Early conceptual models of smart grid structural ecosystems, such as *NIST's framework*[1] and the European model of *Joint Working Group*,[2] consisted mainly of components, goods, and service flow in the power industry structure (CEN and CENELEC, 2010; Framework NIST, 2010). Recently, it has evolved into a technology and business-oriented conceptual model, namely the ecological system model from the value chain perspective, rather than a series of processes that lead to power generation, supply, and consumption. The KSGA (Korea Smart Grid Association) has designed value chains based on key technologies and business fields of smart grids as shown in Fig. 3. It facilitates analysis of technologies and market trends in 9 domains including Advanced Metering Infrastructure (AMI), Energy Storage System (ESS), Energy Management System (EMS), Demand Response (DR), Renewable Energy (RE), Electric Vehicle Infrastructure (E/V), Micro-grid, Intelligent Transmission & Distribution (T&D), and Power Internet Of Things (IoT).

In conjunction with the analysis of the conceptual structure of smart grids, considerable efforts are made in the design and development of cleaner and more efficient energy systems, but the conventional top-down approach is limited in terms of "sustainable interaction design" (Collins and Ketter, 2014; Katzeff and Wangel, 2015). A strategic approach is required to sense patterns of expectation for sustainable technology in linkage with the market and the business fields. It is also worth noting that, an analytical result of tracking the progress of energy technologies, smart grids are classified as a technology group that "needs more effort" (International Energy Agency, 2020).

3. Research design

This study proposes and explores strategies for sensing innovation opportunities in the smart grid value chain through the LBD approach using scientific papers, patents, and business publication data from the S-T-B ecosystem perspective. As shown in Fig. 4, the research process consists of three stages. The first step is to retrieve and pre-process data from the bibliographic databases that correspond to the fields of science, technology, and business. The second step is to perform field-specific topic modeling to derive intellectual trends in smart grid value chains. The third step, obtain similarity measurements of variables between fields are used to analyze the interaction of the smart grids S-T-B ecosystem. As the analysis tool software of this research process, *R Language* (version 4.0.2) was used.

3.1. Data retrieval & preprocessing

To collect the bibliometric data of the S-T-B ecosystem of the smart grid value chain as the target area of the study, the *Web of Science*, *WIPSON,* and *ProQuest*, which correspond to databases of scientific papers, technical patents, and business publications, were used. The period for adopting data sources was set from 2014 to 2020. *(During that period, as the smart grid ecosystem that reflects the systematic characteristics of smart grids was being established in earnest, utilization of digital technologies such as AI, big data, IoT, blockchain, and cloud computing also increased.)* The keyword search query for extracting bibliometric data related to smart grids was constructed as follows:

Query = (energy∗ OR power∗ OR electricity∗) AND ("smart grid∗" OR "smart-grid∗" OR "smart network∗" OR "sector coupling∗" OR "sector-coupling∗" OR "power grid∗" OR "power-grid∗" OR "digital grid∗" OR "digital-grid∗")

From the initial raw datasets *(1714 from Web of Science, 1321 from WIPSON, 1645 from ProQuest)* extracted through queries, data without information on publication year/author/abstract and directly or indirectly irrelevant data was excluded. In particular, patents only collected data from the *WIPSON* patent database filed in Korea, the US, Japan, Europe, and China, excluding expired and revoked cases. In addition, the business publications (trade journals/reports) extracted from the *ProQuest* business data platform excluded data less relevant to technology investment, transactions, strategies, or pilot projects.

After refinement, the final collected datasets *(1527 from Web of Science, 948 from WIPSON, 958 from ProQuest)* were organized as shown in Table 1 by data source corresponding to field and year. The final datasets were relatively rich in scientific papers, followed by similar numbers of patents and business publications. For analysis from the LBD perspective, bibliographic data such as titles, abstracts, subjects, keywords, and years of publication for each field were prepared.

3.2. Topic modeling

As mentioned above, LBD has the potential to discover linkages between disjoint disciplines using information retrieval and natural language processing techniques. In the advanced context, topic modeling that improves some of the shortcomings of LBD, such as large amounts of manual work, difficulty in discovery, and limitations of domain expansion, is an effective method widely used to discover hidden semantic structures based on text mining (Qi and Ohsawa, 2016). Topic modeling is based on the Bayesian statistical techniques of Latent Dirichlet Allocation (LDA) to infer what each word might mean on the basis of adjacent or co-occurrence words (Blei et al., 2003). The focal point of this method is to find latent topics in a document or set of words (Blei, 2012). Utilizing this method to explore hidden topics, we analyzed intelligent trends of smart grids with bibliographic data for each field. After text pre-processing of bibliometric data, LDA was applied to

[1] NIST: National Institute of Standards and Technology

[2] Joint Working Group: CEN(European Committee for Standardization), CENELEC(European Committee for Electrotechnical Standardization)

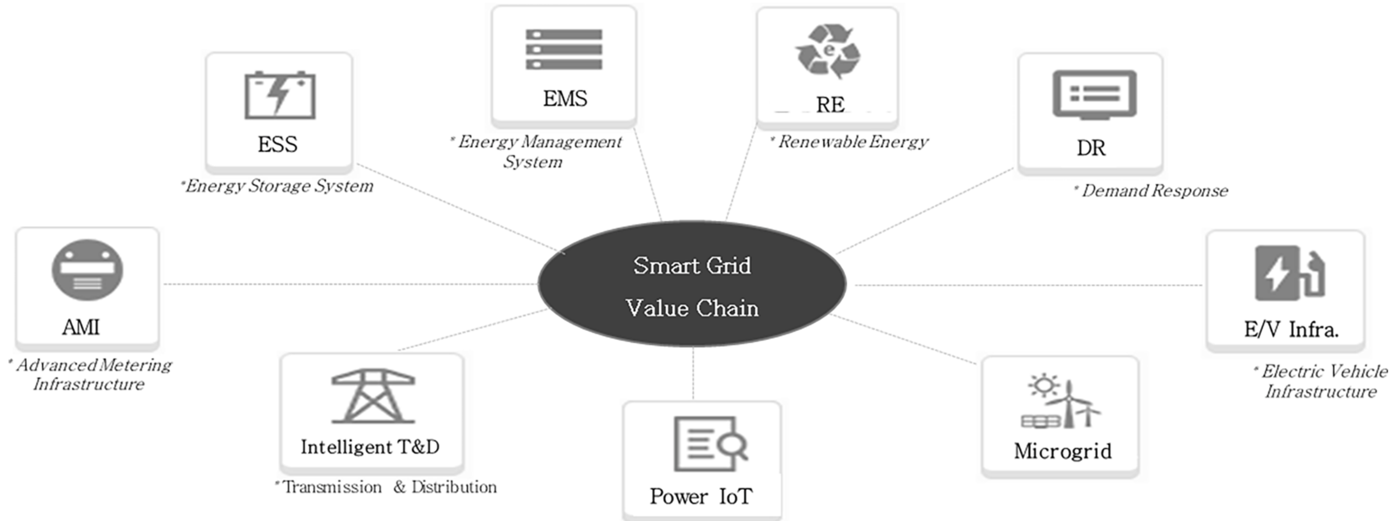

Fig. 3. 9 Value Chains of Smart Grids *(Smart Grids Ecosystem Model 2.0)* were presented by Korea Smart Grid Association analyzed in Smart Grid Data Center (Korea Smart Grid Association, 2019).

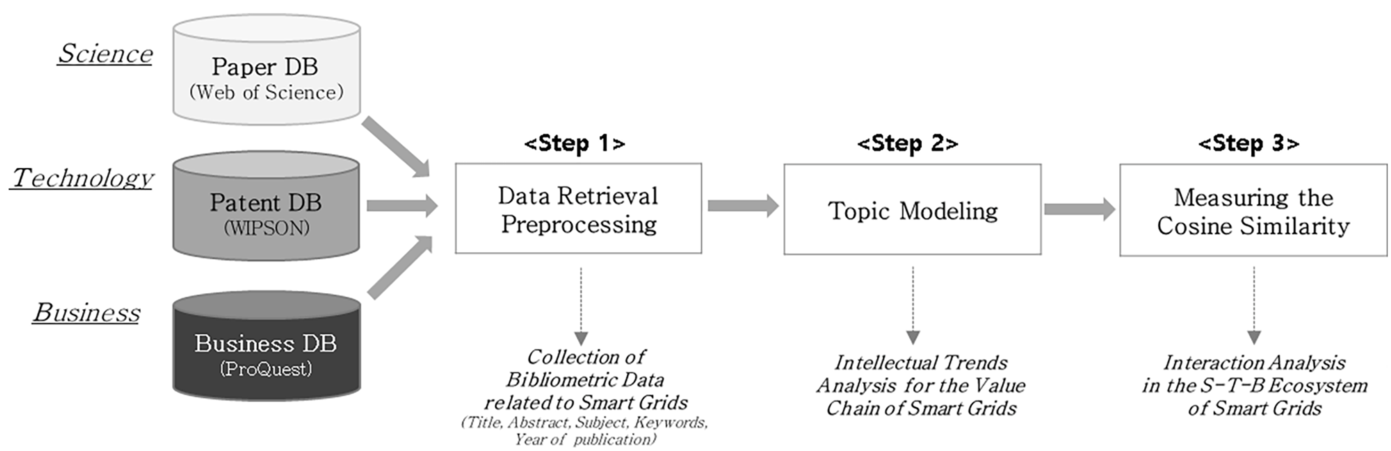

Fig. 4. Research framework.

Table 1
Analysis datasets relevant to smart grids by data source from 2014 to 2020.

Data source	2014y	2015y	2016y	2017y	2018y	2019y	2020y	Total period
Scientific paper	147 (10)	189 (12)	213 (14)	223 (15)	240 (16)	237 (16)	278 (18)	1527 (100)
Technical patent	80 (8)	108 (11)	83 (9)	108 (11)	141 (15)	219 (23)	209 (22)	948 (100)
Business publication	193 (20)	140 (15)	133 (14)	78 (8)	83 (9)	211 (22)	120 (13)	958 (100)

# of sources (%).

identify potential topics, and categorized words and documents corresponding to topic groups. There are 15 topics, which is 1 % to 5 % of the total number of documents per field, considering allocation in the value chain and the interaction analysis between fields. Subsequently, individual topics were named and matched to the value chain associated with the derived topics through a review session with three experts in the field of smart grids. Accordingly, by comparing the frequencies of allocated value chain groups within each field with the time series, intellectual trends for the value chain of smart grids were identified.

3.3. Measuring the cosine similarity

Next, the similarity between each field of the derived topics was measured to analyze the intellectual interaction of science, technology, and business fields of smart grids based on the relationship between science and technology and the S-T-B ecosystem framework mentioned in Chapter 2. The similarity measurement is an important tool to determine the similarity between two or more objects and the cosine, which measures the angle between two vectors, is most often used because it is effectively calculated as the dot product of two normalized vectors (Li and Han, 2013). Among the related metrics, the cosine similarity of the TF-IDF vector[3] is effective in sensing the semantic similarity of heterogeneous literature (Shibata et al., 2011). Accordingly, the TF-IDF cosine similarity was measured with the probability of the top 20 high-frequency words indexed to topics between each field. It is assumed that the more common words shared between each bibliography, the closer the location of the two disciplines. In addition, only matches higher than a threshold established to eliminate less similar relationships were considered to be valid semantic relationships. It was used as a strategy to sense innovation opportunities by deriving interactive relationships between fields within the S-T-B ecosystem framework.

4. Research results

4.1. Intellectual trends of smart grid value chain

Following the research process mentioned above, topic modeling was performed with bibliometric data to analyze the intellectual trends of scientific, technical, and business fields. As shown in Table 2, 15 topics were derived for each field, and subsequently, the topics were named. In addition, value chains were matched through an experts' review session (main keywords and frequency probabilities for each topic are included in Appendix A). Various topics and value chains related to the smart grid for each field were indexed, and it could be inferred that the intellectual focal points are different for each field. Among the value chains of smart grids, electric vehicle infrastructure is rapidly expanding into a wide area as a separate technology market, so only topics related to the concept of sector coupling of smart grids were included and allocated to the ESS.

In addition, topics related to holistic policy studies, such as [S09] Smart grid design and policies as part of a sustainable energy transition, were derived separately.

From the derived topic modeling results, the data (document) frequency including topics assigned within the value chain group were analyzed in time series so that the smart grid intelligent trends could be easily understood visually, as shown in Fig. 5.

First, in the science field, academic literature of various topics included in the value chains of smart grids was published, and the number of academic publications included in the value chain gradually increased. Among the value chains, “DR” was the most derived topic of academic research, followed by “AMI” and “Intelligent T&D’ in the highest order. On the other hand, topics belonging to “ESS”, “EMS”, and “Power IoT” were less common in academic research. Notably, the number and growth rate of documents including topics related to “DR” were found to be the highest, and interdisciplinary studies with heterogeneous research fields such as information/computer science were meaningfully discussed based on academic topics belonging to “DR” ([S01], [S11], [S12], and [S15]). Although the topics of academic research in the “Micro-grid" related to the pilot project have been confirmed relatively insignificantly, it does not mean that the related research is not progressing at all and could be interpreted as meaning that the topic is not specified.

Second, in the technology fields, technical patents of various topics included in the value chains of smart grids were also applied, and the number of technical patents included in the value chain gradually increased, especially in 2018. Among the value chains, “Intelligent T&D" was the most derived topic of technical patents, followed by “AMI” and

Table 2
Derived topics and matched value chains.

Derived topics	Value chain
Scientific paper	
[S01] Cloud and network optimization systems for smart grids demand response management	DR
[S02] AMI bi-directional communication network performance and channel allocation	AMI
[S03] Security and fault tolerance orientation of smart grids devices and applications	Intelligent T&D
[S04] Studies on the collection, contract, and information protection of quantitative data	AMI
[S05] Studies on energy management controllers for commercial and building use	EMS
[S06] Communication network-based power system control and mains protection	Intelligent T&D
[S07] Support for smart grids applications (power system simulators, platforms, software)	Power IoT
[S08] Studies on technologies and methods for improving the operation and reliability of ESS	ESS
[S09] Smart grid design and policies as part of a sustainable energy transition	-
[S10] Integration from renewable energy resources to smart grids	RE
[S11] Studies on optimal real-time price signal-based integrity and blackout avoidance	DR
[S12] Studies on the power supply status and load prediction of smart grid systems	DR
[S13] Energy-efficient information and communication infrastructure on smart grids	AMI
[S14] Interaction between electric vehicles, charging infrastructure, and smart grids	ESS
[S15] Demand response, consumer engagement, and optimization for smart grid integration	DR
Technical patent	
[T01] Intelligent grid management, protection systems, and devices	Intelligent T&D
[T02] Data management and control systems for power/energy profiles and systems	AMI
[T03] Smart home, building energy operation, and fault diagnosis system	EMS
[T04] Smart metering data collection and security/communication devices	AMI
[T05] Hardware devices related to intelligent power grids and distributed control	Intelligent T&D
[T06] Operating devices and systems for power conversion and control in smart grids	ESS
[T07] Applications leveraging smart grid virtualization, power intelligence	Power IOT
[T08] Energy use data, devices, and platforms in smart grids	Power IOT
[T09] Power stability evaluation and management system on the customer side	DR
[T10] AMI user permissions and assignment-based systems	AMI
[T11] Power storage unit and power supply network system using power storage unit	ESS
[T12] Small-scale power system simulation and integrated operating system	Micro-Grid
[T13] Software advancement technology for data conversion of smart grids	Intelligent T&D
[T14] Smart grids network phase detection and stabilization devices	Intelligent T&D
[T15] Smart grids substation circuit breakers and relay facilities	Intelligent T&D
Business publication	
[B01] Measurement, sensing, transmission, and installation of smart energy meters	AMI
[B02] Sustainable and resilient business models leveraging smart grids data	Power IoT
[B03] Micro network-connected power grids of consumer and distributed power	Micro-Grid
[B04] Advanced and intelligent H/W & S/W in smart grids system	Intelligent T&D
[B05] Energy efficiency, security management for micro power grids demonstration projects	Micro-Grid
	Power IoT

(*continued on next page*)

[3] Term frequency-inverse document frequency (TF-IDF) vector is a statistical value indicating how important a word is in a specific document when a group of documents is present. It could be used for purposes such as extracting key words from documents, determining the ranking of search results in a search engine, or finding the degree of similarity between documents. It is not considered a machine learning method, but it shows similar performance (Salton and McGill, 1983).

Table 2 (*continued*)

Derived topics	Value chain
[B06] Project and support services for data-driven power generation, reliability, and efficiency	
[B07] Control and optimization mechanisms related to power peak load rates, price fluctuations	DR
[B08] Power quality diagnosis and communication standards in smart grid systems	Intelligent T&D
[B09] Power transactions projects linked to bi-directional communication development	AMI
[B10] Efficient utilization of energy storage devices and network linkage	ESS
[B11] Increase energy efficiency through energy consumption pattern analysis	DR
[B12] Renewable energy production and operational solutions as distributed power sources	RE
[B13] Build intelligent micro-grids based on renewable energy sources in specific areas	Micro-Grid
[B14] Network distribution and linkage of power loads (with digital tech. Such as blockchain)	Intelligent T&D
[B15] Optimizing performance and cybersecurity in distributed grid environments	RE

"Power IoT" in the highest order. On the other hand, technical patents topics belonging to "ESS" and "EMS" were identified as less common. In particular, the number and growth rate of documents including topics related to "Intelligent T&D" were found to be the highest. Technical patents related to the topics of "Power IoT" ([T01], [T05], [T13], [T14], and [T15]) tend to be applied to intellectual property strategies for securing practical operations and rights by power utilities enterprises, who are the key applicants.

Third, in the business fields, business reports related to investments, transactions, strategies, or pilot projects of various topics included in the value chains of smart grids were published, and the number of business publications included in the value chain did not have a certain tendency, unlike the knowledge (science/technology) fields. Among all value chains, "RE" was the most derived topic of business publications, followed by "ESS" and "Micro-grid" in the highest order. Business publications related to the topics of "RE", "ESS", and "Micro-grid" ([B03], [B05], [B10], [B12], [B13], and [B15]) are major issues in the business field of smart grids. It is meaningful analysis that "RE" and "ESS" are at the top of the corporate and sales statistics by smart grids value chains in Korea.[4] In the case of "Micro-grid", it was found that it was mainly

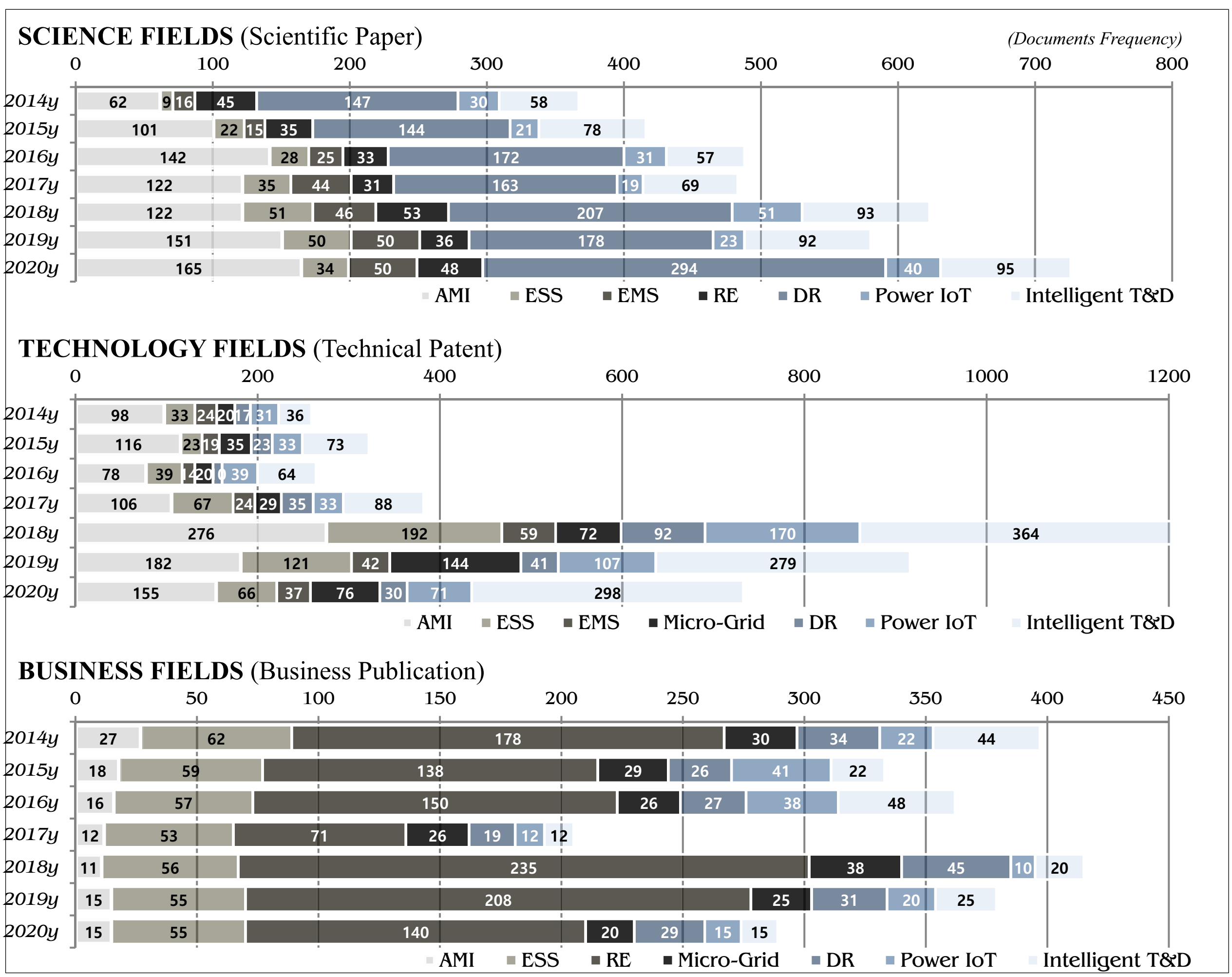

Fig. 5. Topic evolution (intellectual trends) of smart grids value chain from 2014 to 2020.

[4] Status of 240 Corporates related to Smart Grids in Korea (Korea Smart Grid Association, 2020)- Corporate share by Value Chain (as of 2020): RE (57, 24 %), ESS (44, 18.3 %).- Sales by Value Chain (as of 2020): RE (7400 billion won, 86.5 %), ESS (393 billion won, 4.6 %)

Table 3
Analysis results of cosine-similarity.

	T01	T02	T03	T04	T05	T06	T07	T08	T09	T10	T11	T12	T13	T14	T15
Similarity between science and technology															
S01	0.188194	0.158076	0.255233	0.322322	0.024816	0.057416	0.138425	0.262472	0.191016	0.108491	0.558909[a]	0.47528	0.25769	0.090885	0.205308
S02	0.241126	0.097634	0.168657	0.323363	0.107367	0.071534	0.32058	0.179236	0.235157	0.072958	0.284291	0.365268	0.142202	0.167915	0.24132
S03	0.141179	0.055495	0.447314	0.164049	0.142125	0.015413	0.5235	0.214108	0.069134	0.269471	0.255701	0.308107	0.180118	0.14169	0.182225
S04	0.092883	0	0.112951	0.291821	0.075219	0.020209	0.123788	0.025354	0.287265	0.405342	0.103206	0.029527	0.052647	0.02421	0.019315
S05	0.23601	0.344068	0.582285[a]	0.554808[a]	0.408235	0.24511	0.20309	0.307967	0.325768	0.108442	0.178132	0.68366	0.325601	0.396117	0.198861
S06	0.16955	0.179036	0.047153	0.313243	0.198875	0.146427	0.306038	0.091905	0.139272	0.27607	0.122422	0.28695	0.31572	0.551181[a]	0.171507
S07	0.226465	0.550665[a]	0.497727	0.413436	0.110092	0.403001	0.600062[a]	0.198731	0.225661	0.276408	0.264107	0.373894	0.262745	0.098778	0.246755
S08	0.051152	0.386857	0.164525	0.234147	0.157787	0.03253	0.155315	0.127779	0.096338	0.147036	0.562289[a]	0.247253	0.177972	0.044127	0
S09	0.273558	0.137019	0.226419	0.372263	0.197525	0.054013	0.470433	0.121665	0.197795	0.071789	0.193566	0.356178	0.122585	0.077048	0.124562
S10	0.268977	0.108089	0.26353	0.185485	0.177839	0.109967	0.097664	0.213891	0.264173	0.12638	0.565096[a]	0.272182	0.255828	0.019858	0.668703
S11	0.199412	0.228161	0.345575	0.398653	0.15418	0.102136	0.436355	0.278668	0.430493	0.183078	0.21169	0.551495[a]	0.159274	0.050924	0.169578
S12	0.270812	0.213259	0.4185	0.188281	0.289414	0.274789	0.465854	0.239889	0.197235	0.280806	0.212122	0.490118	0.096991	0.269887	0.43941
S13	0.174363	0.077035	0.20694	0.264998	0.076122	0.064583	0.29967	0.144909	0.098482	0.242106	0.254756	0.270795	0.202189	0.080304	0.248801
S14	0.057855	0.417145	0.225873	0.242985	0.089723	0.604342[a]	0.263768	0.146179	0.235908	0.108107	0.193586	0.247516	0.230178	0.295174	0.037189
S15	0.13342	0.287302	0.097879	0.240509	0.135853	0.031869	0.206097	0.085126	0.096207	0.353918	0.231681	0.162158	0.064992	0.33692	0.121283
Similarity between technology and business															
B01	0.121926	0.788501[a]	0.155852	0.393174	0.011494	0.039868	0.207627	0.055546	0.221733	0.227231	0.026184	0.119227	0.082636	0.106915	0.00452
B02	0.068108	0.125205	0.471059	0.385566	0.007708	0.300364	0.601082[a]	0.0882	0.101237	0.056207	0.076978	0.128092	0.079975	0.143922	0.060183
B03	0.20144	0.234961	0.317795	0.20832	0.280876	0.255536	0.094885	0.157371	0.142666	0.076462	0.201507	0.358709	0.075686	0.078623	0.44138
B04	0.155876	0.08862	0.236809	0.263936	0.035819	0.068497	0.293965	0.210012	0.232315	0.13015	0.186189	0.342595	0.14365	0.073825	0.55426[a]
B05	0.110536	0.299776	0.239356	0.304398	0.120984	0.143676	0.33251	0.120022	0.132644	0.134099	0.105538	0.318489	0.105827	0.076403	0.106147
B06	0.212817	0.137873	0.283914	0.324537	0.057666	0.173938	0.252946	0.252294	0.347077	0.043804	0.245796	0.405696	0.10077	0.025251	0.233412
B07	0.218362	0.395414	0.421284	0.225908	0.087859	0.454726	0.177835	0.149468	0.064331	0.139972	0.228367	0.321747	0.074168	0.138958	0.028701
B08	0.135887	0.257043	0.256306	0.315127	0.584388[a]	0.235318	0.211671	0.12911	0.460495	0.192478	0.108954	0.300486	0.072849	0.045192	0.119827
B09	0.07832	0.134551	0.152293	0.671085[a]	0.181709	0.148392	0.14809	0.099613	0.159032	0.27648	0.235183	0.200051	0.095371	0.103828	0.218915
B10	0.397644	0.439939	0.393711	0.472477	0.188185	0.753475[a]	0.284835	0.276849	0.598376[a]	0.18772	0.185261	0.558012[a]	0.18126	0.093103	0.231569
B11	0.182456	0.625466[a]	0.429612	0.384987	0.135045	0.578181[a]	0.324374	0.090137	0.136483	0.081255	0.302032	0.283225	0.077789	0.203788	0.100493
B12	0.329688	0.218174	0.404407	0.400567	0.243391	0.139101	0.287912	0.1758	0.238729	0.183503	0.32627	0.426266	0.076298	0.110304	0.282914
B13	0.116828	0.419702	0.150336	0.567913[a]	0.223929	0.198298	0.1812	0.220016	0.142371	0.559308[a]	0.380615	0.615424[a]	0.192875	0.086045	0.267374
B14	0.133204	0.554714[a]	0.285691	0.336516	0.38844	0.448892	0.146109	0.067269	0.039092	0.217654	0.136984	0.199704	0.058939	0.115789	0.313415
B15	0.230945	0.498048	0.373877	0.365785	0.326843	0.453751	0.249464	0.222985	0.226986	0.212985	0.14891	0.480727	0.167414	0.14022	0.401586

[a] Significant relationship between each field.

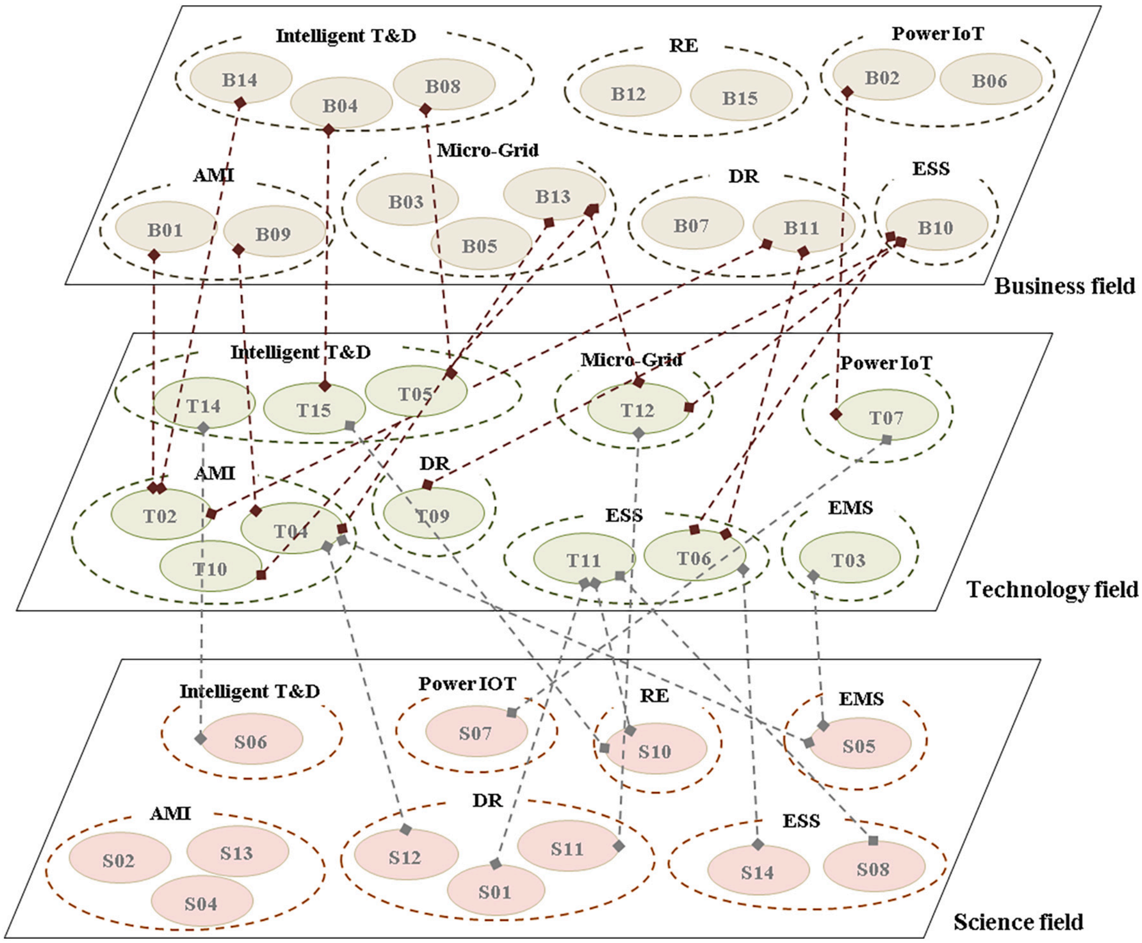

Fig. 6. Linkage between S-T-B ecosystem in smart grids.

discussed in the strategy of pilot projects linked to the vitalization of the smart grid industry.

4.2. Interaction in the S-T-B ecosystem of smart grids

Interactions between each field topic in the S-T-B ecosystem of smart grids were analyzed to sense innovation opportunities in accordance with measuring the cosine similarity explained in Chapter 3. The measured values of cosine similarity between science and technology fields and those between technology and business fields are shown in Table 3. To establish thresholds to eliminate less similar relationships, we applied the third quartiles presented in Shen et al. (2020)'s research on the relationship between science and technology, and only those matches of 0.555 or greater match as valid relationships with high similarity. Fig. 6 shows the correspondent in the S-T-B ecosystem framework according to the similarity measurements in Table 3, and even reflects the grouping of value chains assigned to each topic. Significant relationships with high similarity are connected with a dotted line. Basically, connected relationships are a promising discipline in which innovation is actively underway, and non-connected relationships could be considered as potential innovation opportunities.

Based on the four types (underdeveloped, S-T spurred, T-B spurred, and S-T-B spurred quadrants) of interaction mentioned in the theoretical background, the finding on strategies for sensing innovation opportunities was derived as follows:

***Underdeveloped*:** No significantly lower similarity between science, technology, and/or business fields was identified among the smart grid value chains (i.e., there is no value chain for the underdeveloped type). It is understood that the value chains in the S-T-B ecosystem have at least one meaningful relationship between fields and are interacting actively.

***S-T spurred*:** Topics that correspond to “DR”, “RE”, “power IoT”, “EMS”, “Intelligent T&D", and “ESS” were analyzed as high similarity between science and technology fields. It could be recognized that various discussions are underway within the knowledge domain (science/ technology). Topics corresponding to “AMI” and “Micro-grid" are addressed in scientific and technical fields, respectively but were analyzed with low similarity. This could be considered an opportunity for potential innovation for scientific research or technological development. As discussed in intellectual trends of smart grid value chains, “AMI” and “Micro-grid" are mainly discussed in a practical area, so the interaction is relatively limited in the knowledge domains.

T-B spurred: Topics that correspond to “AMI”, “Power IoT”, “Micro-grid", “Intelligent T&D", and “ESS” were analyzed as high similarity between technology and business fields. It could be recognized that various discussions are underway within the business domain. Topics corresponding to “EMS” and “RE” are addressed in technical and business fields respectively but were analyzed with low similarity. This could be considered an opportunity for potential innovation for intellectual property rights or a transition/diversification strategy to business value. However, “RE” is a very active discipline outside the smart grid ecosystem, such as independent production and operation solutions, so it is difficult to regard it only as a potential opportunity for innovation.

S-T-B spurred: Topics that correspond to “Intelligent T&D", “ESS” were analyzed to be highly similar between science, technology, and business fields. It is considered to be a promising discipline that has achieved a balanced operational state in the smart grid ecosystem.

5. Discussion

This study attempted to derive two strategic discourses (intellectual trends and interactions in the S-T-B ecosystem) from the LBD perspective approach to sense innovation opportunities of smart grid value chains. Through the analysis of intellectual trends, it was found that various intellectual research, technology development, and business activities are being carried out in smart grid value chains and the intellectual focal points are different in each field of science, technology, and business. As expected, technology and business fields are more actively discussed in practical areas than in scientific fields. In addition, intellectual areas closely linked to digital technologies such as AI, big data, cloud computing, and blockchain were on the rise.

Subsequently, the analysis of interactions based on similarity measurements in the S-T-B ecosystem found that there were more intellectual areas with a higher similarity between technology and business fields than between science and technology fields. Overall, the degree of significant interaction between the same value chains between each field was high and could be considered flexible innovation activities. It was also interesting to note that there were several similar topics identified among heterogeneous value chains in the S-T-B ecosystem. Areas with low interaction between science and technology fields or between technology and business fields ("AMI", "Micro-grid", "EMS', and "RE") could be regarded as potential innovation opportunities, such as acquiring new scientific knowledge, utilizing it for practical purposes, and strategic improvement. However, it is difficult to unconditionally regard the areas specified by dissimilarity as an opportunity for potential innovation. This is because constraints such as complex characteristics by value chain areas and uncertainty act as barriers to innovation and should be considered. Furthermore, although this study was analyzed within a limited period, it is necessary to consider the time series difference in the publication of bibliographic data (papers, patents, and business reports) in the S-T-B ecosystem. As such, although this is not an optimized algorithm, heuristic research processes to reach innovation of this study and the results derived could provide rich insights that hold the intellectual trends of a particular sector and leverage strategic tools for sensing innovation opportunities. There are practical and policy implications in that it identifies a niche in the innovation system and provides meaningful information that could contribute to the revitalization of participation in the private sector and consumers.

6. Conclusion and policy implications

This study aimed to formulate strategies for sensing innovation opportunities by integrating the S-T-B ecosystem perspective and LBD research methodology with regards to the value chain of smart grids as a research target. Based on multi-dimensional bibliometric data sources corresponding to scientific and technical business fields, the intelligent trends and interaction analysis between each field in the S-T-B ecosystem identified the evolutionary path of the smart grid value chain and its potential as a strategic tool for future innovative challenges. A limitation of this study is that data based on limited databases were collected and qualitative discussions by expert review were required for the assignation of intellectual domains and value chain grouping, which are linked to improvements in data-based topic analysis. Moreover, subsequent practical studies that identify business models linked to opportunities for innovation and materialize value creation could also be expected valuable studies.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techfore.2022.122210.

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