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Examining the Patent Landscape of E-Fuel Technology

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Abstract: Although the end of combustion engine vehicles seems inevitable under a new climate target for 2030, a complete ban on the combustion engine would be counterproductive. E-fuels, which are produced using renewable electricity from hydrogen and carbon dioxide, could act as a possible large-scale solution for achieving climate-neutral mobility, as they allow us to reduce greenhouse gas emissions while leveraging the existing energy infrastructure. Against such a background, it is critical to examine how the related technological landscape is constructed and might affect the subsequent knowledge generation. By adopting a social-network perspective, the aim of this study is to investigate the degree of technological knowledge relatedness of e-fuel technology using patent data. This is accomplished by analyzing the influence of individual knowledge areas and categorizing them into a matrix model, with each quadrant playing a unique role. The main findings show that the patent landscape is dominated by applications from the private sector, and the main knowledge base is centered around chemical engineering and production techniques for liquid hydrocarbon mixture. Furthermore, the analyzed knowledge flows are dominated by intra-technology knowledge flows, thereby being less prone to convergent technology evolution. In particular, the knowledge areas C10L 01 and C10J 03 demonstrated a high influencer role. The findings can also support R&D advisors and decision makers in policy development in reducing their efforts required for conducting technical intelligence activities and determining adequate policies for R&D portfolio management.

Keywords: e-fuel; synthetic fuel; patent analysis; technology management; clean energy; network analysis

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1. Introduction

The topics "clean energy" and "energy supply" have never been such a big issue as they are today. Due to the imminent threat of global warming, several countries have taken measures to mitigate the risk resulting from fossil fuel consumption. The transition to a climate-neutral society is regarded as both an urgent political challenge and an opportunity to build a sustainable future for all humanity [1]. This goal can be reached by means of developing realistic technological solutions and encouraging international partners to align actions in key areas such as green industrial and environmental policy. According to several studies, the transport sector is responsible for roughly 30 to 40% of carbon dioxide (CO_2) emissions from the end-use sectors [2,3]. Given this background, the reduction in greenhouse gas (GHG) emissions can be achieved by transforming the transportation system from gasoline to electric vehicles (EVs) [4]. Over the years, the sales of EVs have been on the rise (despite the semiconductor chip shortages) [5]. However, they are mainly concentrated in China, Europe and the United States, and electric vehicle (EV) sales in other emerging or developing economies are lagging [6]. Furthermore, the study by Gan et al. (2021) [7] revealed that preferential regulatory treatments of plug-in electric vehicles (PEVs) have resulted in the overall increase in GHG emissions, pointing to a need for redesigning incentive plans. Vehicle electrification is surely the way to go on a long-term basis for the decarbonization of the transport sector, but additional technological options (such as the use of synthetic fuels) need to be evaluated simultaneously. A recent study highlighted the potential for reducing climate impact through the use of synthetic low-carbon fuels based on renewable electricity in internal combustion engine vehicles (ICEVs) [8]. Nevertheless, when the environmental life-cycle assessments of current and future passenger vehicles are made, the related studies do not necessarily consider the synthetic-electricity-based fuels as a transitional solution [8].

E-fuels, also called synthetic fuels, are "low-carbon or carbon-neutral liquid hydrocarbon fuels using renewable hydrogen (H_2) and CO_2 as building blocks" [9]. They are synthesized from hydrogen produced via electrolysis and CO_2 captured from either fossil sources or the atmosphere. In contrast to conventional fuels, e-fuels do not release any additional CO_2, thus being climate-neutral in the overall balance. The resulting liquid fuels can act as substitutes for their fossil counterparts and can be used with existing internal combustion engines and refueling infrastructure, thereby offering a possible large-scale solution for a climate-friendly mobility of the future [10]. Currently, there are three options for reducing CO_2 emissions in the transport sector: (1) vehicle electrification via battery, (2) vehicle electrification via fuel-cell technology and (3) use of non-fossil-based fuels (such as biofuels or e-fuels) for the classical internal combustion engines. Although the most obvious solution for the decarbonization of the energy sector is an extensive electrification of vehicles based on emission-free electricity, such a transformation would require time to mature. Despite the mentioned technological options having their pros and cons, they must be pursued in parallel, as the majority of active combustion engines will remain in operation at least till 2050 [10]. To ease the transition to low-carbon mobility, the conversion of CO_2 to e-fuels is seen as a highly promising field that could address both increasing CO_2 emissions and the energy demand [11]. Especially, e-fuels could add values in different application areas where the decarbonization is hard to achieve by enabling combustion technologies and fuel infrastructures to remain competitive in confronting climate change [12]. However, despite these aspects of e-fuels ("capable of bridging technologies of past and future"), there are contrasting views on the role of e-fuels and the range of applications due to their fragile climate effectiveness and economic viability [10].

Against this background, existing studies have primarily focused on investigating the economic and environmental consequences of e-fuel for the energy mix, providing scenarios in which the e-fuel production could become more cost-competitive [13,14]. These studies have proved helpful in emphasizing the potential of e-fuels as an alternative to conventional fuels, but limited attention has been directed to exploring the technological development trend of e-fuels and their key technological areas based on objective technological profiling. Knowledge on the technological innovation trend might provide an alternative perspective to researchers and policy makers interested in promoting the adoption of e-fuels by revealing the underlying technological characteristics and research directions. The production of e-fuels is being extensively studied from a technical implementation point of view, and the technical prerequisites are in place, which will enable the construction of large-scale industrial plants in the medium term. At the same time, it is important to understand how the key knowledge areas are related to each other and how changing research dynamics might impact the subsequent knowledge generation.

For this purpose, patent data can provide useful technical insights into the innovative activity and nature of competition in a specific technology field [15]. Serving as an early indicator of technological progress, patent data have been widely used in combination with data-driven techniques to outline technological development trajectory [16], discover appropriate technology opportunities [17] and predict future product development directions [18]. Especially, if the technology is in its early stage, patent-based metrics can be helpful in assessing technological characteristics and supporting various decision-making tasks [19,20]. So far, there has been no study systematically investigating the patent landscape of e-fuels, despite its potential for making a meaningful contribution to the global energy transition. There is a need to provide a deeper insight into the current status of e-fuel technology from a perspective other than life-cycle analysis. Understanding the research focus and innovation characteristics of e-fuels might be critical to summarize emerging technology trends and identify potential technology improvement opportunities.

Hence, this study intends to investigate and measure the degree of technological knowledge relatedness of e-fuel technology using patent metadata. We adopted an exploratory approach to investigate the historical trajectory of knowledge development and performed a network analysis based on co-occurring patent classification codes to highlight the impact of key knowledge areas. To this end, a matrix model was introduced to categorize the knowledge areas into four sections, with each section playing a distinct role in the knowledge diffusion. This study is, to the best of our knowledge, one of the first studies that thoroughly assesses the e-fuel patent landscape and categorizes the knowledge areas into their respective roles for assisting R&D policy design. Hence, we expect that this study can help R&D specialists in reducing their efforts required to conduct technical intelligence activities as well as policy makers to determine adequate policies for R&D portfolio management.

The key findings can be summarized as follows: First, this study extends the e-fuel literature by providing the first empirical evidence on which technological fields played a central role in the technological progression based on metrics from the network analysis theory. Second, the patent landscape is dominated by applications from the private sector, and the main knowledge base is centered around chemical engineering and production techniques for liquid hydrocarbon mixture. Third, the applied analysis framework provides a simple but significant perspective for other researchers to characterize the patent landscape and key knowledge areas that might have a lasting impact on further research. Furthermore, the analyzed knowledge flows are dominated by intra-technology knowledge flows, thereby being less prone to convergent technology evolution.

The remainder of this paper is organized as follows: Following the introduction, Section 2 describes the data collection, the analytical framework and applied methods in detail. In Section 3, we present the empirical findings by highlighting the roles played by the key knowledge areas. Section 4 discusses the main findings and what they might indicate for the future development of e-fuel production. Finally, we present the conclusions and outlook for future research.

2. Data and Methods

2.1. Data

For the analysis, we used patent data extracted from Derwent Innovation, a commercial research and analytics platform maintained and curated by Clarivate. The platform is perceived as one of the most comprehensive databases for retrieving global patent information, covering nearly 53 million invention-level patent families drawn from 59 patent-issuing authorities worldwide. A unique attribute of this database is the access to Derwent World Patents Index (DWPI), which provides enriched patent data for supporting faster evaluation of a patent's content, and strategic decision making with regard to R&D investment [21]. The patent records can be retrieved as patent families, which represent a group of patent documents relating to the same priority invention. This allows duplicated patent records to be removed from the search results, thereby offering a true invention-level perspective for the global technology monitoring [22]. Moreover, DWPI also provides editorially curated patent titles and abstracts that are more descriptive and written using standardized terms without complex legal jargon for better technical understanding. This can serve as an informative feature for studying main application areas and highlighting the inventive step of the patent [16].

Accordingly, a number of studies have relied on the use of patent data from Derwent Innovation to derive new technological solutions from the existing knowledge domain [23], perform a systematic analysis of Internet of Things (IoT) technology and its technical subfields [24] and evaluate the patent landscape of the organic Rankine cycle system [25]. This points to the fact that many scholars have already successfully demonstrated its potential for generating improved patent intelligence [26].

In this study, a keyword-based retrieval strategy was adopted to obtain patent data. A defined set of keywords related to the research subject was searched in the title, abstract and claim fields within a patent record. The following search query was implemented: CTB = ((“e-fuel”) or (“e-fuels”) or (“synthetic fuel”) or (“low-carbon fuel”) or (“low-carbon fuels”) or (“carbon-neutral liquid hydrocarbon fuel”) or (“carbon-neutral liquid hydrocarbon fuels”) or (“carbon-neutral fuel”) or (“carbon-neutral fuels”) or (“synthetic fuels”) or (“synfuel”) or (“synfuels”) or (“efuel”) or (“efuels”) or (“synthetic liquid fuel”) or (“synthetic liquid fuels”)) AND PRDS>=(20100101). (Note: CTB stands for keyword-based search in Title/Abstract/Claims of the patent document, whereby PRDS refers to priority date). The analysis period was limited from 2010 to 2021 in order to discuss the most recent development. The data retrieval took place in October 2022. A total of 904 patent families were identified and exported to an Excel file for further processing. After removing incomplete entries and irrelevant patents, 848 patent families were retained for subsequent analysis.

2.2. Analytical Framework

The applied analytical framework involves following four analysis phases, which are listed below in Figure 1. The first phase comprises the collection of patent data and data preprocessing, which would facilitate the subsequent data-mining and visualization steps. The second phase involves the application of descriptive statistics and the construction of an adjacency matrix, which is used as an input feature to express the technological knowledge network. In the third phase, a network centrality analysis is performed to compute the popularity and intermediary behavior of individual knowledge areas. Moreover, the corresponding network graph is visualized. Next, a 2-by-2 matrix is proposed to classify the patent classification codes in terms of their level of influence through two complementary network centrality metrics. The data analysis was performed in Python 3.7.10. Subsequently, the focus will lie on describing the theoretical aspects of the last two steps in detail.

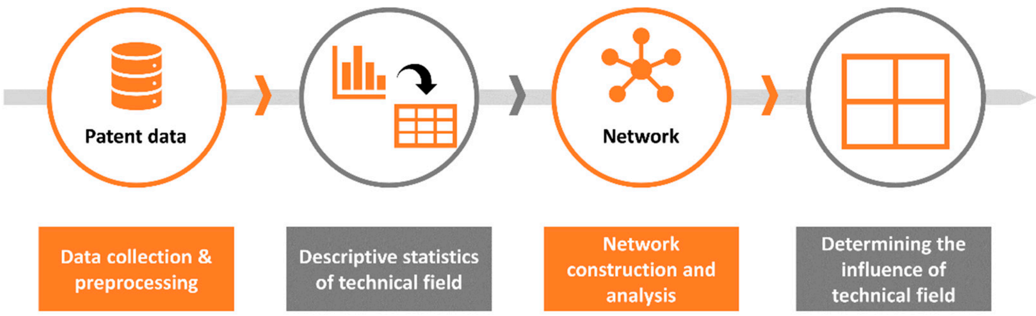

Figure 1. Overview of the analysis framework.

2.3. Network Visualization and Centrality Analysis

This study relied on the concept of knowledge flow for quantifying and visualizing the inter-relation among various patent classification codes [27]. Typically, knowledge flows occur when two separate entities interact and exchange information or resources. Many scholars in the field of innovation studies have focused on measuring technical knowledge flows to study which areas of knowledge discipline or expertise converge and inter-relate [15]. Moreover, upon exploring the nature of knowledge flows, answers to questions concerning the origin of knowledge sources or the magnitude of technological impact on subsequent knowledge generation can be found [28]. Understanding knowledge flows within a technology domain via patent citation network can result in an improved knowledge management process by leveraging the cumulative character of knowledge [29].

In this regard, the examination of co-occurring patent classification codes can shed light on the relationships of interlinked knowledge areas. Each patent classification code can be equated with a specialized knowledge area, whereby analyzing the patterns of how the individual codes are linked to each other can reveal important information on the technological knowledge diffusion process [16]. Hence, the frequency with which two distinct patent classification codes appear together in patent documents reflects the degree of knowledge flow dynamics that exist between those codes. Especially, the combination of different technological fields can be regarded as a recombinant innovation that can trigger technological transitions [30]. Verhoeven et al. (2016) [31] also highlighted the superior technological novelty in patents that contained previously unknown combinations of international patent classifications (IPCs). Recombining knowledge in a unique way could possibly lead to superior innovation performances, as existing knowledge surrounding a technology can affect the combinatorial dimension of technological diffusion.

In the present study, we used the co-classification method to generate the adjacency matrix, which essentially represents the number of co-occurrences (e.g., strength of connection) between two knowledge areas [32]. (Note: The relation between two co-occurring IPCs acts as a proxy for measuring the knowledge flows). The constructed adjacency matrix is characterized by an "m by m" dimensional structure, in which m specifies the number of individual IPCs present in the patent data. Subsequently, the matrix is transformed into a network graph, where the nodes indicate the knowledge areas, and the edges represent the strength of relational ties. The width of the edges is governed by the intensity of the relationships. Figure 2 shows the conceptual flow of transforming the adjacency matrix into a network graph and calculating the centrality score for each node. The numbers in the matrix cell indicate the frequency of knowledge flow dynamics. The network visualization could aid in comprehending the complex interplay of nodes, providing a more thorough view to the characterization of local structure properties [33]. For the visualization task, this study used the open-source visualization software Gephi version 0.9.2.

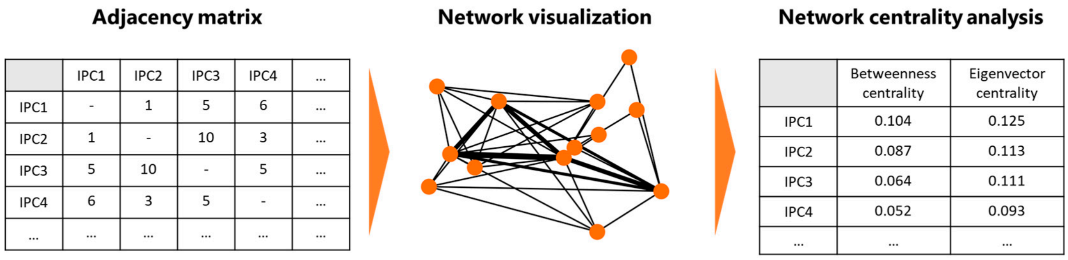

Figure 2. Conceptual flow of network visualization and calculation of centrality metrics. (Note: To simplify the understanding, pseudo-IPC codes have been displayed).

The calculation of network centrality measures, which are commonly used to identify central and potentially influential nodes within a network, has been a major focus of social-network analysis research [34,35]. Central positions within the network have been equated with opinion leadership or popularity, both of which could assert influence on the behavior of network participants [36]. This study computed betweenness and eigenvector centrality measures to characterize the relative importance of individual nodes as well as to classify their roles in the knowledge diffusion process. For calculation, the open-source python library NetworkX (version 2.5) was implemented.

Betweenness centrality centers on the idea of counting the number of times a node acts as a bridge or brokerage. A bridge in a network represents a node, which can connect two distinct (social) groups, thereby allowing the dissemination of information between two (social) groups to occur. Betweenness centrality quantifies how frequently a node appears on all shortest geodesic paths connecting two nodes. Hence, nodes with high betweenness centrality values can potentially influence the spread of information by controlling the flow of communication between subgroups. We used following equation to compute the betweenness centrality of a node $C_{Between}(i)$ [37]:

$$C_{Between}(i) = \sum \frac{g_{jk}(i)}{g_{jk}} \quad (1)$$

where g_{jk} refers to the number of all shortest paths connecting nodes j and k, and $g_{jk}(i)$ denotes the number of such paths containing the node i.

Eigenvector centrality can be understood as an extension of degree centrality. It represents the magnitude to which a node is connected to other central nodes in the network. Eigenvector centrality assigns each node a score proportional to the sum of the centrality scores of the neighboring nodes to which it is connected. Hence, nodes with high eigenvector centrality values can be interpreted as prominent nodes, which might influence many others in the network, either directly or indirectly, through their connections. It is a global measure of a node's importance. The following equation is applied to compute the eigenvector centrality of a node $C_{Eigen}(i)$ [38]:

$$C_{Eigen}(i) = \frac{1}{\lambda} \sum_{j=1}^{n} A_{ji} x_j \tag{2}$$

where A_{ji} represents the adjacency matrix for the network graph, n is the number of nodes present in the network, x_j is the relative centrality score of nodes connected to j, and λ is the largest eigenvalue of A.

2.4. Identification of Influential Key Knowledge Areas

Understanding network centrality is important because it explains which node occupies a critical position in the network. In the domain of technology and innovation management, it has been found to be beneficial in comprehending the relationships between interconnected technical domains [27] and determining the impact of industry sectors on the business ecosystem's constitution [33]. Especially, influential nodes in a network can play a significant role in the diffusion and adoption rate of innovation. In the marketing domain, potential influencers could help corporations improve the effectiveness of their marketing campaigns through word-of-mouth information propagation [39]. In the same sense, influential technology areas could affect the innovation behavior of other areas in the network, from which they could accomplish a greater outreach of knowledge flows resulting from their positional advantages.

This study adopted and modified a matrix model proposed by Litterio et al. (2017) [40] for classifying the knowledge areas. It ranks knowledge areas that simultaneously fulfill the greatest values of both betweenness and eigenvector centrality as potential influencers. Betweenness and eigenvector centralities have desirable properties for locating an influential node in a network [32]. This implies that a combination of both features would include those knowledge areas which are capable of exerting influence on detached groups.

The resulting matrix consists of a two-dimensional scatter plot, with individual nodes displayed based on their betweenness centrality (x-axis) and eigenvector centrality (y-axis) (see Figure 3). Upon introducing a threshold value, the plane can be divided into four quadrants, which enable the classification of every node into four different roles. These four roles can be described as follows:

(1) Influencer role with a high degree of betweenness and eigenvector centrality, thereby demonstrating both high transitive influence and intermediary capability.

(2) Brokerage role with a high degree of betweenness centrality, thereby serving as bridges to connect previously unrelated knowledge areas.

(3) Prominence role with a high degree of eigenvector centrality, thereby serving as a hub of connectivity and having a wide-reaching influence within the network.

(4) No specific role with a low degree of betweenness and eigenvector centrality. Overall, knowledge areas belonging to this role demonstrate a low intensity of knowledge-exchange activities with their neighboring groups.

The separation of quadrants can be performed either by setting the mean value of the centrality measure as a threshold variable or by considering the characteristics of the network. The threshold value should be determined in accordance with the study's objectives, and this process will be covered in more detail in Section 3.3. Consequently, the specific focus lies in providing insights into the functional roles played by key knowledge areas.

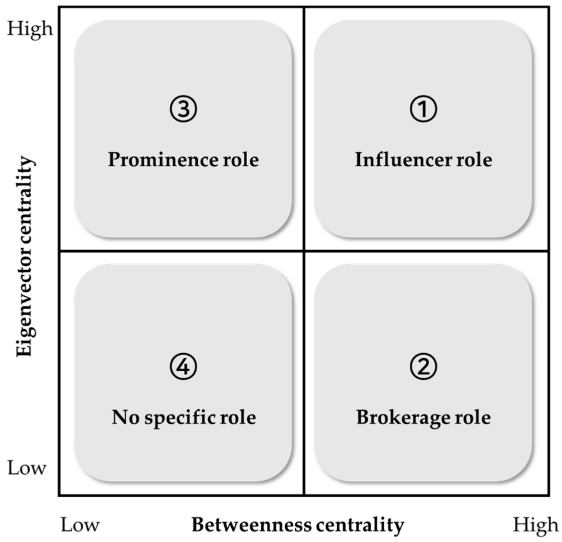

Figure 3. Matrix model for the classification of knowledge areas. (Note: The x-axis represents the betweenness centrality, while the y-axis represents the eigenvector centrality).

3. Results

3.1. Descriptive Statistics

In this section, a brief descriptive overview of key features from the collected patent data is provided to better understand the e-fuel patent landscape. In particular, we focused on presenting the historical patent development trend, the distribution of frequently occurring IPC codes and the distribution of priority countries, where the initial patent filing was submitted. Figure 4 shows the number of patent families filed between 2010 and 2021. In total, we investigated 848 patent families over the defined analysis period.

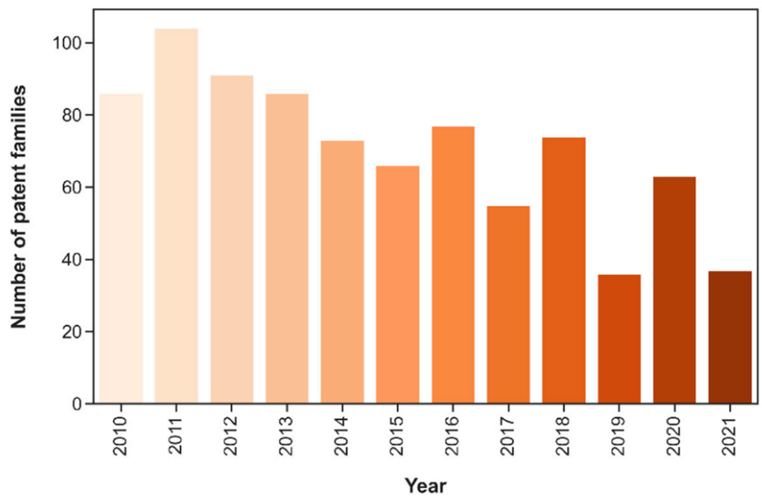

Figure 4. Patent development trend of e-fuel technology. (Note: The x-axis represents the priority year, while the y-axis represents the number of patent families).

According to the above bar chart, the e-fuel technology cannot be seen as an emerging field, which has progressively gained attention in recent years. From 2011 onwards, the number of patent families has decreased gradually with an inconsistent flow. Nevertheless, considering the delayed publication of patent information after its application, the actual numbers in the most recent years might go up. By comparing the findings with the publication analysis derived from Scopus database, which is one of the largest citation databases for scientific literature, a similar inconsistent publication trend was observed regarding the e-fuel technology (see Figure 5). In this case, however, the number of research publications between 2019 and 2021 has significantly increased compared to previous years. (Note: The same search query for patent retrieval was adopted to retrieve data from Scopus). Typically, there is a positive correlation between patents and publications at a time lag of two years [41]. Hence, the e-fuel technology might eventually experience a higher demand at the patent level in the near future.

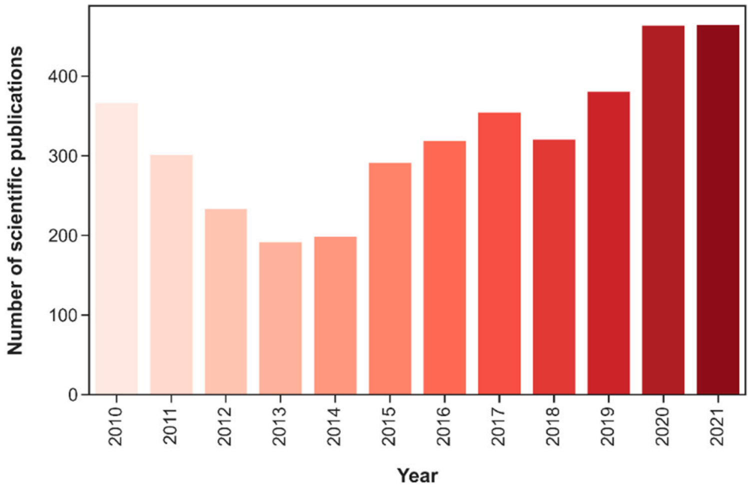

Figure 5. Number of scientific publications in the domain of e-fuel technology. (Note: The x-axis represents the publication year, while the y-axis represents the number of scientific publications).

Figure 6 illustrates the most frequently occurring IPCs (top 20) within the e-fuel technology field. To keep the interpretation complexity at a manageable level, we considered the group-level IPCs for illustrating the underlying technological field (Note: The descriptions of the IPCs from Figure 6 can be found in Appendix A.1. Alternatively, the readers could also look up for the relevant information in the following website: https://ipcpub.wipo.int/ (accessed on 4 February 2023). In total, there were 587 different IPCs with varying degrees of significance that are involved in the characterization of the e-fuel knowledge base. Because the majority of the analyzed patent families is labeled by more than one IPC, the sum of its frequencies is larger than the number of studied patent data. The most common code is “C10L 01”, followed by “C10J 03”, “C01B 03”, “C10G 02” and “C10L 05”. These codes all belong to Section C, which stands for “Chemistry; Metallurgy”. As the e-fuel technology evolves around the production of liquid carbonaceous fuels and gases containing carbon monoxide and hydrogen, it is natural that most of the codes are related to chemical sciences and engineering. “B01D 53” (Chemical or biological purification of waste gases) is related to the production process of e-fuels. “B01J 19” and “B01J 08” are related to chemical, physical or physicochemical processes, which are conducted in the presence of fluids. As e-fuels are regarded as a potential alternative to fossil fuels and produced in a specific chemical reaction, it is not surprising that the related knowledge base is centered around chemistry-related topics. The e-fuels are characterized by the same chemical properties as the original fuel derived from a conventional petroleum refinery. Depending on the final product form required (e.g., gas or liquid), e-fuels can be produced via either a power-to-gas or power-to-liquid process [42].

Figure 7 shows the distribution of patent families according to their priority country. A closer examination reveals that the knowledge generation activities were concentrated in a small number of geographic areas. A considerable share of patents originated from organizations based in Asian countries, such as China, Japan and Korea, followed by the United States and Germany.

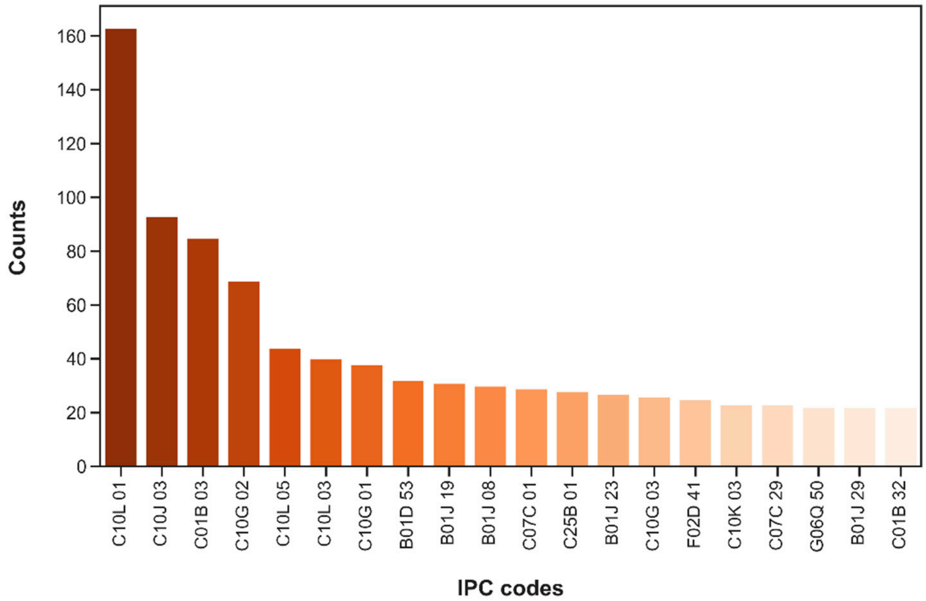

Figure 6. Top 20 frequently occurring IPCs. (Note: IPCs also refer to knowledge areas in subsequent descriptions).

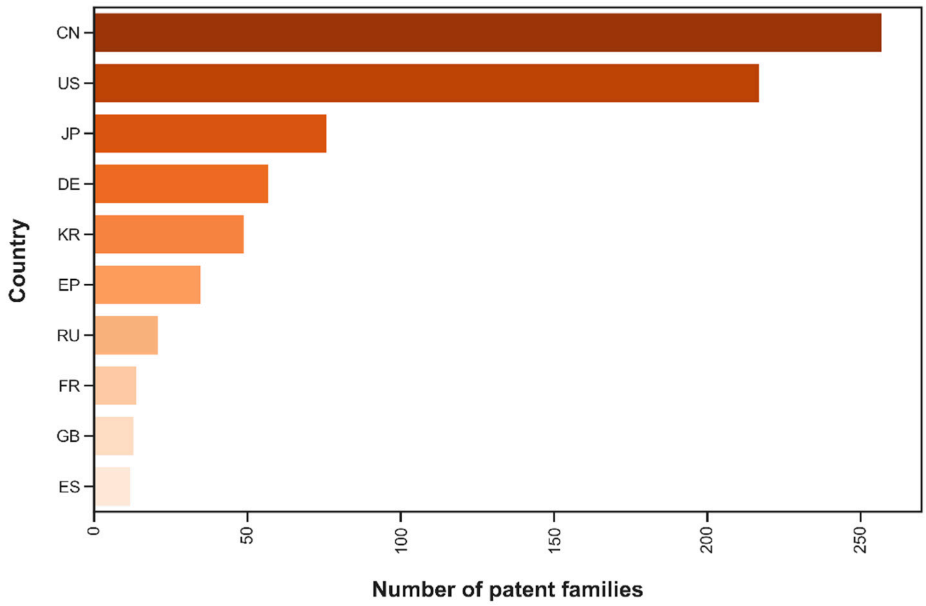

Figure 7. Distribution of patent families by priority country.

If we further break down the assignee types in public and private sector organizations in the top five countries, the following insights could be drawn (see Table 1): Except for Korea, there were significantly more organizations performing R&D from the private sector. Assignees from the public sector consist of universities, research institutes and government departments specialized for energy technology development. To complement the electromobility, it is expected that vehicles with an internal combustion engine would continue on the roads up to 2050 and beyond [43]. For an ideal life-cycle management, the e-fuel technology can help reduce emissions during the transition period by leveraging the existing fueling infrastructure and vehicle fleets [42].

Table 1. Distribution of distinct assignee types in the top 5 countries.

Countries	Assignees from Public Sector	Assignees from Private Sector
CN	45	212
US	18	199
JP	3	73
DE	3	54
KR	35	14

3.2. Network Analysis

We calculated the network centrality metrics to determine the influence of individual knowledge areas in the network. Figure 8 depicts the complete network architecture, which outlines a static snapshot of interconnected knowledge areas, providing only a limited interpretability of the results. To enhance the visualization performance and interpretation of knowledge areas, we emphasized the top 5% of most frequent interconnections on the right side of Figure 8. In align with former empirical results [32,44], the threshold value of 5% allows a clear overview of key knowledge flow dynamics. Moreover, the highlighted dynamics represent knowledge areas that require greater attention.

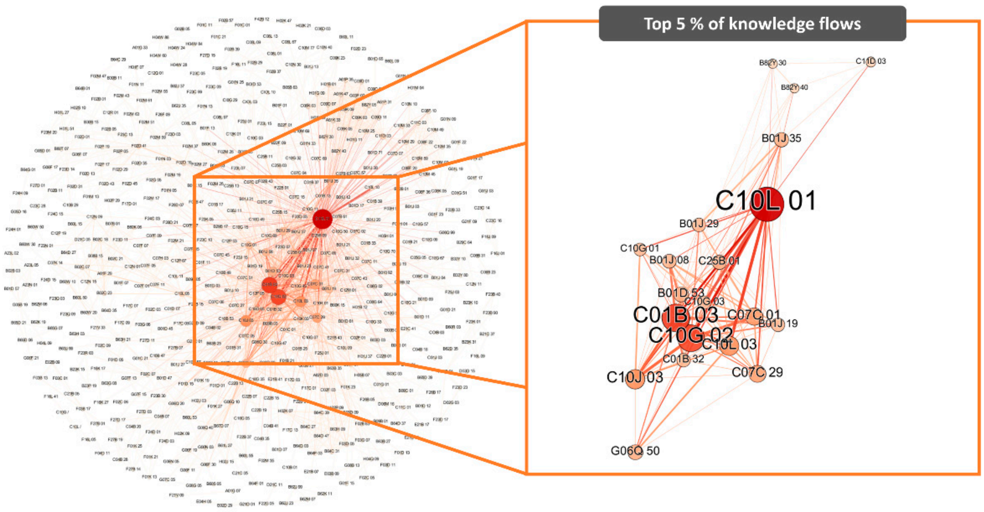

Figure 8. Visualization of knowledge flow network for the e-fuel patent landscape (2010–2021).

The network was visualized using the Fruchterman–Reingold layout, which is a force-directed algorithm. It brings the more highly related nodes closer [45]. The color scale is representative of the size of a node's degree. Therefore, the more links connected to the node, the darker the node color.

The complete network consists of 551 nodes and 2382 links. The average number of links per node in the network is 4.323, demonstrating a comparably low density compared to studies adopting a similar methodological approach [15,32]. Hence, we may state that there are only a few well-connected nodes in the network graph. In fact, the network is not a single coherent network, but the entire network is composed of 23 subgraphs, which enclose different network topologies and sizes. Nevertheless, there are 490 nodes in the single largest subgraph, implying that the majority of the relevant knowledge areas are contained in that subgraph. At the same time, there are some isolated island-like occurrences (located at the peripheral site), which are disconnected from the main knowledge network. In the following, the findings will be derived from the mentioned largest subgraph. Table 2 summarizes the top 15 knowledge flows between interconnected knowledge pairs. They are measured by the absolute number of knowledge flows. To explore whether there exist convergent tendencies between interconnected knowledge areas, we decided to use four-digit IPC codes, which can serve as valid proxies for measuring the macroscopic scope of a patent [46,47].

Table 2. Top 15 knowledge flows. (Note: The description of IPCs from Table 2 can be found in Appendix A.2).

Interconnected Knowledge Pairs		Number of Knowledge Flows
C10G	C10L	102
C10G	C07C	101
C10G	B01J	90
B01J	B01J	86
C07C	C07C	84
B01J	C07C	78
C10G	C10G	77
B01J	C01B	72
C10G	C01B	61
C10L	C10L	51
C01B	C07C	51
C07C	C10L	47
C25B	C25B	38
C10G	G06Q	34
G06Q	G06Q	33

The values in Table 2 can be used to judge whether certain knowledge areas exhibit uncommonly high levels of cross-boundary knowledge flows. According to Table 2, the highest number of knowledge flows was found between C10G and C10L. C10G represents "production of liquid hydrocarbon mixture", while C10L denotes "fuels not otherwise classified; liquefied petroleum gas". The second-highest knowledge flows occurred between C10G and C07C (acyclic or carbocyclic compound), followed by the interconnection between C10G and B01J (chemical or physical processes, e.g., catalysis or colloid chemistry). These are knowledge areas involved in the production of synthetic fuel. For example, a process encompassing the recycling of atmospheric CO_2, the electrolytic synthesis of H_2, and their catalytic reaction to yield CH_3OH (methanol), all supported by renewable energy sources, is a promising setup for the production of synthetic methanol fuel [48]. Overall, it seems that on the four-digit IPC level, the spectrum of involved knowledge areas is rather limited, and they tend to develop knowledge flows between thematically similar or related knowledge areas. It is also remarkable to note that C07C, C10G, C10L and C25B (electrolytic or electrophoretic processes for the production of compounds or nonmetals) are characterized by self-loops, which present intra-technology knowledge flows among related chemical knowledge areas. Hence, it can be stated that the production process requires a heavy chemical knowledge accumulation in the form of synthesis rules and reaction kinetics. Except for the linkage between C10G and G06Q (data processing systems and methods), a convergent knowledge flow pattern was not visible. Patents involving G06Q are subject to digital systems specially adopted for administrative purposes to manage feedstock and regulate the conversion process [13,49]. This is in line with the recent emphasis that the demand side management is (besides e-fuel production) a critical component for reasonably achieving a reduction in global warming potential through predictable methods and enabling optimal use of renewable electricity [50]. The findings point out that the study of knowledge flow dynamics provides a useful lens to comprehend the interdisciplinary character of the knowledge structure. In this context, the dominance of intra-technology knowledge flows could be explained by the diversity and coreness of previous knowledge stock. According to Battke et al. (2016), core knowledge is more likely to be transferred within the same technology field, while less diversified knowledge tends to follow existing technological trajectories [51].

Table 3 lists up the computed betweenness and eigenvector centrality values, which are used to define the influential characteristics of individual nodes. Herein, the top 20 highest centrality values are displayed. Unlike discussing the interconnected knowledge pairs, these values can produce a differentiated view on the node's influence, as a node's structural position could possibly regulate which information or resources can be transmitted across the network.

Table 3. Centrality values for the key knowledge areas (sorted by eigenvector centrality). (Note: The description of IPCs from Table 3, which are not listed in Appendix A.1, can be found in Appendix A.3).

Knowledge Area	Betweenness Centrality	Eigenvector Centrality
C10G 02	0.0374	0.4020
C01B 03	0.0708	0.4008
C10L 01	0.2592	0.3639
C10J 03	0.1296	0.2562
C10L 03	0.0438	0.2516
C07C 01	0.0185	0.2124
B01J 08	0.0173	0.1781
C10K 03	0.0054	0.1696
C10G 03	0.0124	0.1577
C07C 29	0.0964	0.1467
C10G 45	0.0182	0.1417
B01J 19	0.0376	0.1414
G06Q 50	0.0497	0.1368
G06Q 30	0.0214	0.1323
C12P 05	0.0024	0.1227
B01D 53	0.1362	0.1181
B01J 23	0.0039	0.1164
C25B 01	0.0671	0.1160
C01B 32	0.0485	0.1115
C10G 01	0.0225	0.1028

First, it is important to note that both centrality metrics demonstrate a strong positive correlation ($r = 0.6524$, p-value < 0.001) to each other [52]. Hence, influenceability (which refers to the level of impact a knowledge area can exert on others within the network) and intermediary (or brokerage) capability could theoretically be jointly accounted for using a single metric. Second, the calculated centrality values indicate that the frequently occurring knowledge areas (from Figure 6) also tend to have high eigenvector centrality values. Although C10G 02 (production of liquid hydrocarbon mixtures of undefined composition from oxides of carbon) and C01B 03 (hydrogen; gaseous mixtures containing hydrogen; separation of hydrogen from mixtures containing it; and purification of hydrogen) are ranked first and second in terms of influenceability, their brokerage capability is less pronounced. On the contrary, C10L 01 (liquid carbonaceous fuels) and C10J 03 (production of gases containing carbon monoxide and hydrogen), which are critical knowledge components for the production of e-fuels, are characterized by high betweenness centrality values. Knowledge areas with high betweenness centrality have the ability to separate or strengthen relationships between certain nodes and cliques, which makes them capable of establishing opinion leadership. Given this opportunity to diffuse and coordinate information, these knowledge areas could selectively share information with others that are perceived to be of high value [53]. Similarly, B01D 53 (separation of gases or vapors; recovering vapors of volatile solvents from gases; and chemical or biological purification of waste gases) shows a high betweenness centrality and is thematically related to C10J 03. Furthermore, G06Q 30 (commerce, e.g., shopping or e-commerce) signifies that there might be some ongoing research targeted towards monitoring the in- and out-flow of feedstock and fuel distribution, highlighting the importance of digital awareness in renovating the energy infrastructure. Taken together, knowledge areas pertaining to chemical engineering dominate the e-fuel patent landscape in terms of their transitive influence. They mainly contribute to sustainable e-fuel production routes.

3.3. Classification of Influential Knowledge Areas Based on a 2-by-2 Matrix

In this subsection, the proposed 2-by-2 matrix model was used to classify the knowledge areas into their respective functional roles. To determine the threshold value for demarcating the boundaries of predefined roles, we first investigated how dispersed the values are by creating histograms. Accordingly, Figure 9 shows the histogram for each of the considered centrality values. Moreover, we calculated the skewness and kurtosis statistics for them to test for data normality and the presence of outliers. Both skewness and kurtosis could be used to discover the asymmetrical behavior of the data distribution, and the derived values clearly exceeded the condition for normally distributed data. They are both heavy-tailed and right-skewed data, where the majority of data points have low values, and the range of the variable is wide. (Note: Skewness and kurtosis for betweenness centrality were 8.52 and 100.93, respectively, while skewness and kurtosis for eigenvector centrality were 5.83 and 40.90).

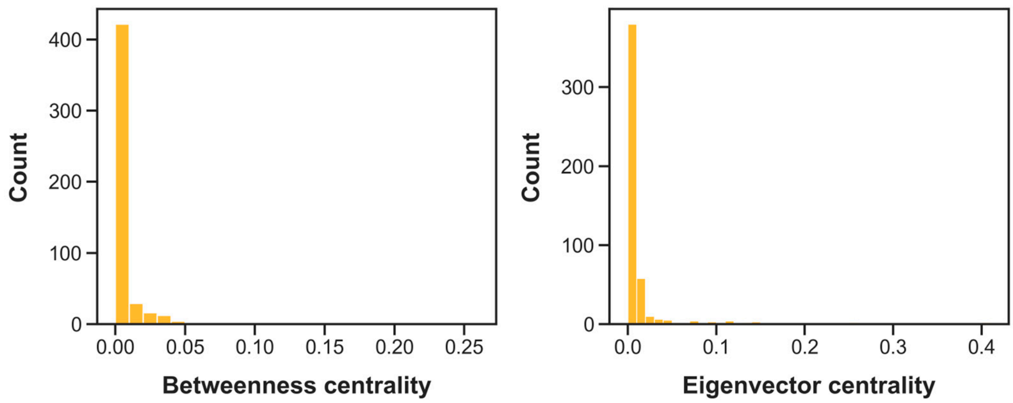

Figure 9. Histogram for the betweenness and eigenvector centrality values.

Due to these specific characteristics, we decided to be more conservative in terms of setting the threshold value. Hence, the 95th percentile was chosen as the threshold level for the classification task. This is in line with the values set from the study by Litterio et al. (2017) [40].

Figure 10 delineates the various roles of the knowledge areas categorized into four quadrants. The results of the classification are summarized in Table 4. Here, we only highlighted the knowledge areas located in the upper-right quadrant, which capture the "Influencer" role, through the addition of labels. For the "Influencer" role, 13 different knowledge areas could be identified. They can be perceived as elites in terms of controlling the overall flow of information, thereby affecting the speed and extent of knowledge diffusion. Subsequently, they are responsible for stimulating R&D by allowing neighboring knowledge domains to benefit from them. In the "Brokerage" role, we determined 12 different knowledge areas. In this case, previously unobserved knowledge areas, such as F23G 07 (incinerators, specially adapted for combustion of specific waste or low grade fuels) and F02D 19 (controlling engines characterized by their use of nonliquid fuels, pluralities of fuels), have appeared. These could be regarded as an interface layer that can enforce gatekeeping power and are capable of connecting the domain of "vehicles" with "fuels". In the "Prominence" role, we identified 12 different knowledge areas, which act as hubs connected with other influential knowledge areas. They are involved in the knowledge generation process but rely on their connectivity to acquire and disseminate knowledge. For instance, G06Q 30, C10K 03 (modifying the chemical composition of combustible gases containing carbon monoxide to produce an improved fuel), C12P 05 (preparation of hydrocarbons) and C10G 01 (production of liquid hydrocarbon mixtures) fall under this role. About 92% of knowledge areas were assigned with "No specific role". Under this category, knowledge areas related to chemical engineering and reaction dynamics, which play a rather supportive role in the e-fuel production, are subsumed.

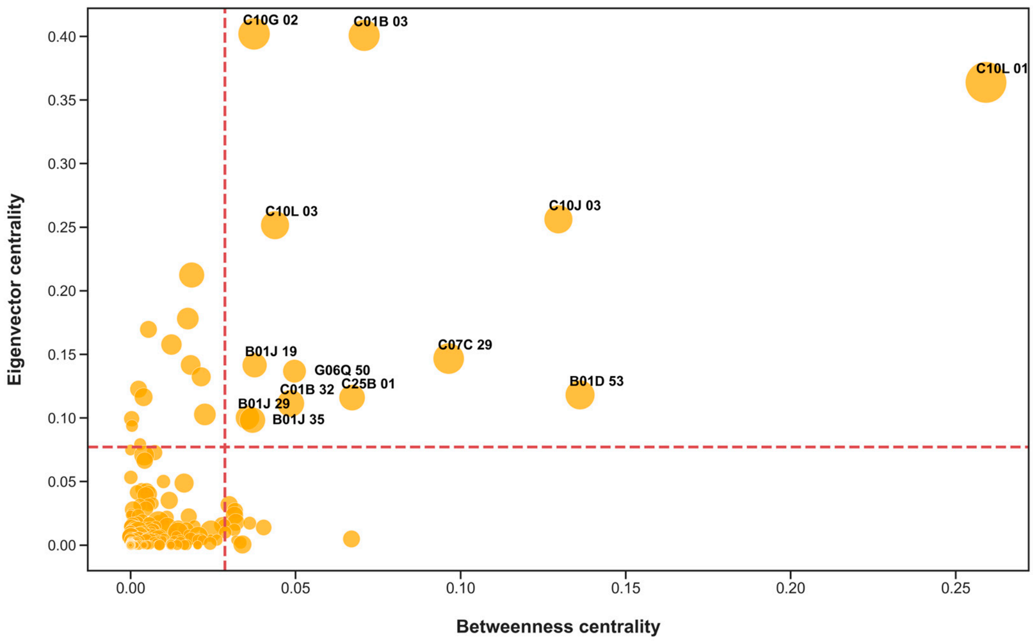

Figure 10. Matrix model applied to the e-fuel patent landscape. (Note: The x-axis represents the betweenness centrality, while the y-axis represents the eigenvector centrality).

Table 4. Selected list of knowledge areas pertaining to each role. (Note: To not overwhelm the readers with too many details on the "No specific role", only a partial list of knowledge areas has been provided).

Roles	Knowledge Areas	Number of Knowledge Areas
Influencer	C10G 02, C01B 03, C10L 01, C10J 03, C10L 03, C07C 29, B01J 19, G06Q 50, B01D 53, C25B 01, C01B 32, B01J 29, B01J 35	13
Brokerage	C25B 09, C12M 01, G06Q 10, C10L 05, F01D 15, F23G 07, G01F 01, F23K 05, F02D 19, F23D 11, F02M 25, F02D 41	12
Prominence	C07C 01, B01J 08, C10K 03, C10G 03, C10G 45, G06Q 30, C12P 05, B01J 23, C10G 01, C10G 65, C10G 47, C10L 10	12
No specific role	C07C 05, C10K 01, C07C 41, B01J 37, C07B 61, B01J 07, C07C 02, C10B 49, C10G 69, C10G 50, C07C 31, C10B 53, C07C 11, C07C 27, C25B 15, C01C 01, C10G 11 [. . .]	453

In sum, this matrix model is capable of differentiating the specific roles played by the involved knowledge areas and can help better understand the influential knowledge areas, from which the subsequent knowledge generation process might be governed.

4. Discussion and Conclusions

In the past couple of years, the shift to electric mobility has gained significant momentum, as rising concerns about the climate change and the advancement of battery technologies have prompted attempts to decarbonize the transportation sector and to promote the use of alternative energy sources [54,55]. For the mobility transition to succeed, multiple strategies for achieving climate-neutral mobility must be pursued in parallel. Additional research and investments are required for the introduction of cost-efficient electric vehicles and for the general public to accept electric vehicles [56]. Against such a background, the production of e-fuels (or synthetic fuels) could contribute to the realization of cleaner energy consumption [57].

From the perspective of technology management and policy development, it is of strategic importance to understand which knowledge area acts as a driving force behind the technological progress [58]. Instead of simply counting patents, a more profound analysis of the combinatorial structure of technologies can give insights into the knowledge diffusion pattern. This is achieved by relying on the concept of knowledge flow and analyzing patent data related to the e-fuel technology. The results of this study can reveal the intelligence locked in patent information, which represents a rich source of data for studying innovation, and point to the following key findings:

1. In terms of patent development, a rather inconsistent trend was observed, while the inventive activity was led by private firms owing the majority stake of patent families. Although a decrease in the number of patents does not necessarily reflect a falling-off in the rate of inventive achievements, it could imply a decline in the demand for patents on the inventor's side. This behavior might be linked to the fact that the economics of e-fuel production are still inefficient, and the implementation of e-fuels currently only makes sense in sectors such as heavy-duty transport (long-haul truck transport, shipping and aviation), where direct electrification is hard to achieve [11]. Hence, the transition to e-fuels will require a strategic initiative that includes the installment of a required infrastructure roadmap [59]. Taken together, the findings provide the first indications about the patenting activity related to e-fuels.
2. The derived knowledge network is largely characterized by knowledge areas related to the chemical engineering and production technique for liquid hydrocarbon mixture. In particular, the knowledge areas C10L 01 and C10J 03 showed high transitive influence. Furthermore, the analyzed knowledge flows are dominated by intra-technology knowledge flows. Hence, despite the diversity of involved knowledge areas, there are less convergent patterns among the related technology domains. To better address the technical feasibility and economic profitability of e-fuel production, either a breakthrough in catalytic chemical reaction or the pursuit of recombinant innovation, which accentuates the significance of technological diversity as a key feature of technological transitions, seems necessary [30]. Production of synthetic fuel still has comparably high costs, but has a niche market application for the right scenario [60].
3. Instead of simply using the computed centrality metrics, this study positioned the individual knowledge areas into four quadrants, with each having a special role to perform. With regard to the matrix model, there is some degree of freedom for setting the demarcation criteria. This flexibility could be strategically exploited to generate a differentiated perspective on the functional roles of e-fuel innovation. Thus, R&D managers and policy makers could rely on such information to foster data-driven consensus building, as well as to formulate effective policies for maintaining balanced knowledge flows across boundary-spanning knowledge ties.

In sum, the proposed analysis framework is a simple but effective tool for categorizing the knowledge areas into their respective roles and can be adopted in other research contexts to explore the potential influence of individual nodes.

Despite its contributions, this study is not without limitations, paving ways for future explorations. Although the proposed matrix model is capable of distinguishing the diverse roles, the results might vary depending on the selected threshold value. Hence, additional research is required to optimally determine its value. Moreover, this study did not consider the citation information, nor did it exploit textual patent data, which contain many technical terms. Future research could embrace text-mining techniques to generate additional insights into the underlying technology topics as well as conduct a comparative analysis with other fuel alternatives.

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Appendix A

Appendix A.1 Description of IPCs (International Patent Classification Codes)

Codes	Description
C10L 01	Liquid carbonaceous fuels
C10J 03	Production of gases containing carbon monoxide and hydrogen, e.g., synthesis gas or town gas, from solid carbonaceous materials by partial-oxidation processes involving oxygen or steam
C01B 03	Hydrogen; gaseous mixtures containing hydrogen; separation of hydrogen from mixtures containing it; purification of hydrogen
C10G 02	Production of liquid hydrocarbon mixtures of undefined composition from oxides of carbon
C10L 05	Solid fuels
C10L 03	Gaseous fuels; natural gas; synthetic natural gas obtained by processes not covered by subclasses C10G, C10K; liquefied petroleum gas
C10G 01	Production of liquid hydrocarbon mixtures from oil shale, oil sand, or nonmelting solid carbonaceous or similar materials
B01D 53	Separation of gases or vapors; recovering vapors of volatile solvents from gases; chemical or biological purification of waste gases, e.g., engine exhaust gases, smoke, fumes, flue gases, or aerosols
B01J 19	Chemical, physical or physicochemical processes in general; their relevant apparatus
B01J 08	Chemical or physical processes in general, conducted in the presence of fluids and solid particles; apparatus for such processes
C07C 01	Preparation of hydrocarbons from one or more compounds, none of them being a hydrocarbon
C25B 01	Electrolytic production of inorganic compounds or nonmetals
B01J 23	Catalysts comprising metals or metal oxides or hydroxides, not provided for in group B01J 21/00 (B01J 21/16 takes precedence)
C10G 03	Production of liquid hydrocarbon mixtures from oxygen-containing organic materials, e.g., fatty oils, fatty acids
F02D 41	Electrical control of supply of combustible mixture or its constituents
C10K 03	Modifying the chemical composition of combustible gases containing carbon monoxide to produce an improved fuel, e.g., one of different calorific value, which may be free from carbon monoxide
C07C 29	Preparation of compounds having hydroxy or O-metal groups bound to a carbon atom not belonging to a six-membered aromatic ring
G06Q 50	Systems or methods specially adapted for specific business sectors, e.g., utilities or tourism (healthcare informatics G16H)
B01J 29	Catalysts comprising molecular sieves
C01B 32	Carbon; compounds thereof (C01B 21/00, C01B 23/00 take precedence; percarbonates C01B 15/10; carbon black C09C 1/48)

Appendix A.2 Description of Four-Digit IPCs

Codes	Description
C10G	Cracking hydrocarbon oils; production of liquid hydrocarbon mixtures, e.g., by destructive hydrogenation, oligomerization, or polymerization
C10L	Fuels not otherwise provided for; natural gas; synthetic natural gas obtained by processes not covered by subclasses C10G or C10K; liquefied petroleum gas; use of additives to fuels or fires
C07C	Acyclic or carbocyclic compounds
B01J	Chemical or physical processes, e.g., catalysis or colloid chemistry; their relevant apparatus
C01B	Nonmetallic elements; compounds thereof
G06Q	Data processing systems or methods, specially adapted for administrative, commercial, financial, managerial, supervisory, or forecasting purposes; systems or methods specially adapted for administrative, commercial, financial, managerial, supervisory, or forecasting purposes, not otherwise provided for

Appendix A.3 Description of IPCs

Codes	Description
C10G 45	Refining of hydrocarbon oils using hydrogen or hydrogen-generating compounds
C12P 05	Preparation of hydrocarbons
G06Q 30	Commerce, e.g., shopping or e-commerce

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