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Identifying technological opportunities using enhanced tech mining: The case of the E-health industry

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ABSTRACT

This study suggests enhanced tech mining as a tool to identify promising market opportunities based on a technological opportunity gap. Compared with existing research on technology opportunity analysis, we derived a technological opportunity gap by investigating existing and potential technological opportunities. In this study, we introduce a general framework of enhanced tech mining and then demonstrate how enhanced tech mining works by examining a technological opportunity gap in the e-health industry. We derived seven exploited technological opportunities, including telemedicine, televeterinarian, and virtual clinical trials, based on topic modeling of news articles. In the case of latent technological opportunities, 25 latent technological opportunities, including telenursing, telesurgery, and telephysiotherapy, were extracted from content analysis results of academic journal articles. We built an opportunity gap discovery framework based on analysis results to explore promising e-health opportunities for future business. We contributed to the related research field by improving the existing opportunity identification approach. We also showed the benefits of applying the proposed method by deriving the technological opportunity gap in the e-health industry.

1. Introduction

The discovery of technological opportunities has been a core interest of academicians in related fields, such as technology innovation management (TIM), since it can help companies expand their business scope based on recognized technological opportunities in the field (Song et al., 2017). As both technologies and products life cycle shorten due to fast changing market, the importance of technological opportunity discovery (TOD) is also growing (Yoon et al., 2015). Because a company's TOD capability can help acquiring an advantageous position in the market by supporting profit creation through expanding business and technology portfolios (Yoon et al., 2015; Yoon et al., 2014). In connection with this, many studies have been conducted on opportunity discovery and emerging technology identification. Extant studies vary in terms of TOD approach, for instance, identifying technological opportunities based on gaps between science and technology (Ba et al., 2024; Li et al., 2023; Takano and Kajikawa, 2019; Shibata et al., 2010), predicting technological convergence to identify potential opportunities (Park and Geum, 2022), discovering opportunities considering the coupling patterns between science and technology and lead-lag distance (Ba et al., 2024), discovering opportunities based on a technology roadmap with a focus on linkages between products/services to technologies (Noh et al., 2021).

Among extant studies, Li et al. (Li et al., 2023) aims to identify technological opportunity using SAO semantic mining and outlier detection method. They viewed that technological opportunities lie in outlier points in scientific journal articles. They showed how their proposed framework works by conducting case study on triboelectric nanogenerator technology. Their framework consists of two parts: extracting technological problems and solutions, and deriving technological opportunities by analyzing gaps between science and technology. Based on related patents and scientific journal articles, they extract technological problems and solutions based on SAO structures derived from SAO semantic analysis. By doing so, they analyzed the gaps between scientific journal articles and patents. And then, outlier points in scientific journal articles were detected using outlier detection method, such as K-nearest neighbor (KNN) and local outlier factor (LOF) algorithm for local outlier detection, and isolation forest algorithm for global outlier detection. They identified technological opportunities by combining the analyzed overall gaps between scientific journal articles and patents, and the gaps identified between outlier scientific journal articles and patents. Their study is meaningful in that they highlighted

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the significance of identifying gaps between science and technology to discover technological opportunities. Similar with other existing studies, they have focused on the relationship between science and technology, for this reason, they failed to consider which products or services exist in the market while they identifying technological opportunities.

Both shortened technology and product life cycles and an intense competition in the market have heightened the importance of TOD capability (Yoon et al., 2015; Shibata et al., 2010). Technological opportunities not only exist in newly introduced technological developments, but also can be discovered from existing products and services in the market (Yoon et al., 2015). Based on this idea, we propose a new methodology, enhanced tech mining, which complements the existing TOD methods by identifying the technological opportunity gap between market and science. In this study, we aim to investigate technological opportunities using enhanced tech mining with a focus on three things: exploited technological opportunities (i.e., available in the market), latent technological opportunities (i.e., soon to be available and/or promising in the market), and the technological opportunity gap between exploited and latent technological opportunities. Considering that e-health represents various applications of digital technologies in the healthcare field while having great potential to innovative opportunities, the e-health industry is selected as a case study to verify the feasibility of our proposed method.

The remainder of this study is organized as follows. First, previous studies on technological opportunity analysis (hereafter, TOA) are reviewed, and the distinctions between existing TOA methods and our proposed method are discussed. Details of our proposed method is then explained. Enhanced tech mining is then demonstrated based on a case study on the e-health industry. Finally, the contributions and limitations of this study are discussed.

2. Theoretical background

In this section, we briefly summarize existing literature on TOD and then discuss distinctions between our proposed method and existing methods. Section 2.1 provides an overview of the concept of TOD with a focus on three points: types of TOD, how previous studies identify and present technological opportunities, and how the results can be utilized. Next, how the proposed method differentiates itself from the existing methods is discussed by highlighting its major features and novelty.

2.1. Overview of technological opportunity discovery

The concept of technological opportunity was first proposed by Porter and Detampel in 1995 (Porter and Detampel, 1995). Since then numbers of research on TOD proposing various TOD approaches were introduced to the academia. Technological opportunity encompasses a possibility for technological progress such as technological improvement through research and development (R&D), modification of product specifications, and etc. (Ba et al., 2024). In the case of TOD which focus, technological opportunity is defined as a set of prospective technological advancements with a potential business value in the forms of technologies and products (Yoon et al., 2015; Wang et al., 2017). Technological opportunities can be divided into two types, those new to the market and those derived from existing technologies (Yoon et al., 2015). The former one can be realized by exploring vacuum area with a potential business value while the later one can be accomplished by either advancing existing technologies and products (Wang et al., 2017).

Many studies were conducted to develop analytical TOD methods based on objective data, such as patent and scientific journal articles, to provide a valuable insight for decision makers. TOD methods are rooted in TOA, which provides fundamental bases for concepts and techniques (Zhang et al., 2021). As summarized in Table 1, existing studies focusing on TOA show that various attempts have been made in TIM to discover an opportunity gap. In many cases, research on technological opportunity discovery describes itself as tech mining, a compound word of technology and text mining (Daim et al., 2016). Tech mining uses data analytics tools to examine science and technology information to understand changing and emerging technologies (Porter and Cunningham, 2005; Vicente Gomila and Palop Marro, 2013).

Table 1
A summary of previous studies on technological opportunity analysis.

References	Data sources	Research Methods	Presenting Technological Opportunities
Ma et al. (2021)	Derwent Innovation Index (DII) Patents	Topic modeling, SAO[a] semantic analysis	TRM[b] based on SAO[a] structures
Feng et al. (2022)	Academic journal articles, patents, and business journals and reports	Biterm topic model, SAO[a] semantic analysis	A data-driven roadmap based on topics and their SAO[a] relationships
Mejía and Kajikawa (2019)	News media and academic journal articles	Topic modeling, sentiment analysis, network analysis, text similarity analysis	A scatter plot on the linkage between news coverage and academic publishing
Zhang et al. (2014)	Patents and scientific publications	SAO[a] semantic analysis	TRM[b] based on problem and solution patterns and SAO[a] structures

[a] Subject-Action-Object.
[b] Technology Roadmap.

As indicated in Table 1, many extant studies have applied quantitative methods such as topic modeling and Subject-Action-Object (SAO) semantic analysis to derive topics and keywords related to technological opportunities by analyzing technological information. Academic journal articles, patents from industry, and news media for society are the most commonly used data sources for TOA (Mejia and Kajĭkawa, 2022). Traditionally, patents and academic journal articles are frequently used as primary data sources for tech mining. Recently, researchers in the field have introduced various forms of data, such as social media, news articles, reports, and websites, in association with methods such as topic modeling, SAO semantic analysis, and web scrapping (Daim et al., 2016). Existing literature often tries to visualize extracted opportunities based on SAO structure using a technology road map (hereafter TRM). By doing so, existing studies have highlighted problems on which those opportunities are based and provided explanations on how these opportunities can solve recognized problems.

As shown in extant studies, TOD can be utilized in various purposes, such as a competitor analysis, developing business plans for new products and services, and exploring technological trends in the market. For instance, Motohashi and Zhu (Motohashi and Zhu, 2023) investigated technological opportunities based on patent portfolios and publicly available information on corporate websites. They extracted potential technological opportunities by constructing technology-market and market-technology matrix, which describe the way a company translates their technology into products or services. Their research showed that TOD method can be useful in competitor analysis such as analyzing competitor's existing businesses, technical domains, and core competences. Some studies indicate that extracted technological opportunities can be a valuable technological intelligence in planning future businesses (Ba et al., 2024; Takano and Kajikawa, 2019; Park and Geum, 2022). Companies can explore a vacuum area in the market using TOD and identified technological opportunities can be further developed as innovative outcomes such as innovative technologies, new products and services. Moreover, in some cases, TOD results can be linked to TRM to highlight linkages between technologies to products and services, potential collaborators, and target markets. Building TRM based on technological opportunities can help companies in business decision makings by providing an overview on a specific subject including the relationship between potential opportunities and market factors.

2.2. Distinctions between traditional TOA methods and enhanced tech mining

As we discussed so far, many researchers have tried to develop and advance the way of technological opportunity identification. Despite several attempts to develop new methods for technological opportunity identification, those methods displayed inherent limitations in terms of the types of opportunities identified and the extraction process. Technological opportunities can be classified in two ways: those already realized in the market and those yet to be realized. Most previous TOA research studies investigated the latter without considering market needs or the current market situation. Therefore, traditional TOA methods often result in one-dimensional findings on potential opportunities. For instance, Ma et al. (Ma et al., 2021) and Feng et al. (Feng et al., 2022) have combined topic modeling and SAO semantic analysis to identify potential technological opportunities in emerging fields. They both used topic modeling to extract hot topics and related SAO structures from text data and then identified potential opportunities by investigating relationships between topics. The former TOA methods only focused on opportunities that seemed to be promising. They overlooked currently available and realized opportunities in the market. Considering that TOD means identifying opportunities with potential business value, it is important to understand existing opportunities (i.e., existing technologies and products) and potential opportunities to discover more specific and feasible opportunities (Yoon et al., 2015).

In this study, we will introduce enhanced tech mining using content analysis, topic modeling, and SAO semantic analysis to complement conventional TOA methods. In many cases, TOA studies are limited to exploring technological opportunities without considering a gap between the current status (i.e., exploited technological opportunities) and future direction (i.e., latent technological opportunities). However, enhanced tech mining derives a technological opportunity gap by examining both existing and promising opportunities. Moreover, our proposed method helps get answers to two important questions in a certain technological field: 1) what is happening? Moreover, 2) what does the market need? The distinction between traditional TOA methods and the proposed method mainly comes from differences in analytical data and method.

Compared with traditional TOA methods, enhanced tech mining uses two different data sources, articles from news outlets and academic journal articles, to answer questions mentioned earlier. By diversifying data sources, enhanced tech mining investigates existing technological opportunities through news outlets and surveys topics going viral in academia. Particularly, enhanced tech mining not only presents existing technological opportunities extracted from news outlets but also applies content analysis to analyze technological opportunities described in academic journal articles by allowing a more in-depth understanding of a certain technology field. Enhanced tech mining can provide relatively more realistic technological opportunities than former TOA methods.

3. Research methodology

In this study, we propose enhanced tech mining to identify technological opportunities based on technological opportunity gap between exploited and latent technological opportunities. In this section, we delineate how the proposed method works. Previous studies on TOD proposed novel approaches to identify technological opportunities while also demonstrated the applicability of the proposed approaches by conducting a case study. Considering extant studies on TOD, we first delineate the proposed method and then validate its feasibility through case study. As indicated in Fig. 1, the research framework consisted of three stages: data collection, opportunity space creation, and opportunity identification. A brief detail of each stage is discussed as follows.

3.1. Case selection

Opportunities can be found during crisis or radical environmental changes in response to the changes in consumer needs (Liu et al., 2020). A recent global crisis, COVID-19 pandemic, had posed both positive and negative challenges to our society, from daily life, to numbers of businesses in various industries (Seetharaman, 2020; Singh et al., 2020). Among various industries, the e-health industry is experiencing radical changes during the current COVID–19 situation because the pandemic has accelerated the application and adoption of digital technologies such as remote diagnosis and patient monitoring (Shen et al., 2021). Considering the drastic changes in the field, we believe that the e-health industry is appropriate for applying the proposed method to investigate the technological opportunity gap.

3.2. Data collection

In this study, two data types, academic journal articles and news articles, were used to examine latent and exploited technological opportunities. Similar to the idea that patents (i.e., research outcomes)

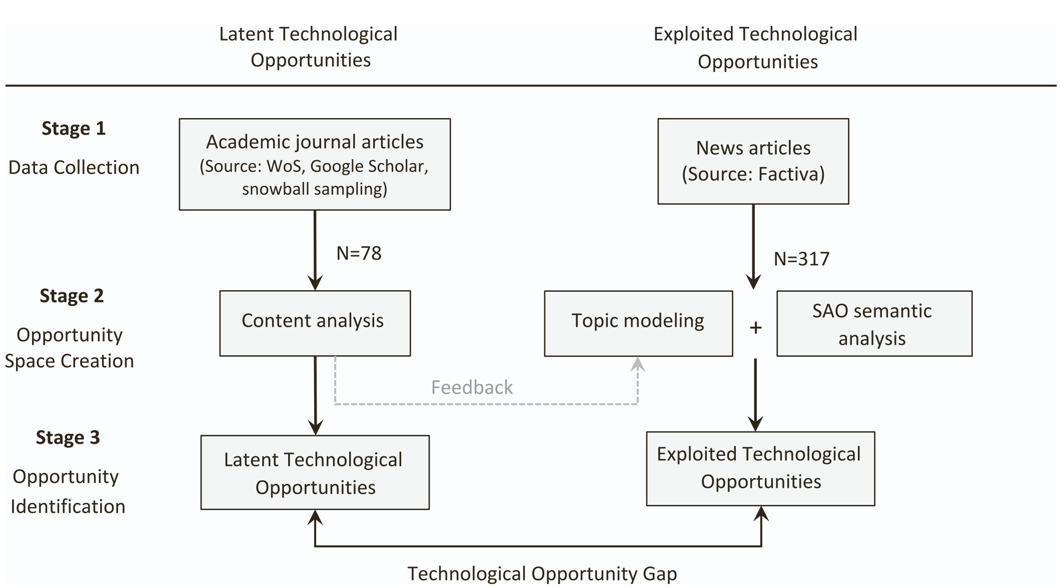

Fig. 1. Technological opportunity gap discovery framework.

require time to be commercialized in the market, academic journal articles, which contain detailed information regarding recent research outcomes, can be good sources for exploring technological trends in the market (Gerken et al., 2015). For this reason, we used academic journal articles to examine latent technological opportunities in the market. In the case of exploited technological opportunities, we used news articles, which could provide snapshots of the current market status as a source, to investigate business opportunities available in the market. Inherent differences between academic journals and news outlets complement each other's limitations. For example, news outlets provide concise information about the current market situation but are limited in providing detailed and complicated technological information on promising opportunities. For this reason, academic journal articles can provide a balanced view on such a topic by providing information on promising technologies and related outputs. The data retrieval period was set between January 2020 and December 2021 because we were interested in e-health technological opportunities during the COVID-19 pandemic. Research databases, such as Web of Science, Google Scholar, and Factiva, a renowned business intelligence platform run by Dow Jones, were used as major data sources. Regarding academic journal articles, we used keyword searches and snowball sampling to retrieve relevant articles from research databases such as Web of Science and Google Scholar. Regarding news articles, we used a keyword search with Factiva search builder to narrow down news articles according to subjects and industries to extract news articles related to technological opportunities in the e-health industry. As a result, we collected 317 news articles and 78 academic journal articles for further analysis.

3.3. Data analysis

As indicated in Fig. 1, stages 2 (Opportunity space creation) and 3 (Opportunity identification) consist the data analysis part of the proposed method. After data collection, we created an opportunity space for technological opportunity identification before identifying the technological opportunity gap in the e-health industry. The opportunity space for latent and exploited technological opportunities was created by applying content analysis to academic journal articles and applying topic modeling and SAO semantic analysis to news articles, respectively.

For latent technological opportunities, we conducted content analysis on extracted academic journal articles in stage 2 to identify latent technological opportunities. The content analysis helps us understand the data's context and unexpressed meanings (Given, 2012). In this study, we used Atlas.ti 9, a computer-assisted qualitative data analysis software, to conduct content analysis. As described in Fig. 2, the content analysis was carried out in five steps. After collecting data for content analysis, we set criteria for coding to ensure that codes are aligned with the research objective (Saldaña, 2009). Since the goal of content analysis is to extract latent technological opportunities described in academic journal articles, we assign codes in consideration of three things: a technological basis, purpose, and a possible application of an observed opportunity. Qualitative coding, the core of content analysis, plays a pivot role in the process of meaning extraction and interpretation by allowing researchers to derive concepts from qualitative data by assigning codes to words, phrases, sentences, and paragraphs that articulate connotations in them the most (Saldaña, 2009; Basit, 2003). As indicated in Fig. 2, qualitative coding was conducted in two steps: the first cycle coding and the second cycle coding (Saldaña, 2009). The first cycle coding fractures data into small segments. During the first cycle coding, we conducted open coding, which is also known as initial coding, to generate initial codes for further analysis. The second cycle coding starts with the codes generated from the first cycle coding. During the second cycle coding, researchers refine codes and categorize them into categories. In this study, we used axial coding as our second cycle coding method to categorize and interpret meaning from extracted codes (Lewis-Beck et al., 2012). The coding result was validated using Krippendorff's alpha, which indicates an adequacy of the quality of

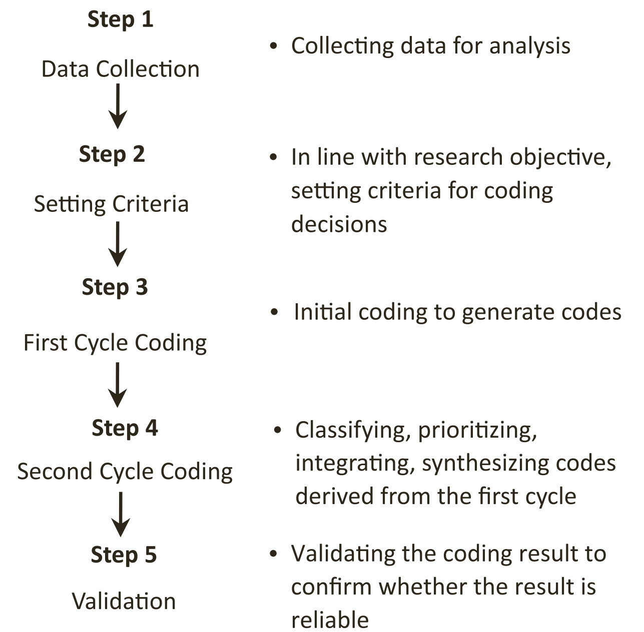

Fig. 2. Overview of content analysis process.

coding result (Krippendorff, 2004). To test inter-coder reliability, two coders coded 10 % of randomly selected data and the resultant Krippendorff's alpha was above 0.8, considered to be a good agreement (Krippendorff, 2004; Beckler et al., 2018; Paek et al., n.d.).

For exploited technological opportunities, we conducted topic modeling on extracted news articles. Similar to content analysis, topic modeling helps us explore technological opportunities currently available in the market based on text data. One of the major strengths of topic modeling is that it can extract helpful insight and hidden topics from large textual data based on a statistical method (Hannigan et al., 2019). However, the quality of topic modeling results greatly depends on the length and the degree of formalization of text data (Sbalchiero and Eder, 2020). For this reason, topic modeling tends to use short and structured text such as news articles (Yoon et al., 2014; Sbalchiero and Eder, 2020). As indicated by a dotted arrow named 'feedback' in Fig. 1, we went through a post-processing procedure called the human-in-the-loop approach to refine and validate initial topic modeling results. The human-in-the-loop approach begins with the notion that topic modeling efficiently provides an overview of extensive text collections. However, the result sometimes does not match a researcher's information needs, thereby hampering the user's understanding of the result (Kumar et al., 2020).

In stage 3 (Opportunity identification) of Fig. 1, we first dive into exploited technological opportunities using a product-function-technology portfolio map (hereafter PFT portfolio map) and a product-function-technology relationship map (hereafter PFT relationship map). And then we built an opportunity gap discovery framework to derive technological opportunity gap.

Firstly, we built a PFT portfolio map and PFT relationship map on exploited technological opportunities to enrich and enhance our understanding of currently available technological opportunities in the market by examining hidden linkages rather than keywords. SAO is a semantic structure that refers to subject (S), action (A), and object (O) from text. It allows key concepts to be represented in means-end relationships (Choi et al., 2013). In the SAO structure, S indicates a technological basis and related product or service, while O represents motives of actions, such as problems to solve and possible outcomes (Choi et al., 2013). Furthermore, A explains S's actions (i.e., technology, product, or service) to solve a given problem and achieve a certain goal (Moon and Lee, 2021). To extract SAO structures, we go through three steps: data preparation, parsing, and SAO extraction. Before extracting SAO structures, we partitioned the body of news articles into sentences. The partitioned sentences were separated into smaller grammatical units, such as noun, verb, adjective, adverb, and etc. While extracting SAO structures, we reviewed and selectively adopted SAO structures containing information related to e-health industry while expressing a direct relationship between technologies and e-health opportunities. For instance, SAO structures derived from sentences such as 'Millennials are the largest pet-owning demographic, and more than 50% consider pets children' are removed. Based on SAO structures, we constructed a PFT portfolio map and a PFT relationship map to examine exploited technological opportunities based on product (S/O), function (A), and technology (S/O) layers (Choi et al., 2013; Lee et al., 2008). The PFT portfolio map shows the importance of SAO elements based on the absolute number of occurrences and the increased rate in the frequency of occurrences, while the PFT relationship map provides information regarding relationships among SAO elements (Choi et al., 2013).

Secondly, we derived the technological opportunity gap based on an opportunity gap discovery framework. As indicated in Fig. 3, the opportunity discovery framework can be used to identify the opportunity gap (i.e., slashed area) by comparing analysis results on the same topic across two different knowledge databases (Mejia and Kajïkawa, 2022). Examining the opportunity gap of a certain topic using different knowledge databases lets researchers reflect diverse perspectives on a single topic. The opportunity gap discovery framework has been used by many scholars attempting to find a gap between science and technology (Li et al., 2023; Shibata et al., 2010). As Li et al. (Li et al., 2023) mentioned, market information can be used to identify the technological opportunity gap between market demand and research. Therefore, in this study, we used news outlets and academic journals to discover the technological opportunity gap in the e-health industry.

4. Discovering technological opportunities in the E-health industry

This section identifies a technological opportunity gap in the e-health industry by exploring exploited and latent technological opportunities using enhanced tech mining. Regarding exploited technological opportunities, we conducted topic modeling for 317 news articles related to technological opportunities in the e-health industry. We first identified the optimal topic number and set hyperparameters for analysis. We determined the optimal topic number based on a method suggested by Griffiths and Steyvers (Steyvers and Griffiths, 2015), which could estimate the posterior probability of that set of models given observed data. The optimal number of topics is determined by finding a knee point. The knee point is defined as the number of topics that do not significantly improve the normalized metric score, even when the number of topics is increased (Sbalchiero and Eder, 2020). In our case, we found that the optimal criterion was met for 17 topics located at the knee of the plot (see Fig. 4). In terms of hyperparameters, we determined $\alpha = 50/K$ and $\beta = 0.01$ in reference to Steyvers and Griffiths (Steyvers and Griffiths, 2015), who found them to work well with various texts and suggested them as a broad choice for topic modeling.

After post-processing the initial topic modeling result, we finalized topics as shown in Table 2. Table 2 shows topic modeling results in a topic-word matrix in each topic group consisting of ten words related to each topic. Because topic modeling regards a document as a random mixture of latent topics where topics are distributed over words, the topic modeling result provides groups of words considered as related and/or describing a certain topic (Jelodar et al., 2019). To interpret topics, we reviewed the ten most probable words in each group and named each group in the best way to represent each group's unique properties (Pröllochs and Feuerriegel, 2020). For example, we named topic group 1 'patient monitoring', which included keywords like health, support, pandemic, provide, service, people, therapy, conditions, treatment, and physical.

We conducted content analysis for 78 academic journal articles regarding latent technological opportunities. We attained 565 codes after the initial coding procedure (i.e., open coding). We then categorized these codes into groups to derive latent technological opportunities through the axial coding. Based on topic modeling and content analysis results, we derived seven exploited technological opportunities and 25 latent technological opportunities. As indicated in Table 3, we identified four opportunity spaces by aggregating exploited and latent technological opportunities: e-health for sustainable medical treatment, e-health for infectious disease, e-health for enhancing efficiency in the medical field, and e-health for early detection and diagnosis. Four opportunity spaces embrace various forms of e-health in response to the pandemic. As shown in Table 4, opportunity spaces are linked with exploited and latent technological opportunities. Details of exploited and latent technological opportunities are discussed as follows.

In the case of e-health for sustainable medical treatment, most business items in the market focus on remote medical services, such as remote monitoring and care, tele-veterinarian, telepsychiatry, and telemedicine. Some similar e-health opportunities are also found in latent technological opportunities. Analysis results indicate that medical treatments using ICT technologies are actively utilized for patients requiring continued care, such as those with diabetes and depression. However, most latent technological opportunities in this category are differentiated from exploited opportunities by widening the scope of current remote medical services. For example, telenursing, AI-based medical chatbots, telepharmacy, and medicine delivery allow effective medical support for the elderly, disabled, and residents in suburban areas. In addition, some latent technological opportunities aim to make continued medical services possible regardless of physical location, such as telesurgery, telepresence robots, remote-controlled medical robots, telerehabilitation, and telephysiotherapy. Among various e-health opportunities in this category, telesurgery is highly expected for further advancement and application in the future due to the introduction of 5G technology that offers a high speed with a low latency (Shen et al., 2021; Kamal et al., 2022).

In the case of e-health for infectious diseases, both opportunities focus on providing remote medical services. E-health for infectious diseases is similar to general e-health. However, it differentiates itself by targeting infectious disease patients and minimizing face-to-face contact

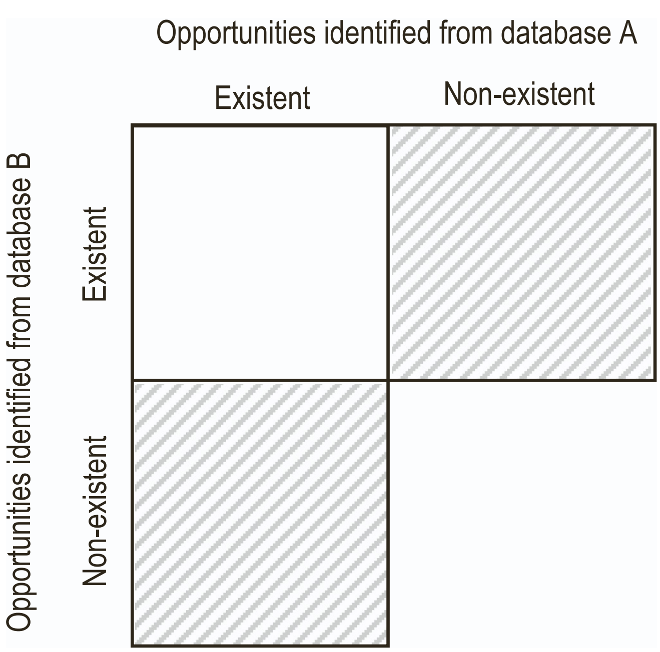

Fig. 3. An opportunity gap discovery by comparing the same topic across different knowledge databases.

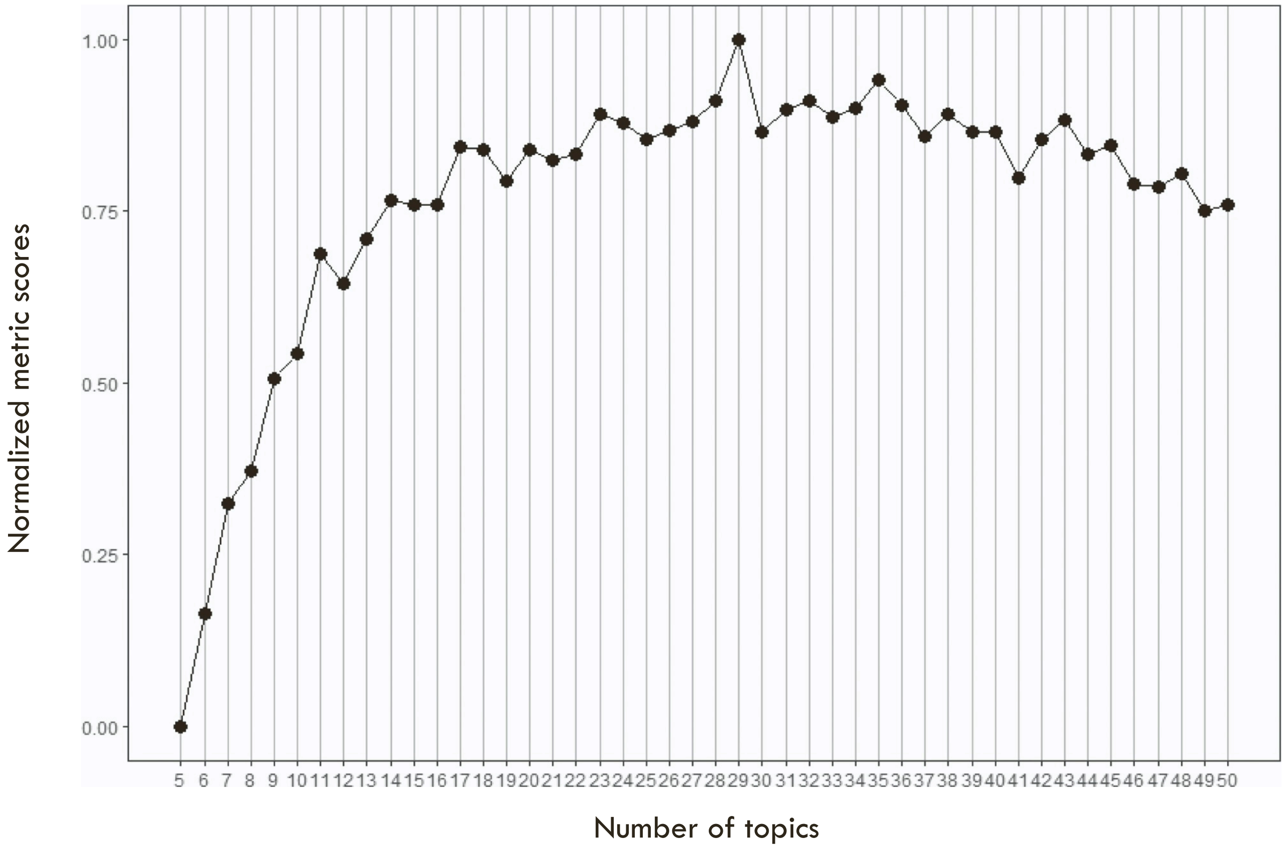

Fig. 4. Determining the number of topics.

Table 2
Topic modeling results (topic-word matrix) in the e-health industry.

No	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7
	Patient monitoring	Remote monitoring and care for Covid–19 infected people	Management solutions for healthcare organizations	Telemedicine	Virtual clinical trials	Telepsychiatry	Telemedicine for pets
1	Health	Patients	Data	Online	Clinical	Services	Pandemic
2	Support	Monitor	Access	Doctor	Research	Mental	Information
3	Pandemic	Remotely	Systems	Video	Company	Telemedicine	Response
4	Provide	Check	Software	Delivery	Trial	Provide	Veterinary
5	Service	Home	Organizations	Platform	Development	Clinic	Impact
6	People	Risk	Critical	Access	Announced	Practice	Plan
7	Therapy	High	Information	Safe	Demand	Country	Pet
8	Conditions	Coronavirus	Analytics	Virtual	Study	Offer	Local
9	Treatment	Treatment	Challenges	Connect	Build	Medicine	Risk
10	Physical	Distancing	Resources	Home	Significant	Physician	Serve

Table 3
Opportunity space in the e-health industry.

Opportunity space	Definition
E-health for sustainable medical treatment	E-health aiming to provide a stable medical service regardless of physical distance and environmental restrictions while reducing the impact of the pandemic by applying various technologies
E-Health for infectious disease	E-health providing medical services for patients with infectious disease
E-health for enhancing efficiency in the medical field	E-health aiming to increase the overall efficiency of the medical field by streamlining medical treatments and the scientific research process
E-health for early detection and diagnosis	E-health providing medical data analytics to facilitate the early detection and diagnosis of infectious disease

as much as possible while providing the medical care that patients need. E-health for infectious diseases includes telemedicine based on video chat and mobile apps, virtual follow-ups, and patient monitoring. In the case of exploited technological opportunities, the analysis result indicates that telemedicine and the remote monitoring of patients with infectious diseases are widely implemented in the market. E-health for infectious diseases is currently limited to a traditional form, such as providing remote medical treatment, consultation, and checking a patient's condition. However, latent technological opportunities show potential for further development in a related field by showing great potential for business opportunities, specifically patient monitoring services using drones, artificial intelligence (AI), the Internet of Medical Things (IoMT), and wearables.

In terms of e-health to enhance efficiency in the medical field, products and services to improve hospital operational efficiency seem promising. In the case of exploited technological opportunity, virtual

Table 4
Exploited and latent technological opportunities in the e-health industry.

Opportunity space	Exploited technological opportunities	Latent technological opportunities
E-health for sustainable medical treatment	Remote monitoring and care of patients (E1)	Telenursing (L1) Telepsychiatry (L2) AI-based medical chatbot (L3) Telepharmacy and medicine delivery (L4)
	Televeterinarian (E2)	Monitoring patients with chronic diseases (L5) Chronic pain coaching apps (L6) Telerehabilitation (L7)
	Telepsychiatry (E3)	Telephysiotherapy (L8) Telemedicine (L9) Telesurgery (L10)
	Telemedicine (E4)[a]	Remote-controlled medical robots (L11) Telepresence robots (L12) Disinfection robots (L13)
E-health for infectious disease	Telemedicine (E4)	Covid–19 risk assessment and monitoring apps (L14) IoMT-based patient monitoring (L15)
	Remote monitoring of patients with infectious disease (E5)	Wearables for patient monitoring (L16) AI-based patient monitoring (L17)
	Resource management solutions for medical institutions (E6)	Drones and robots for patient monitoring (L18)
E-health for enhancing efficiency in the medical field	Virtual clinical trials (E7)	AI-based triage (L19) Resource management solutions for medical institutions (L20) Smart hospitals (L21) Medical information sharing system (L22)
E-health for early detection and diagnosis	–	AI-based image/voice analysis (L23) Detecting Covid–19 infection using wearables (L24) Cardiovascular monitoring using biosensors (L25)

[a] Telemedicine belongs to two opportunity spaces (e-health for sustainable medical treatment and e-health for infectious disease).

clinical trial platforms can assist medical scientists in overcoming restrictions of conducting clinical trials during the COVID–19 pandemic. By digitalizing the process of clinical trials, the virtual clinical trial platform has helped researchers successfully perform clinical trials despite the COVID–19 pandemic risk. Some promising technological opportunities include AI-based triage, medical information-sharing systems, and smart hospitals. These business items are expected to contribute to the effective management of patients and resources in medical institutions. For example, AI-based triage can accelerate the efficiency of medical treatment procedures by classifying patients based on their severity. In the case of the medical information-sharing system, its benefits are receiving attention from academia. Because of its name, the medical information-sharing system seems similar to smart hospitals and resource management systems. However, it is distinguished from smart hospitals and resource management systems in terms of its contribution, such as reducing clinical bias, ensuring the integrity of electronic health records, improving the controllability of sensitive medical information, and improving healthcare outcomes. Overall, technological opportunities in this category imply efficient usage of limited medical resources through patient triage and resource management solutions while increasing the efficiency of medical service delivery using smart hospitals and medical information-sharing systems (Singh et al., 2020).

Lastly, e-health for early detection and diagnosis seems underdeveloped. It has great potential for new business opportunities. Considering the analysis results, it seems this field is not actively exploited in the market. It has the potential for future business opportunities. Analysis results indicated that digital technologies such as AI, biosensors, and wearables could contribute to early disease detection and diagnosis by collecting and analyzing medical data. Notably, several studies have highlighted the possibility of diagnosing diseases based on X-ray or CT scan analysis using AI technology (Allam, 2020; Firouzi et al., 2021; Bansal et al., 2020). In addition, studies have emphasized that AI can reduce medical professionals' workload by improving the accuracy of diagnosis through extensive medical data learning (Bragazzi et al., 2020; Bhattacharya et al., 2021). In the case of early detection, two methods have been introduced: detection of symptoms early using wearable devices and biosensors and self-assessment based on mobile applications (Heo et al., 2020; Ndiaye et al., 2020). Furthermore, exploited technological opportunities show that biosensors and wearables can actively assist medical activities in data collection and patient monitoring. Considering this, extracted latent technological opportunities such as AI-based image/voice analysis, wearables for detecting infectious diseases, and biosensors for monitoring purposes imply that new e-health businesses must satisfy such emerging market urges.

Before identifying the technological opportunity gap in the e-health industry, we constructed a PFT portfolio map and a PFT relationship map to guide us in exploring the opportunity gap by improving our understanding of currently available technological opportunities in the market. To construct the PFT portfolio map and the PFT relationship map, we first partitioned news articles into sentences and then parsed sentences into smaller units such as subject, verb, and object to extract SAO components. Fig. 5 shows an example of how a SAO structure is extracted. We derived essential components for the SAO structure, such as subject ("a virtual solution"), action ("enable"), and object ("clinical trials") from the example sentence. During this procedure, we excluded irrelevant sentences that did not involve e-health-related contents. After the refinement, we finally got 352 SAO structures for further analysis.

Based on SAO structures, we built the PFT portfolio map and the PFT relationship map, as shown below. Fig. 6 shows the distribution of SAO components depending on the absolute size and the rate of increase. The absolute size indicates a sum of each SAO components, while the rate of increase indicates the rate of change between 2020 and 2021 in terms of the number of each SAO components. The distribution of components in three layers is mostly concentrated in the fourth quadrant (established product/function/technology). This indicates that exploited technological opportunities in the e-health industry are mostly based on predictable technologies and functions instead of newly developed ones. Typical examples are remote patient care service (P11) and telemedicine (P16) of the product layer, remote treatment (F15) of the function layer, a mobile app (T11) and a web-based platform (T15) of the technology layer. Components in the first quadrant of each layer are located next to the second quadrant's borderline. These include a diagnostic solution (P6), a medical chatbot (P8), analyzing test results (F1), chatbot (T5), and drone (T8). Considering a high rate of increase, components in the

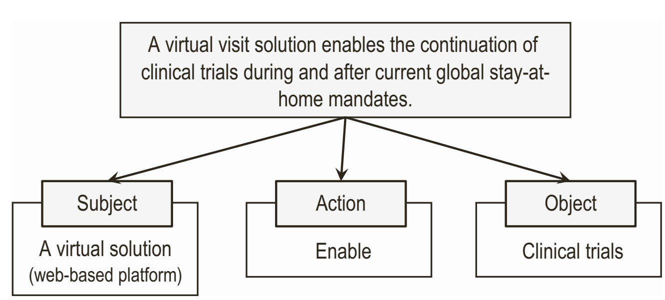

Fig. 5. A Subject-Action-Object (SAO) structure extraction.

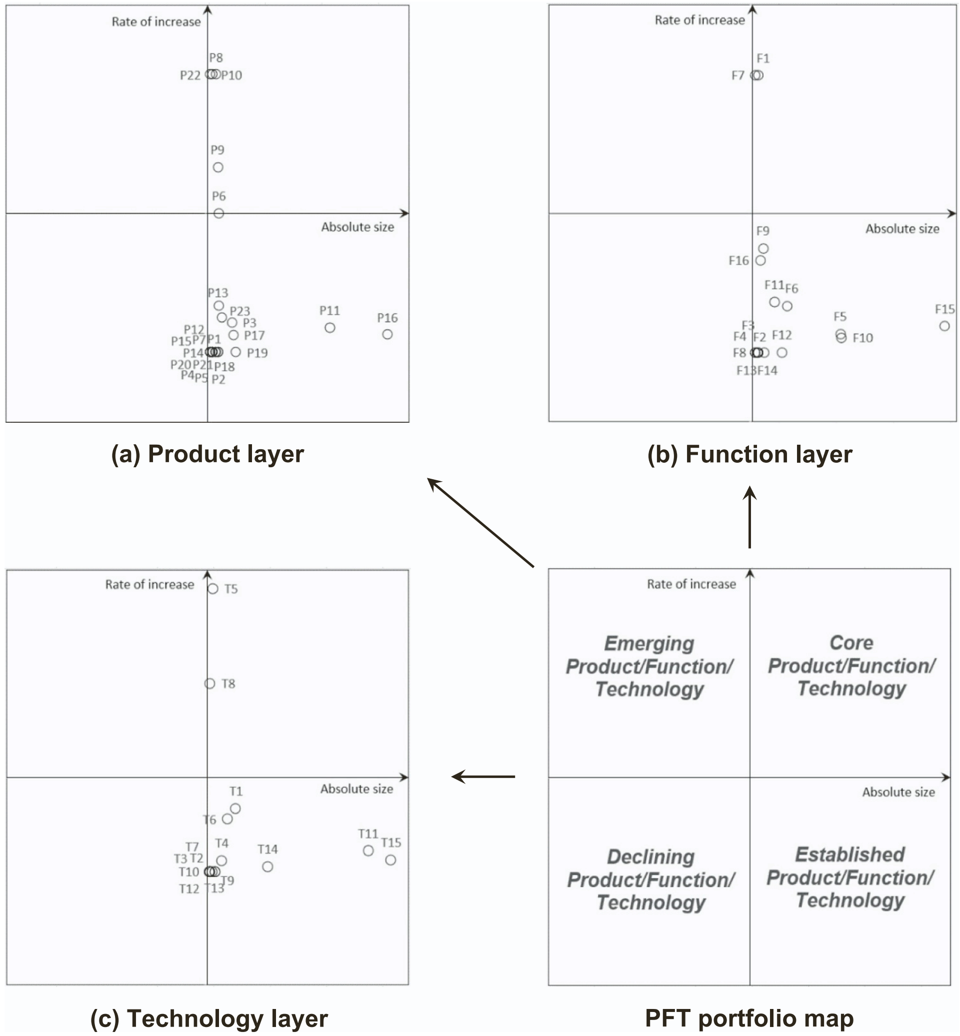

Fig. 6. A product-function-technology portfolio map.

first quadrant indicate that products, functions, and technologies are gaining sudden attention in the market. In contrast, their presence (i.e., absolute size) in the market has not yet reached a significant level. For this reason, components in the first quadrant might have a high market potential in the e-health industry.

Based on SAO structures, we built PFT portfolio map with a focus on PFT combinations to investigate which combination shows a surge in the market (See Fig. 7). The absolute size shows the total number of PFT combinations between 2020 and 2021. The rate of increase indicates the changes of the number of PFT combinations between 2020 and 2021, for example, the rate of increase can be a negative number if the number of PFT combination decreases in 2021 compared to 2020. As shown in Fig. 7, PFT combinations located on the second quadrant (emerging product/function/technology) showed a high rate of increase in the market despite their small absolute size in comparison with PFT combinations located in the fourth quadrant (established product/function/technology). As indicated in Fig. 7, thirteen PFT combinations seemed promising in the market. These include cloud based remote patient care (PFT 15), AI based diagnostic solution (PFT 71), vital signs measurement and monitoring (PFT 51–53), resource management solution (PFT 19, 64), medical chatbot (PFT 75, 76), medical information sharing system (PFT 77, 78), and medical supplies delivery using drones (PFT 3). The PFT combinations located in the fourth quadrant showed a low level of increase in comparison with a larger proportion they account for. The fourth quadrant includes PFT combinations related to telemedicine (PFT 31–33) and remote patient care and treatment app (PFT 5, 11).

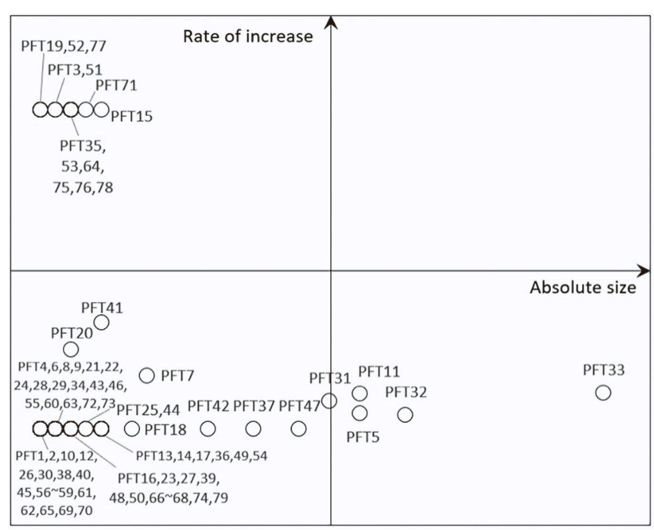

Fig. 7. A PFT portfolio map with a focus on PFT combinations.

Considering the lower rate of increase, PFT combinations in the fourth quadrant are very likely to move to the third quadrant in the near future if their size and increase rate keep decreases. As shown in Fig. 7, almost

80 % of PFT combinations are positioned in the third quadrant, which shows a relatively low level of increase and small number. From a business viewpoint, PFT combinations in the third quadrant are not attractive enough compared to other PFT combinations in either the second and the fourth quadrants. Considering the potential to growth in the future, there is a strong possibility that technological opportunities can be discovered from PFT combinations in the second quadrant.

Based on relationships in retrieved SAO structures, we developed a PFT relationship map in reference of Choi et al. (Choi et al., 2013) as shown in Fig. 8. The basic idea of PFT relationship map is to visualize the relationships among factors in technology, function, and product layers. The vertical axes of the PFT relationship map consists of three layers: product, function, and technology. Despite the PFT relationship map is similar with SAO based TRM in terms of its form, however, unlike traditional TRM, which uses time as horizontal axes, the PFT relationship map uses the thickness of nodes to visualize the overall relationships. Components of each layer in Fig. 6 are expressed as nodes and relationships between components in product, function, and technology layers are represented as edges. Each edge's thickness differs according to the frequency of observed relationships. Therefore, nodes connected with a thick edge indicate a stronger relationship than the rest of the relations in the PFT relationship map.

Among components in the technology layer, T15 (web-based platform), T11 (mobile app), and T14 (video chat) showed stronger connections in comparison with others. Particularly, T15 (web-based platform) and T11 (mobile app) showed many connections with components in the function layer, indicating a wide application in the e-health industry. In the case of the function layer, F15 (remote treatment), F10 (monitoring), F5(consulting), and F12 (remote clinical trials) showed a strong presence in connecting technologies to related products in the e-health industry. In the case of the product layer, P16 (telemedicine), P11 (remote patient care service), P19 (virtual clinical trials), and P17 (telepsychiatry) were the most frequently observed forms of products currently available in the market.

Exploited technological opportunities are mainly based on web-based platforms, mobile apps, and video chats. Among them, web-based platforms (T15) and mobile apps (T11) were the most frequently utilized in providing various e-health products. Analysis results indicated that exploited technological opportunities were focused on mitigating the impact of COVID-19 on the healthcare sector and responding to infectious diseases. To minimize the impact of COVID-19 on daily healthcare, e-health opportunities such as televetarinarian, telepsychiatry, and telephysiotherapy rose to prominence. During 2020, COVID-19 symptom monitoring showed a strong presence in providing remote treatment via mobile app, while COVID-19 management solution allowed effective management of COVID-19, helping medical institutions allocate resources and identify at-risk patients based on data. In addition, web-based platforms for virtual clinical trials have been introduced to keep medical research on track during the pandemic. Remote healthcare services such as telemedicine, remote patient care, and vital sign monitoring showed a strong presence in dealing with a wide range of patients, including inpatients, outpatients, patients with infectious diseases, and patients with chronic diseases.

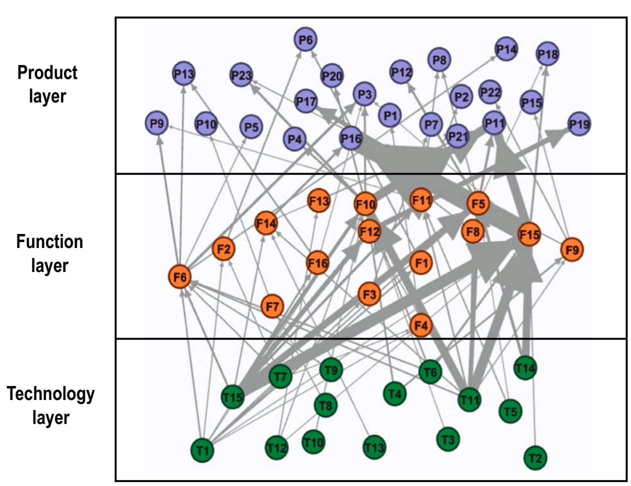

Fig. 8. A product-function-technology relationship map.

Referring to a study by Mejía and Kajikawa (Mejia and Kajïkawa, 2022), we used the opportunity gap discovery framework to identify the technological opportunity gap in the e-health industry. Fig. 9 shows the technological opportunity gap in the e-health industry. Technological opportunities in the upper left were commonly found in both exploited and latent technological opportunities. Considering these opportunities appeared both in the market and academia, it was assumed that they were confirmed to be promising in both ways. The lower left side shows technological opportunities observed only in exploited ones, while the upper right shows those observed only in latent technological opportunities. The former case can be interpreted as technological opportunities with little chance for further development because of the lack of academic discussions underway. On the other hand, the latter case can be interpreted as opportunities with a high potential for further development in the future.

As shown in Fig. 9, we grouped common opportunities according to their purposes. Group (a) comprised two exploited and three latent technological opportunities. These opportunities had one thing in common: they were related to e-health for providing remote treatment, care, and monitoring of outpatients and patients with chronic diseases. Group (b) represented e-health for mentally ill patients. Compared with the two groups mentioned above, Group (c) was a technological opportunity to mitigate the impact of the pandemic. The analysis showed that various resource management solutions for medical institutions were introduced and discussed in the market and academia. This supports the need for increased efficiency in medical institutions due to a dramatic increase in healthcare demand triggered by the pandemic. Group (d) was related to e-health for patients with infectious diseases, such as contactless monitoring using wearables, drones, and robots. E-health opportunities in Group (d) were similar to those in Group (a), considering they aimed to provide remote patient care. However, e-health opportunities in Group (d) were differentiated from those in Group (a) regarding their target customer.

The technological opportunity gap in the e-health industry exists between the lower left and upper right sides of Fig. 9. Two technological opportunities on the lower left side (televeterinarian and virtual clinical trials) are currently available in the market. However, academic discussions related to these two opportunities are lacking. Market needs for these two opportunities have been recognized and satisfied by existing business opportunities. Technological opportunities in the upper right indicate those that are needed but either still not yet commercialized or new to the market. For this reason, opportunities located in the upper right might have more chances to succeed in the market. Technological opportunities in the upper right side can be classified into three groups. Group (e) consists of e-health for sustainable medical treatment, such as telepharmacy and medicine delivery, telerehabilitation, and telesurgery. These are closely associated with opportunities in group (a). Various forms of e-health aiming to enhance efficiency in the medical field belong to group (f), for example, AI-based triage, smart hospitals, and medical information-sharing systems. In addition, e-health for early detection and diagnosis appears promising, such as AI-based image/voice analysis and detection of Covid-19 infection using wearables and biosensors.

5. Conclusion

In this study, we proposed enhanced tech mining, a TOA method to identify a technological opportunity gap by comparing exploited and latent technological opportunities. Our proposed method not only can

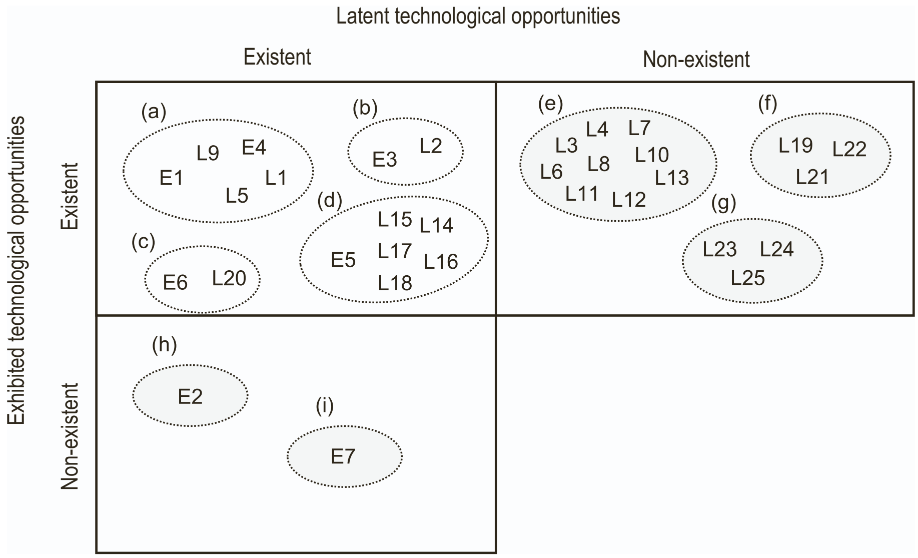

Fig. 9. A technological opportunity gap in the e-health industry.

help companies searching for business opportunities but also can support decision-makings in companies by providing a comprehensive overview on the current market status and scientific developments in the field. We demonstrated how the proposed method can help in identifying technological opportunities by investigating existing and potential technological opportunities in the e-health industry, deriving a technological opportunity gap. In connection with the research objective, our analysis result can be summarized into three points.

Firstly, we investigated exploited technological opportunities in the market by analyzing news articles related to e-health industry. The showed that exploited technological opportunities lie in three opportunity spaces including e-health for sustainable medical treatment, e-health for infectious diseases, and e-health for enhancing efficiency in the medical field. In addition, we identified exploited technological opportunities those seemed promising in the market based on PFT portfolio and relation maps. Particularly, the PFT portfolio map helped us in exploring exploited technological opportunities' potential to grow in the future. Also, in-depth analysis on technological opportunities currently available in the market can enhance our understanding of actual customer needs.

Secondly, latent technological opportunities were discovered based on academic journal articles. Similar with extant studies using scientific journal articles as a source of TOD, we also analyzed technological developments in academic journal articles to investigate potential technological opportunities. The result showed that latent technological opportunities are linked to four opportunity spaces including e-health for sustainable medical treatment, e-health for infectious disease, e-health for enhancing efficiency in the medical field, and e-health for early detection and diagnosis. In comparison with exploited technological opportunities, some latent technological opportunities were related to e-health for early detection and diagnosis, which was not observed from exploited technological opportunities. Each opportunity spaces consist of various technological opportunities that were not discovered in the market.

Finally, we used the opportunity gap discovery framework to identify the technological opportunity gap based on exploited and latent technological opportunities derived from the analysis result. The opportunity gap discovery framework helped us to identify which technological opportunities are confirmed to be commercially viable. We assumed that technological opportunities that exist both in exploited and latent technological opportunities are having potential business value. Because technological opportunities appeared both in the market and academia are considered to be meeting customer needs. While exploited technological opportunities that only exist in the market (televetarinarian and virtual clinical trials) may signal a lack of R&D needs or a lack of business value in such field. Latent technological opportunities that are not appeared in the market can be interpreted as opportunities that are currently underdeveloped in the market. These opportunities have potential to be out in the market soon.

In comparison with existing studies on TOD, our study has theoretical and managerial contributions as below. Firstly, enhanced tech mining can effectively discover more feasible opportunities reflecting reality. Most of extant studies on TOD use technological information such as patents and scientific journal articles as main sources of opportunity discovery. Patents and scientific journal articles are a good source for identifying technological trends and emerging technologies in the field, however, they do not provide a snapshot of the current market situation. In this study, we used a news outlet as one of sources for TOD in order to explore the current market situation, including what products and services are available, which technologies do they based on, and aims of those products and services.

Secondly, enhanced tech mining contributes to a better understanding on currently available opportunities by conducting in-depth analysis on exploited technological opportunities using PFT portfolio and relationship maps before deriving technological opportunity gap. Previous approaches on TOD with a focus on identifying opportunities by examining technological trends based on technological information, such as scientific journal articles and patents. However, they failed to consider consumer needs which can be done by analyzing exploited technological opportunities in the field.

Thirdly, the proposed method can be used in supporting business decision-makings. Enhanced tech mining can provide managerial insights in terms of the need for technological advancement or developing new technologies. By exploring latent technological opportunities based on academic journal articles, companies can not only examine technological trends but also learn recent technological advancements in the field. For this reason, analyzing latent technological opportunities can help companies in planning future businesses such as planning for R&D project related to their core products and services. Moreover, identifying technological opportunity gap between exploited and latent technological opportunities can help companies exploring a vacuum area in the market which can be turned into new businesses. Moreover, understanding the technological opportunity gap can let entrepreneurs have future business pathways since the enhanced tech mining result can provide insights into unmet market needs.

Fourthly, companies can analyze the current market situation based on an objective data. As a part of enhanced tech mining, companies can analyze exploited technological opportunities such as currently available products and services in the market. By doing so, enhanced tech mining can give companies valuable information in terms of potential competitors including launching trends of new products and services, in which technologies do they based on, and target segments of such products and services. This information is critical in preparing business strategies including realigning business portfolio and identifying potential collaborators in connection with a core business.

Despite the abovementioned implications, future research is needed to deepen and verify this study's results. Firstly, further studies on other industries are needed to verify the performance of enhanced tech mining. Since we only examined the e-health industry, further studies on other industries will ensure the effectiveness of applying enhanced tech mining to identify a technological opportunity gap. Secondly, this study used academic journal articles and news articles as major data sources. Since patents and technical documents are frequently used in traditional tech mining, various data sources, such as corporate reports, patents, and technical documents, must be considered for future research. By combining various sources of data, enhanced tech mining result can be enriched providing much more realistic insights on potential technological opportunities.

CRediT authorship contribution statement

Seungyeon Moon: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft. **Heesang Lee:** Project administration, Resources, Supervision, Validation, Writing – review & editing, Funding acquisition.

Data availability

Data will be made available on request.

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