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A Method for Inspiring Radical Innovative Design Based on Cross-Domain Knowledge Mining

Fei Yu [1,2,3], Xiuchuan Jia [1,4,*], Xiaowei Zhao [1,2] and Jing Li [1,4]

1 National Engineering Research Center for Technological Innovation Method and Tool, Hebei University of Technology, Tianjin 300401, China; fyu@hebut.edu.cn (F.Y.); zxw17603276742@163.com (X.Z.); lijing_5454@163.com (J.L.)
2 School of Mechanical Engineering, Hebei University of Technology, Tianjin 300401, China
3 Yueqing Institute of Technological Innovation, Yueqing 325600, China
4 School of Architecture and Art Design, Hebei University of Technology, Tianjin 300130, China
* Correspondence: csj_jiaxiuchuan@163.com

Abstract: The reasonable application of cross-domain knowledge tends to promote the generation of radical innovation. However, it is difficult to accurately capture the cross-domain knowledge needed for radical innovation. To solve this problem, this paper proposes a method for inspiring radical innovative design based on FOS and technological distance measurement. First, the functional analysis of the problem product is carried out to determine the target function. Second, the patent sets of problem domain and target domains are constructed based on FOS. Then, this study optimizes the method of technological distance measurement and uses it to determine the optimal target domain. After further categorizing and screening the patents contained in the optimal target domain, specific cross-domain knowledge is pushed to designers. This method can help firms select the most appropriate cross-domain knowledge to design solutions for different problems, thus increasing the possibility of generating radical innovation. In the end, the method is validated in the design of a stovetop cleaning device.

Keywords: radical innovation (RI); radical innovative design; function-oriented search (FOS); cross-domain knowledge; technological distance (TD)

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Citation: Yu, F.; Jia, X.; Zhao, X.; Li, J. A Method for Inspiring Radical Innovative Design Based on Cross-Domain Knowledge Mining. *Systems* **2024**, *12*, 102. https://doi.org/10.3390/systems12030102

Academic Editor: Mitsuru Kodama

Received: 18 February 2024
Revised: 8 March 2024
Accepted: 15 March 2024
Published: 17 March 2024

1. Introduction

In the fierce modern market competition, innovation is one of the primary mechanisms that allow for an enterprise to increase its competitiveness and ensure its long-term continuity in the market [1]. Radical innovation (RI) is the revolutionary improvement of a product or process with new technology, which has attracted extensive attention from the academic and industrial communities [2–4]. For example, 3D printing technology has dramatically increased productivity in traditional manufacturing [5]. Although many firms have been pursuing RI, most innovations remain incremental due to the lack of research from an ex ante perspective to guide firms in radical innovative design [6,7].

In new product development (NDP), the conceptual design stage plays a crucial role as it determines 70–80% of the cost, performance, and quality of the product [8,9]. RI begins with generating and developing radical concepts or ideas that provide a fresh solution to the problem [10]. Knowledge from outside the problem domain (cross-domain knowledge) is an essential inspiration for radical concept generation and development [11,12]. As a result, many scholars have focused on how to help firms acquire helpful knowledge from external sources to facilitate radical innovative design [13,14].

Function-oriented search (FOS), as a tool in the Theory of Inventive Problem Solving (TRIZ), can help companies acquire a large amount of cross-domain knowledge after generalizing a problem [15]. However, it is worth noting that not all cross-domain knowledge can inspire radical innovative designs, and further research is needed on choosing the optimal cross-domain knowledge. Some studies have introduced the concept of technological distance (TD) between firms, determining the suitability for knowledge transfer by calculating the differences in patents held by each firm [16]. This method provides a new idea to recommend appropriate cross-domain knowledge for large firms that have a large number of patents. However, for those small- and medium-sized enterprises (SMEs) that lack patent data, it is difficult for them to use the TD between them and other enterprises as a reference for knowledge transfer. As a result, there still needs to be a universal approach to help all types of firms capture and manage cross-domain knowledge to inspire radical innovative design.

To address the above issues, this paper attempts to establish a generalized methodology to inspire radical innovative design based on FOS and optimize the measurement of TD, which can help firms to select the most appropriate cross-domain knowledge and thus increase the possibility of RI generation. The rest of this paper is organized as follows: Section 2 reviews and summarizes the research on RI, FOS, and TD; Section 3 proposes a method for inspiring radical innovative designs, including the construction of patent sets based on FOS, optimization of TD measurement, determination of optimal target domains, and recommendation of patent schemes; Section 4 deals with a case study to validate the feasibility of the proposed method; and Section 5 discusses and summarizes the main contributions and research limitations of this paper and future research opportunities.

2. Related Research

2.1. Definition and Features of RI

The traditional dichotomy divides technological innovation into incremental innovation (II) and RI according to the different degrees of innovation [17]. As shown in Figure 1, the difference between RI and II can be understood with the help of technological S-curves. The whole process of II occurs on the same S-curve, such as the two curves a–b and c–d in Figure 1. A discontinuous break in the S-curve occurs from b to c, and a new S-curve is created and gradually replaces the current curve, which is the result of RI. Even though the performance of the new S-curve is not as superior as that of the current technology at the beginning, it will break through the performance limit of the current technology with time.

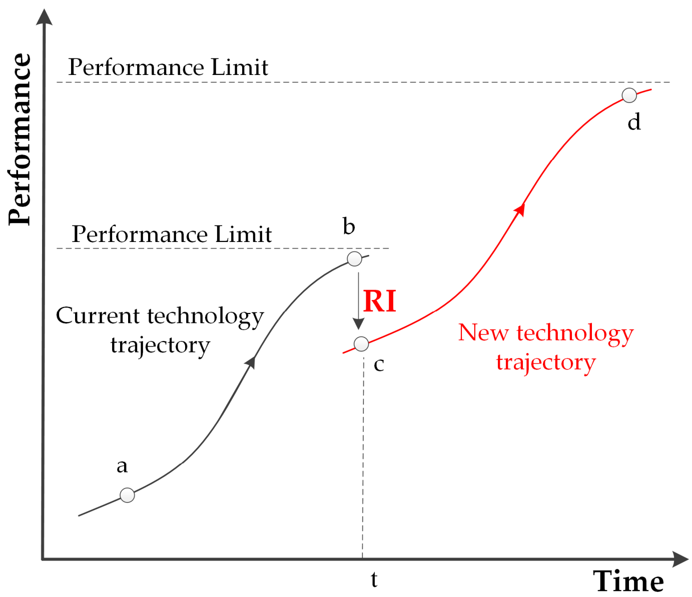

Figure 1. S-curve: RI and II [18].

Over the past several decades, scholars in various fields have studied and defined RI from three perspectives, as shown in Table 1:

(1) Focus on the antecedents of RI, including the novelty of the technology and scientific knowledge;
(2) Focus on the cost, performance, function, and other significant changes in the product itself or entirely new features;
(3) Focus on the macro impact on the industry and market, including the market layout, business model, and improving customer benefits.

Table 1. The definitions of relevant RI.

Perspective	Opinion
(1), (3)	RI not only introduces new technologies but also establishes new business models [19].
(1), (3)	RI is a change in an existing service from forming a new technology or product architecture [20].
(1), (3)	RI plays an important role in transforming existing markets, creating new ones, and promoting technological advances [21].
(1)	RI as a new product, not only its core technology and the industry's existing product technology in the nature of the difference but also to provide customers with a higher level of benefits [22].
(1), (3)	RI is a kind of innovation in which new technology replaces the original technology and opens up a new market [23].
(2)	RI has one of the following characteristics: (a) New to the world performance features, (b) Significant (e.g., 5–10x) improvement in known features, or (c) Significant (e.g., 30–50%) reduction in cost [24].
(2)	RI as a product or service process that either has unprecedented performance characteristics or is a significant change from its original function or cost [25].
(3)	RI defines new demand and competition relationships, enabling enterprises to gain first-mover advantage and higher market share [26].

Based on the above literature analysis, the recognized traits of RI are substantially consistent, involving technology breakthrough, performance change, and market breakthrough. Technology breakthrough means the core technology of the product changes. It is the internal driving force of radical innovation, which leads to changes in product performance, function, cost, and other aspects. RI appears when these technological changes make the market breakthrough, meaning that new markets are developed and higher customer benefits are offered.

2.2. Applications of FOS

As shown in Figure 2, FOS aims to achieve the target function by searching the generalized problem model and transferring the cross-domain knowledge solutions to the problematic engineering system [15,27]. The traditional search engine searches knowledge based on keyword search, which is challenging to extend to other domains, but FOS can solve this problem and improve problem-solving efficiency.

There are three main types of applications for FOS. One is to search for biological knowledge in bionics and transfer specific unique structures, functions, and principles from nature to engineering [28]. The second application is to search abstract generic principles, including inventive principles, standard solutions, and effects in TRIZ. For example, Wang et al. [29] proposed an effect-solving method, including problem identification, functional analysis, effect selection, and structural mapping, which facilitated radical innovative design. However, utilizing biological knowledge or general principles to form a specific design solution requires the designer to have multi-disciplinary knowledge and rich design experience, so the innovative design is quickly limited by the designer's knowledge level [30].

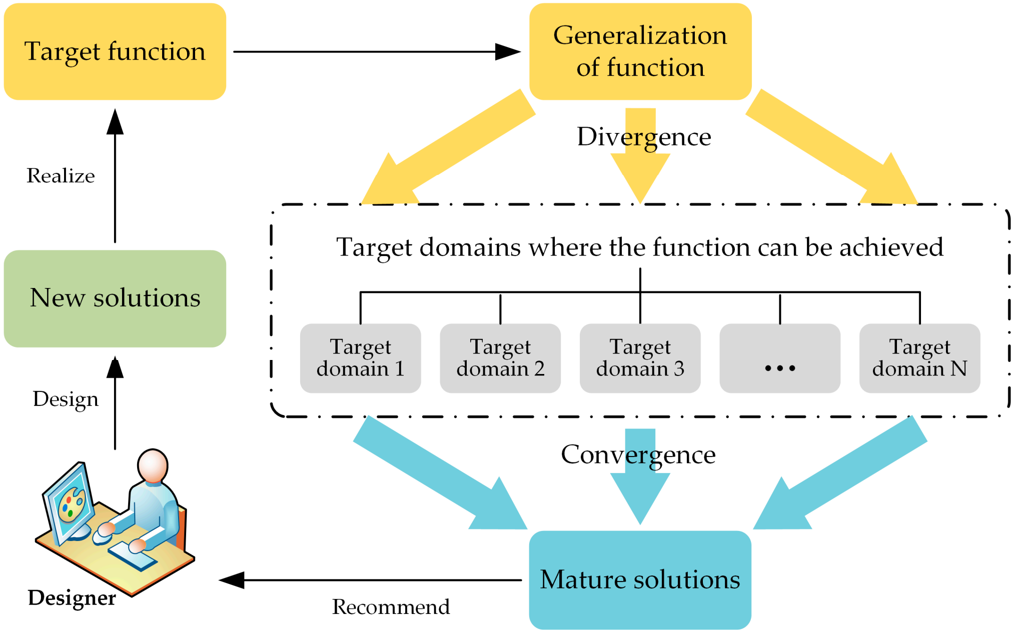

Figure 2. The process of FOS.

To solve this problem, some scholars have proposed the third application of FOS, which provides designers with more specific cross-domain knowledge based on patent mining. Patent knowledge is an essential source of knowledge for inspiring design as it contains more than 90% of the world's technological innovations [31,32]. Choi et al. [33] constructed a well-structured technology database by automatically extracting the subject–action–object (SAO) structure from patents using relevant technologies for effective FOS implementation. Fantoni et al. [34] associated subject-specific patent knowledge with the function–behavior–structure model, which created a database of product FBS models. Yu et al. [14] proposed an approach to rapidly extract cross-domain technologies from patents to promote radical innovative design by generalizing the function of the core subsystem of a product and combining it with the SAO structure.

However, the biggest problem with FOS is not in the divergence process but in the convergence process. After searching a wide variety of cross-domain knowledge and technologies, how to choose the one that best inspires radical innovative design is an urgent problem.

2.3. The Measurement of TD

The radical behavior of RI depends on the differentiation of the new technology from what is already available in the industry, which is usually brought about by introducing such cross-domain knowledge or technology. As cross-domain knowledge has less overlap with existing product development technologies within the industry and more variability in the technological space, it is a great inspiration and incentive for firms' technological innovations, especially RI [35,36].

However, knowledge from different domains has different impacts on firms' innovation performance, and to measure the relationship between them, Jaffe [37,38] proposed the concept of TD. As shown in Figure 3, there is an inverted U-shaped relationship between TD and innovation performance [39,40]. The introduction of cross-domain knowledge with a small TD, while conducive to absorptive capacity, is detrimental to generating high-level innovations and makes it challenging to achieve RI. On the contrary, the introduction of cross-domain knowledge with a large TD can hinder firms' absorptive capacity due to its high novelty value, again not conducive to radical innovative design. Therefore, cross-domain knowledge at a moderate TD is relatively more conducive to facilitating radical innovative design [16].

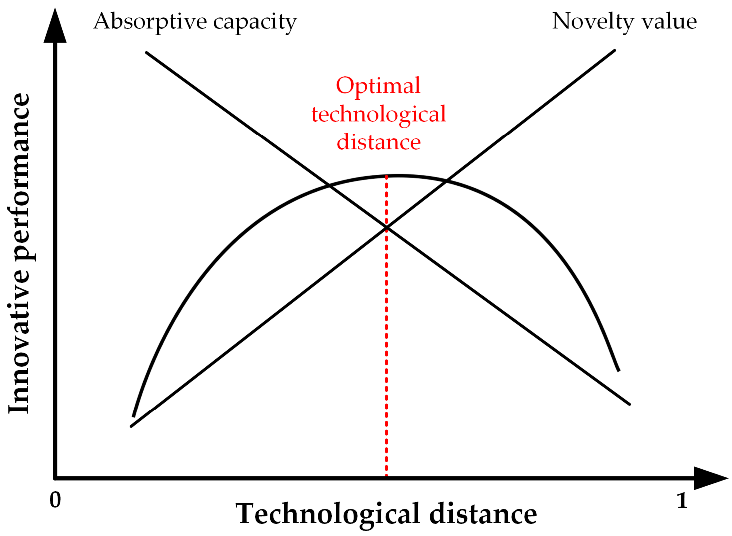

Figure 3. Inverted U-shaped and the optimal TD.

In existing studies, the calculation of TD primarily relies on patent data and is carried out using patent vectors as a basis for computation. Most of the existing studies used IPC to represent patent vectors [16]. The International Patent Classification (IPC) system is an effective tool for patent classification, widely utilized by countries worldwide. Additionally, since the IPC code consists of letters and numbers, it is not limited by language; thus, patent vectors using the IPC system can better reflect the technological focus and distribution of firms or patent sets. As a result, the patent vector is defined as the number of patents in each IPC divided by the set of total patents of the firm, as shown in Equation (1):

$$P = (p_1, p_2, \ldots, p_k, \ldots, p_n), p_k \geq 0, \sum_{k=1}^{n} p_k = 1 \quad (1)$$

where P is the patent vector of the firm, k is the classification number of the patent, p_k is the ratio of the number of patents under classification k to the total patents of the firm, and n is the total number of patent classifications of the firm.

To calculate the distance between patent vectors, three methods have been studied: the cosine angle distance, the Euclidean distance, and the min-complement distance. Jaffe [38] first used the cosine angle distance to measure the distance between patent vectors. The higher the cosine value, the larger the overlap between patent vectors and the smaller the technological distance. The range of the Euclidean distance is $[0, \sqrt{2}]$, where a larger distance value indicates a larger TD, contrary to the meaning represented by the cosine angle distance values [41]. Bar and Leiponen [42] argued that the cosine angle distance and Euclidean distance take into account the number of patents in non-common domains between two patent vectors during the calculation process, which can affect the accuracy of the calculation results. Thus, they proposed using the min-complement distance to eliminate the effect of irrelevant patents on TD. Stein et al. [43] compared and analyzed the above three calculation methods using electric mobility as an example and believed that the min-complement distance is more suitable for measuring TD. Zhang and Tan [16] depicted firms' patent vectors based on the IPC section (the first classification level). They used the min-complement distance to determine which firms' technologies could be introduced. Similarly, Zhang et al. [44] introduced the min-complement distance measure method on the basis of product scenario analysis to determine suitable parasitic technologies, thereby assisting in product design.

The studies mentioned above, which use the differences in patent data between firms to reflect the TD between them, not only provide a new approach for enterprises to capture appropriate cross-domain knowledge but also offer reference points for establishing knowledge transfer, alliances, and partnerships among firms.

However, the existing research on the measurement of TD lacks generalizability and accuracy. First, the lack of generalizability means that this method of comparing differences in patent vectors between firms is not applicable to SMEs. Due to the limited number of patents held by these enterprises, their patent vectors are not sufficiently reflective of their technology and knowledge distribution to inform knowledge transfer. Second, the need for more accuracy refers to the fact that describing patent vectors based only on the section of the IPC system and making subsequent measurements are insufficient to reflect the true TD among firms. For example, if the patents of firm α are mainly concentrated in A01 (Agriculture et al. husbandry) and the patents of firm β are concentrated in A62 (Life-saving; Fire-fighting), the TD between the two firms is large, but if the first level of the IPC system is used for the calculation, the data obtained are much smaller than the actual value. Similarly, if the second level of the IPC system is used for the calculation, the data obtained are larger than the actual value.

2.4. Summary

The following conclusions can be drawn from the review and analysis of relevant studies:

(1) Cross-domain knowledge is crucial for inspiring radical innovative design, but how to accurately search for the most appropriate cross-domain knowledge is the current problem.
(2) There is a complementary relationship between FOS and the measurement of TD, which can provide a new way for firms to achieve RI. This is reflected in the fact that using FOS can obtain the patent sets of the problem domain and the target domains, which can be used to replace the patent set of firms and transfer the comparison of technology distribution from firms to products or knowledge domains, to solve the problem of lack of generalizability in the measurement of TD. In addition, selecting the most appropriate source of knowledge by measuring the TD between the problem domain and target domains can improve the completeness of the FOS.
(3) To improve the accuracy of measuring TD, the first and second levels of the IPC system can be used to indicate the patent vectors, combined with the min-complement distance, to calculate the TD.

3. Proposed Method

Based on the summary in Section 2.4, this paper proposes a method to inspire radical innovative designs. The method mainly consists of seven steps, as shown in Figure 4:

(1) After identifying the product and function, construct the patent set of the problem domain;
(2) Generalize the target function to search relevant patents;
(3) Categorize the searched patents and construct the set of patents in the target domain;
(4) Measure the TD between the problem domain and the target domains;
(5) Determine the best target domain;
(6) Recommend the patent schemes to the designer;
(7) Design and evaluate the new solution.

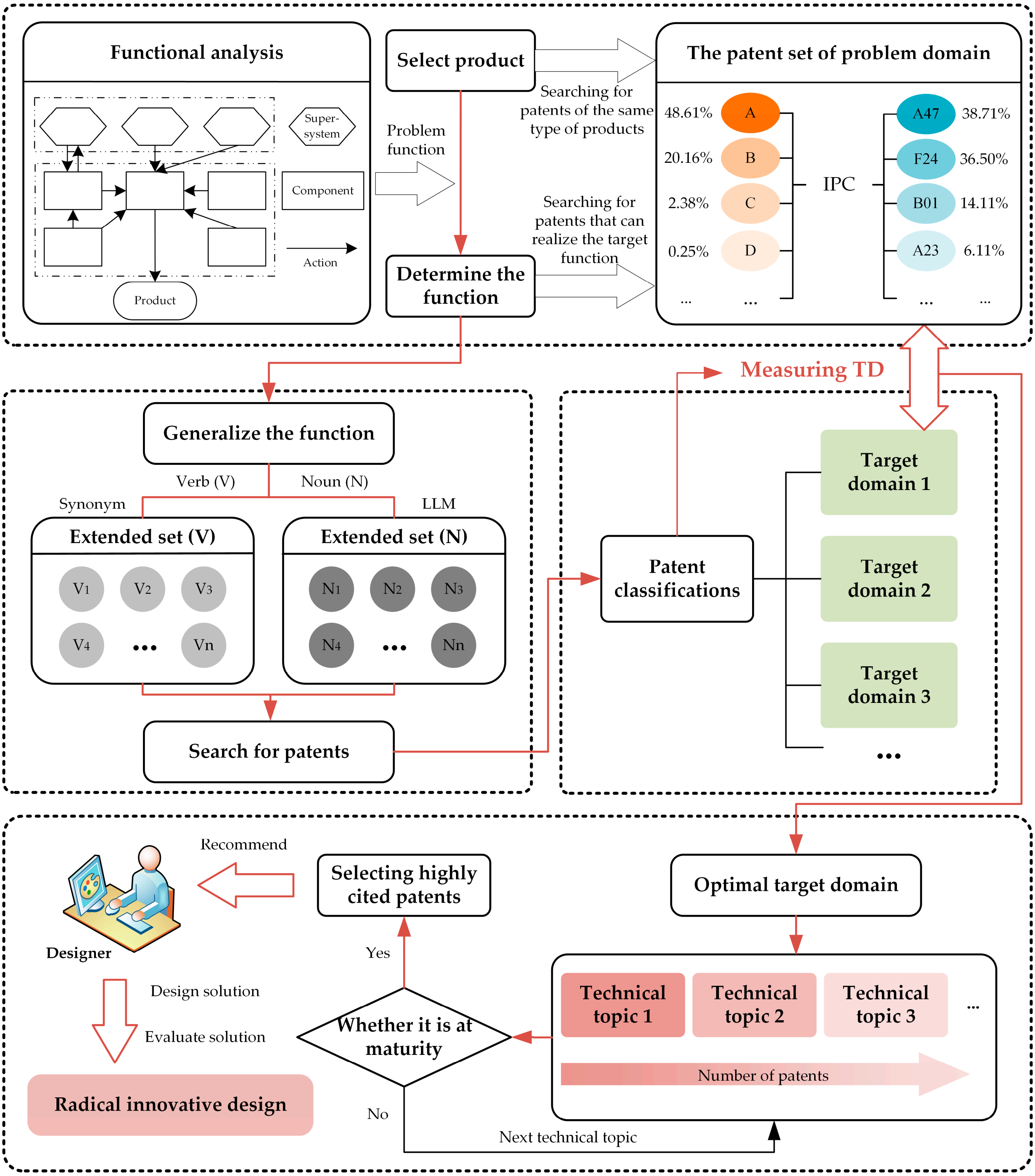

Figure 4. The overall flow of the proposed method.

3.1. The Construction of Patent Sets Based on FOS

3.1.1. The Patent Set of Problem Domain

After selecting the product to be designed, the product is analyzed functionally based on the functional model to determine the current major problem and target function. The patent set of the problem domain is constructed by searching for patents of the same type of products and patents that can realize the target function. Moreover, it is represented as patent vectors according to the IPC system for subsequent measurement of TD.

3.1.2. The Patent Set of Target Domains

The target function is first generalized; for instance, the generalized form of the function of mowing separates solids, which is part of the divergence process of FOS to search for as much cross-domain knowledge as possible. Functions can be expressed with a combination of verbs and nouns. Therefore, the generalized function can be split into verb and noun and expanded separately to expand the search scope.

The main focus for the expansion of verbs is on their synonyms, as observed in the functional categorization table proposed by Stone and Wood [45] in Appendix A. For the expansion of nouns, large language models (LLM) can be used to search for nouns it contains, e.g., adhesion on solid surfaces including metal oxides, marine fouling organisms, scale, etc. The extended verb set and noun set are combined to form different keywords to search for many patents that include cross-domain knowledge and construct the patent sets of different target domains.

3.2. The Optimization of TD Measurement

The first level of the IPC system consists of eight sections, while the second level consists of hundreds of classes. This categorization results in TD_1, measured using data from the first level of the IPC system, being less than the actual TD, while TD_2, measured using data from the second level of the IPC system, is bigger than the actual. Therefore, in this paper, the two levels of classification number data will be calculated separately based on the min-complement distance, and the two calculated values will be formed into a value range [TD_1, TD_2] to represent the TD between each domain. The min-complement distance is calculated as shown in Equation (2) [42]:

$$\mathrm{M} = (\mathrm{P_I}, \mathrm{P_J}) = 1 - \sum_{k=1}^{n} \min\{\mathrm{P_{Ik}}, \mathrm{P_{Jk}}\} \tag{2}$$

where M is the TD between domain I and domain J, and P_I and P_J are the technical positions of the domain I and domain J. $M \in [0, 1]$, and when $M = 0$, the TD between the two domains is the closest.

3.3. The Determination of Optimal Target Domain

To determine the optimal target domain, the specific value of the optimal TD should first be defined. Noteboom et al. [39] argued that, when TD $\in$ [0, 1], the domain that provided the optimal cross-domain knowledge should be the one that lies in the category of TD = 0.5. After hypothesizing and validating knowledge transfer between firms, Wuyts et al. [46] concluded that the optimal TD is 0.38. Gao [47] analyzed the effect of TD on RI, and the study showed that the optimal value of TD is approximately 0.4. The optimal TD is not unique because novelty value and absorptive capacity are not equivalent [48].

Therefore, this paper uses the value range of 0.38–0.5 as the range of optimal technical distance. The optimal target domain is determined by comparing the overlap between the range of TD and [0.38, 0.5]. The higher the overlap, the more likely knowledge in that target domain will inspire radical innovative designs. As shown in Figure 5, the following are the five possible situations and the specific equations for calculating them:

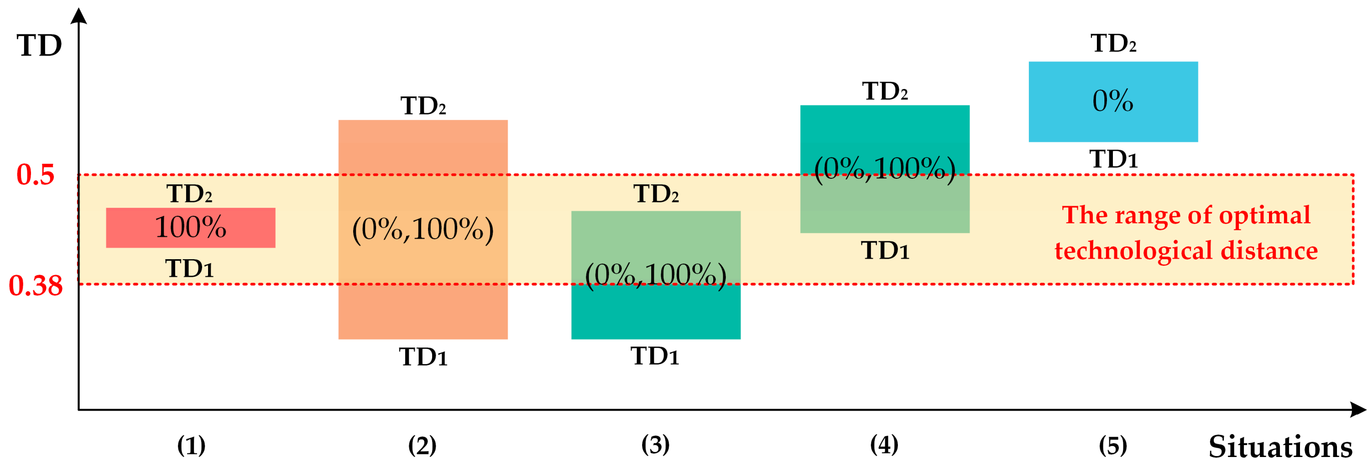

Figure 5. Five possible situations and their overlap to the range of optimal TD.

1. $TD_1 \in [0.38, 0.5]$ and $TD_2 \in [0.38, 0.5]$, the overlap between this range of TD and the range of optimal TD is 100%;
2. $TD_1 \in [0, 0.38]$ and $TD_2 \in [0.5, 1]$, the overlap between this range of TD and the range of optimal TD is calculated as shown in Equation (3);

$$\text{Overlap} = \frac{0.5 - 0.38}{TD_2 - TD_1} \times 100\% \tag{3}$$

3. $TD_1 \in [0, 0.38]$ and $TD_2 \in [0.38, 0.5]$, the overlap between this range of TD and the range of optimal TD is calculated as shown in Equation (4);

$$\text{Overlap} = \frac{TD_2 - 0.38}{TD_2 - TD_1} \times 100\% \tag{4}$$

4. $TD_1 \in [0.38, 0.5]$ and $TD_2 \in [0.5, 1]$, the overlap between this range of TD and the range of optimal TD is calculated as shown in Equation (5);

$$\text{Overlap} = \frac{0.5 - TD_1}{TD_2 - TD_1} \times 100\% \tag{5}$$

5. TD_1 and $TD_2 \in [0.5, 1]$ or TD_1 and $TD_2 \in [0, 0.38]$, the overlap between this range of TD and the range of optimal TD is 0%.

3.4. The Recommendation of Patent Schemes

Prioritizing technologies and knowledge in mature domains can shorten the design cycle and improve the reliability of conceptual solutions [49]. Thus, after determining the optimal target domain, all patents included in the domain can be categorized according to technical topics. Each technical topic is ranked according to the number of patents with priority given to technical topics with a large number of patents at a mature stage.

Patent application data can be used as a basis for judging whether a technical topic is at a mature stage or not. The judgment indicators include the technology growth rate (V) and the index of technology maturity (α), as shown in Equations (6) and (7). When both V and α have a decreasing trend, the technology topic is at the maturity stage [50].

$$V = \frac{a}{A} \tag{6}$$

$$\alpha = \frac{a}{a+b} \tag{7}$$

where a is the number of invention patent applications in that year, b is the number of utility model patent applications in that year, and A is the total number of invention patent applications in the past five years.

The technology and knowledge embedded in highly cited patents are of significant value and influence and can lead to technology development [51]. Therefore, the ten most cited patent schemes were selected from the technical topic in the optimal target domain and recommended to the designers.

3.5. The Evaluation of New Solution

After designing a new solution based on recommended patent schemes, there are two methods that can be used to evaluate whether the new solution can develop into RI.

Liu et al. [10] proposed an equation for identifying radical solutions based on the degree of change in the technological subsystem, as shown in Equation (8):

$$\text{Radicality} = \frac{1}{1 - e^{-z}}, Z = -106.065 + 18.621 \times \text{WE} + 10.129 \times \text{CE} + 3.502 \times \text{EE} \quad (8)$$

where WE is the expected attributes of the working unit, CE is the expected attributes of control, and EE is the expected attributes of the engine. The measurement criteria of the above indicators are divided into four levels that are physical principle, working principle, implementation method, and detail change, which are assigned scores of 10, 6, 3, and 1, respectively.

Yu et al. [52] proposed six indicators for evaluating radical solutions from the dimensions of technology, product, and market, as shown in Table 2. An equation for evaluating RI is proposed based on a comparative analysis of a large number of cases, as shown in Equation (9):

$$S = \frac{\sum_{k=1}^{n} \omega_k I_k}{\sum_{k=1}^{n} \omega_k} \quad (9)$$

where ω_k represents the weight of the kth indicator, and I_k represents the value assigned to the kth indicator. When $S \geq 0.648$, the new solution has the potential to develop into RI.

Table 2. Indicators for evaluating radical schemes [52].

No.	Indicators	Weight (ω_k)	Criteria for Assignment (Comparison with Mainstream Products in Market)	
1	Key technology	0.0834	Whether the key technology to realize the main function has changed. *	Yes:1; No:0
2	Production process	0.0871	Whether the production process of the new solution has changed.	Yes:1; No:0
3	Input system	0.1029	Whether the input system of the new solution has changed.	Yes:1; No:0
4	Main function	0.0813	Whether the new solution results in a new main function.	Yes:1; No:0
5	Consumers	0.0862	Whether the new solution develops new consumers.	Yes:1; No:0
6	Key supplier	0.1275	Whether the supplier of key technology has changed.	Yes:1; No:0

* The main function is the purpose or use for which the object is created, i.e., the object of the invention or innovation is created to achieve that function.

The above two methods provide a theoretical basis for identifying radical solutions at the conceptual design stage. Therefore, this study will use these two methods to comprehensively evaluate the newly designed solution. If consistent and positive results can be obtained, it will demonstrate that the method proposed in this paper is conducive to inspiring radical innovative design.

4. Case Study

As an essential cooking equipment, the stove (shown in Figure 6a) has been widely used in commercial and home kitchens. However, the stovetop (shown in Figure 6b) is often clogged with sludge and other greasy substances, resulting in an insufficient flame or even the inability to complete the sending flame, increasing the probability and cost of equipment maintenance. For this problem, the existing solution mainly relies on manual physical cleaning, which is not only inefficient but also susceptible to damaging the stovetop. Therefore, this paper will verify the effectiveness of the proposed method by designing a stovetop cleaning device.

(a) (b)

Figure 6. (**a**) The display drawing of the stove; (**b**) Manual cleaning of the stovetop.

Over the past several decades, China has observed a vast incremental increase in the number of patents and gradually become the country that submits the most significant number of patent applications [53]. Therefore, the patent schemes covered in this section are from the China National Intellectual Property Administration (CNIPA).

4.1. Establishing the Patent Set of Problem Domain

Since the problem product was identified as the stovetop, all the knowledge related to those products used for cooking food belongs to the problem domain knowledge. Hence, 25,463 patents related to the problem product were searched in Patsnap [54] (a patent database covering more than 170 countries with more than 180 million patents). After its functional analysis using the functional model (as shown in Figure 7), the target function of the product can be identified as removing sludge and other greasy substances, and 11,348 patents were retrieved based on this function.

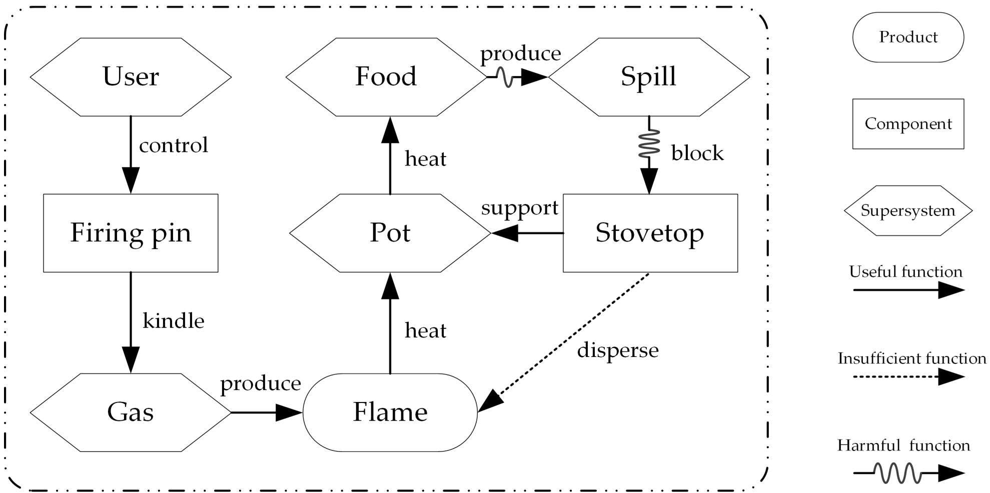

Figure 7. The functional model.

A total of 36,197 patents were retrieved from the two searches, which constituted the patent set of the problem domain. These schemes were categorized according to the first and second levels of the IPC system, and the data for each classification number are shown in Figures 8 and 9. The sum of the number of patents contained in each IPC is greater than the total number because each patent scheme may belong to more than one IPC.

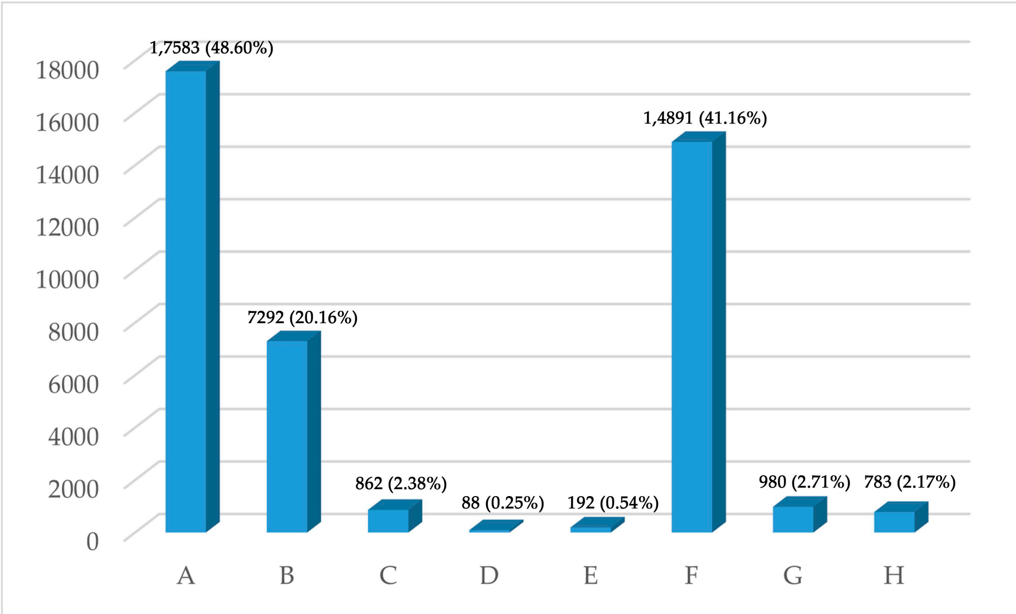

Figure 8. The number of patent schemes in each IPC section.

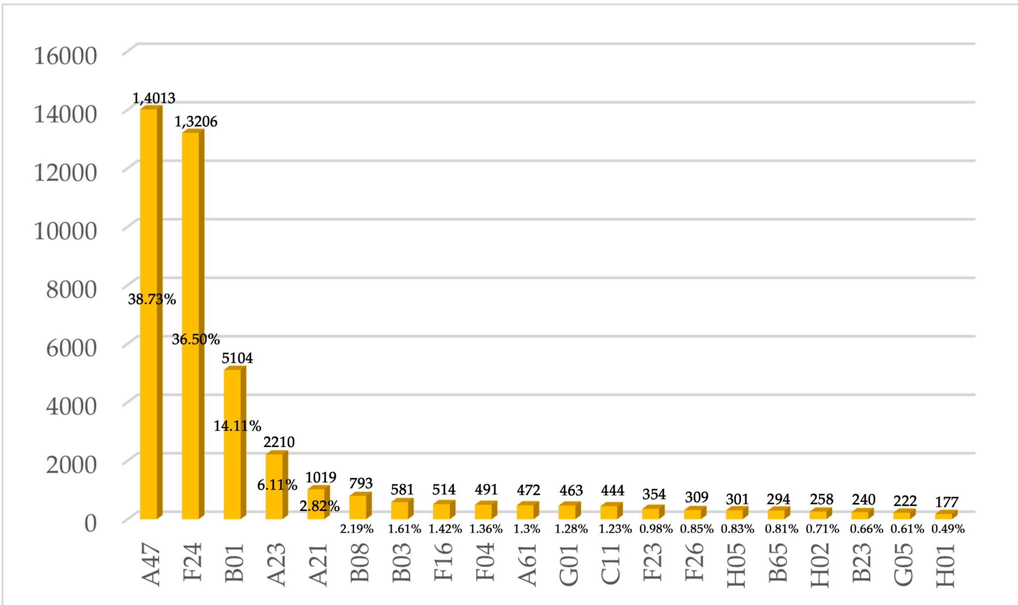

Figure 9. The number of patent schemes in each IPC class.

Since there are hundreds of IPC classes and this study uses the min-complement distance to measure TD, those IPC classes with a small number of patent schemes will not significantly impact the final results of TD. However, this does not mean that those small number of patents are completely ignored; they are simply not included in the process of measuring TD. In other words, the number of patents in each target domain has not decreased; it is just that, when measuring technological distance, relying on the majority of patents is sufficient to ensure the accuracy of the calculation results. In this study, only those IPC classes with more than a 0.5% share of the number of patent schemes were used, and the subsequent TD was retained to two decimal places.

4.2. Establishing the Patent Set of Target Domains

The generalized form of the target function is separating attachments. First, according to Appendix A, the synonyms for separate include switch, divide, release, and so on. Then, when using LLM to expand noun, it is important to define the scope to avoid retrieving a large number of irrelevant nouns. This study considers states (gaseous, solid, liquid, or mixed state) and scenarios as conditions for restricting noun retrieval. Taking attachments as an example, one should retrieve solids that adhere to the surface of solids and limit the number to 50. Due to the fact that many of the retrieved words were duplicates, this study categorized them into seven groups after screening and summarizing, as shown in Table 3.

Table 3. Nouns retrieved based on LLM.

No.	Categories	Nouns
1	Attached organisms on the hull surface	Marine attached organisms, Barnacles, Oysters
2	Metal oxide	Metal oxides, Rust
3	Dirt from daily life	Sweat, Dirt, Oxides
4	Mineral scale	Scale, Slag
5	Attachments on road surface	Snow, Ice, Mud, Slush
6	Fine particles in the air	Particulate matter, Dust, Pollen
7	Coatings and other adhesives	Glue, Paint, Pigment, Tape

The verbs and nouns obtained from the expansion were combined into keywords and searched in the patent database to obtain the patent sets of the seven target domains, as shown in Tables 4 and 5.

Table 4. Number of patent schemes in each IPC section.

Domain No.	All	A	B	C	D	E	F	G	H
1	663	168	320	192	7	85	24	45	22
2	16,116	182	13,246	2875	31	692	889	298	245
3	15,003	3422	7582	1871	517	1329	2836	821	581
4	4511	607	1589	1091	93	252	2002	173	96
5	17,401	1036	4252	664	13	13,001	998	1352	756
6	82,668	8071	55,282	1426	2567	5947	15,109	11,426	14,953
7	3578	120	2729	372	67	324	114	118	207

Table 5. Number of patent schemes in each IPC class.

Domain No.	All	A47	F24	B01	A23	A21	...	B23	G05
1	663	0 *	32	0 *	32	34	...	0 *	0 *
2	16,116	0 *	0 *	0 *	0 *	462	...	911	0 *
3	15,003	1427	198	1427	198	2035	...	137	0 *
4	4511	358	82	358	82	488	...	0 *	0 *
5	17,401	412	0 *	412	0 *	1145	...	0 *	193
6	82,668	4742	428	4742	428	16,614	...	2279	0 *
7	3578	32	0 *	32	0 *	757	...	65	0 *

* The number of patent schemes in the IPC is recorded as 0 if it is less than 0.5 percent of the total.

4.3. Identifying Optimal Target Domain based on the Measurement of TD

After obtaining the patent data in Sections 4.1 and 4.2, the range of TD between the problem domain and each target domain is obtained by measuring according to Equation (3), as shown in Tables 6 and 7.

Table 6. Results of TD_1.

Domains	A	B	C	D	E	F	G	H	TD_1
Problem domain	0.486	0.201	0.024	0.002	0.005	0.411	0.027	0.022	---
Target domain 1	0.253	0.483	0.290	0.011	0.128	0.036	0.068	0.033	0.43
Target domain 2	0.011	0.822	0.178	0.002	0.043	0.055	0.018	0.015	0.67
Target domain 3	0.228	0.505	0.125	0.034	0.089	0.189	0.055	0.039	0.30
Target domain 4	0.135	0.352	0.242	0.021	0.056	0.444	0.038	0.021	0.17
Target domain 5	0.060	0.244	0.038	0.001	0.747	0.057	0.078	0.043	0.60
Target domain 6	0.098	0.669	0.017	0.031	0.072	0.183	0.138	0.181	0.44
Target domain 7	0.486	0.201	0.024	0.002	0.005	0.411	0.027	0.022	0.65

Table 7. Results of TD_2.

Domains	A47	F24	B01	A23	A21	...	B23	G05	TD_2
Problem domain	0.387	0.365	0.141	0.060	0.028	...	0.007	0.006	---
Target domain 1	0	0	0.051	0.048	0	...	0	0	0.81
Target domain 2	0	0	0.029	0	0	...	0.057	0	0.90
Target domain 3	0.095	0.042	0.136	0.013	0	...	0.009	0	0.58
Target domain 4	0.079	0.180	0.107	0.018	0	...	0	0	0.51
Target domain 5	0.024	0	0.066	0	0	...	0	0.011	0.85
Target domain 6	0.057	0.046	0.201	0.005	0	...	0.028	0	0.62
Target domain 7	0.009	0	0.212	0	0	...	0.018	0	0.77

The range of TD between the problem domain and each target domain is composed of TD_1 and TD_2, and their overlap with the range of optimal TD is calculated according to the five situations proposed in Section 3, as shown in Figure 10 and Table 8. The results show that target domain 3 has the highest priority relative to the others and that technologies and knowledge from this domain should be prioritized to inspire radical innovative designs for stovetop cleaning.

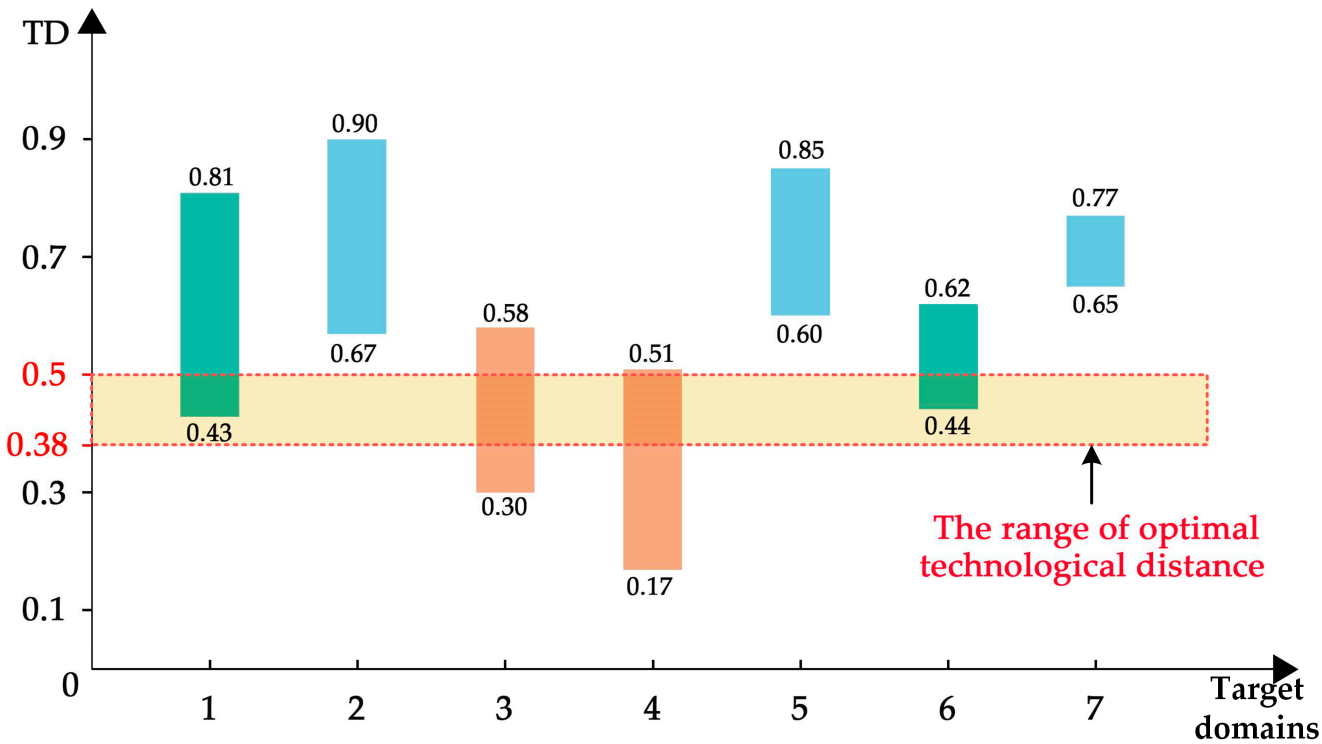

Figure 10. The range of TD between the problem domain and each target domain.

Table 8. Prioritization of target domains.

Domain No.	TD_1	TD_2	Overlap	Prioritization
1	0.43	0.81	18.42%	4th
2	0.67	0.90	0	5th
3	0.30	0.58	42.86%	1st
4	0.17	0.51	35.29%	2nd
5	0.60	0.85	0	5th
6	0.44	0.62	33.33%	3rd
7	0.65	0.77	0	5th

4.4. Recommending Patent Schemes to Designers

Since the target domain 3 includes 15,003 patents, further categorization is needed to more accurately recommend appropriate knowledge to the designers. This study used Patsnap [54] to categorize these patents according to the technical topic to which they belong, as shown in Figure 11. The technical topic of mechanical engineering includes the most significant number of patent schemes, accounting for approximately 60% of the total. So, the technical topic should first be judged whether it is in the mature stage.

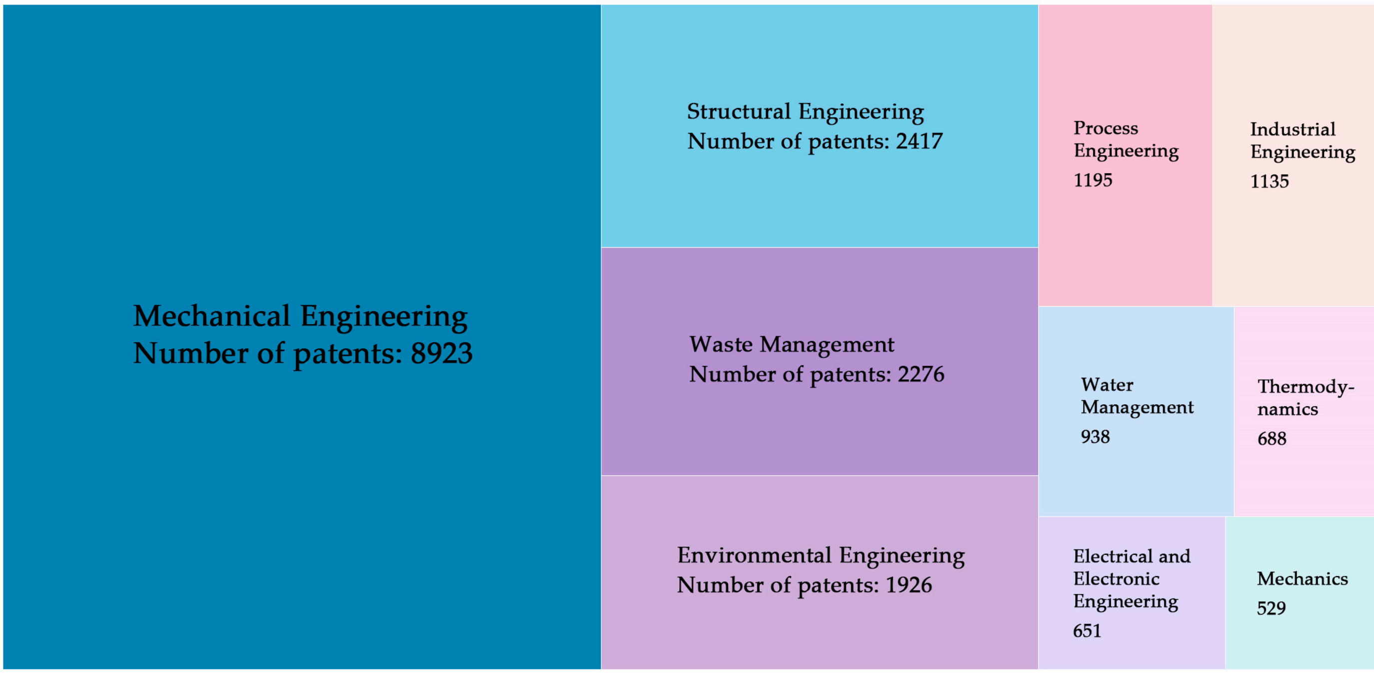

Figure 11. The number of patent schemes in each technical topic.

After counting the number of patent applications per year within the technical topic, the trend of V and α is obtained based on Equations (6) and (7), as shown in Table 9 and Figure 12. Observing the last ten years of data, the peak of V and α occurred in 2018, after which there is an occasional rebound, but the overall linear trend is decreasing. The technical topic can, therefore, be judged to be at a mature stage.

Table 9. Number of patents in the last ten years.

Data	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
a	23	20	41	62	128	144	230	229	348	322
b	77	55	44	91	114	1014	1692	1563	1721	772
A	65	82	113	163	274	395	605	793	1079	1273
V	35.38%	24.39%	36.28%	38.04%	46.72%	36.46%	38.02%	28.88%	32.25%	25.29%
α	23%	26.67%	48.24%	40.52%	52.89%	12.44%	11.97%	12.78%	16.82%	29.43%

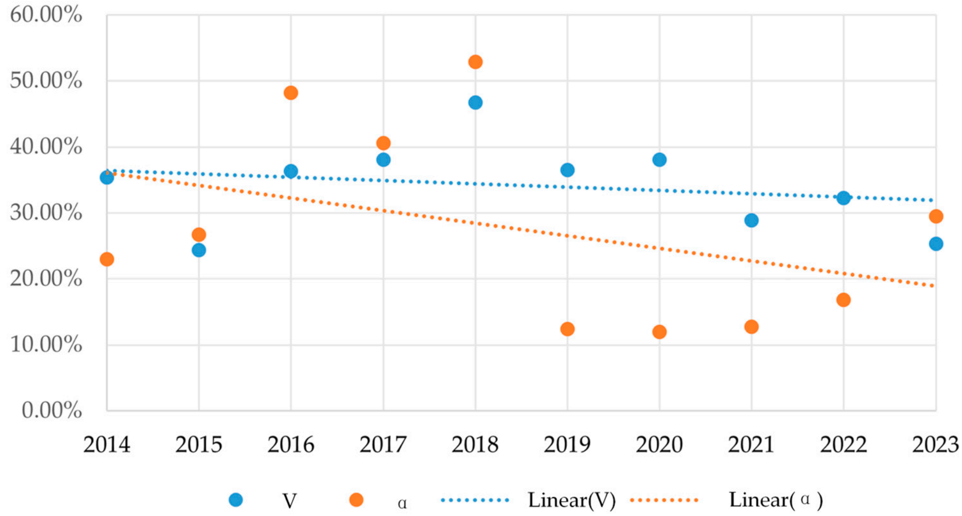

Figure 12. The linear trend of V and α in the technical topic.

The problem domains account for approximately 90% or more of the patent solutions in the three IPCs, A47, F24, and B01. To ensure the novelty value of the recommended patent schemes, the highly cited patent schemes in other IPCs were finally selected to be recommended to the designers, as shown in Table 10. It has been demonstrated that the technology and knowledge contained in highly cited patents are valuable and influential and can lead to the development of subsequent technologies [51,55]. Therefore, the number of citations can be used as a key indicator for patent screening [56].

Table 10. Specific recommended patent schemes.

PAPN	Title	Citations
CN205146813U	A pipeline cleaning device	30
CN203923705U	A washing machine capable of automatically cleaning the inner tube's outer wall dirt	20
CN206430627U	Rubber ball automatic dirt removal and cold-water unit cleaning device	17
CN210788470U	A pipeline dredging device for municipal environmental protection	14
CN203801738U	Electric arc ignition atomizer and electronic cigarette	12
CN205732110U	An automatic cleaning device for plastic bottle flakes	11
CN106000953A	The outdoor LED screen automated cleaning robot	11
CN204448731U	The conveying pipeline medium-driven dirt removal machine	10
CN204340382U	An automatic cleaning device for printing machine rubber rollers	10
CN206104486U	A large-scale pipeline cleaning device	10
CN210922326U	A condenser fouling removal device	10
CN211070976U	A cleaning device for AG glass production	10
CN211340688U	A water gate cleaning device for hydraulic engineering projects	10

4.5. Design and Evaluate New Solution

After reading and analyzing the patent schemes in Table 8, it was found that most of them use water washing to clean the target object. However, since the stovetop is a vital part of the sending flame, adding a device for water washing directly around it is not suitable. Thus, the stovetop needs to be disassembled for cleaning. The scheme's feasibility for automatically cleaning a washing machine's inner and outer walls mentioned in CN203923705U is relatively higher. Therefore, a solution was designed based on the cross-domain knowledge gained, as shown in Figures 13 and 14. When the inner tube rotates, the brush is driven to rotate around the inner tube and the outer tube along the circular ring, rotating to clean the placed stovetop. This solution is reasonable and straightforward, easy to manufacture, and low cost and can improve the cleaning effect of the stovetop and extend its service life.

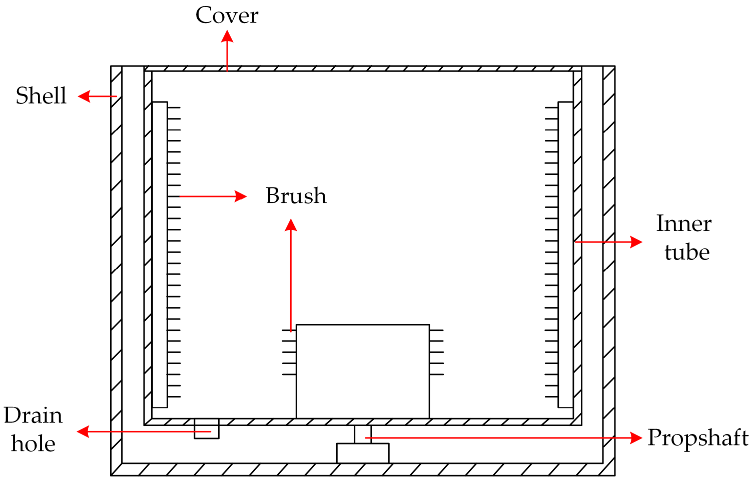

Figure 13. Conceptual design solution for a stovetop cleaning device.

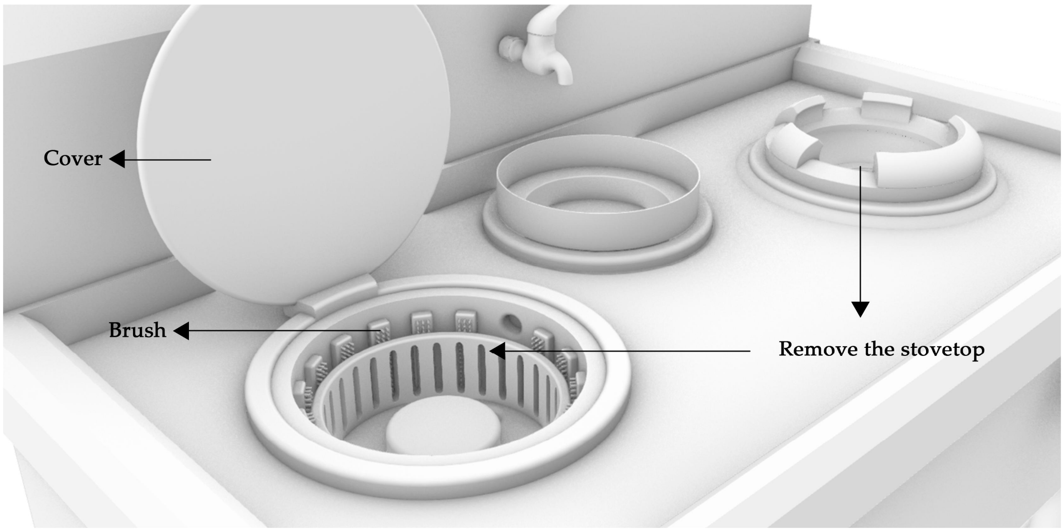

Figure 14. 3D rendering of the conceptual solution.

Compared to the traditional manual or machine physical scraping of the surface of the stove adherents, the changes in various indicators of the new solution are shown in Table 11.

Table 11. The changes in various indicators and the evaluation results of the new solution.

Methods and Equations	Indicators	Assignment	Explanation	Results
Equation (8) proposed by Liu et al. [10]	WE	10	Physical principle is changed (centrifugal separation principle)	Z = 113.584 and Radicality = 1.
	CE	3	Implementation is changed (linear reciprocating motion device to the rotary device)	
	EE	1	Details are changed	
Equation (9) proposed by Yu et al. [10]	I_1	1	Key technology to realize the main function has changed	$S = 0.705 > 0.648$
	I_2	1	Production process of the new solution has changed.	
	I_3	1	The input system of the new solution has changed	
	I_4	0	The new solution does not result in a new main function	
	I_5	0	The new solution does not develop new consumers.	
	I_6	1	The supplier of key technology has changed	

Finally, the radicality of the new solution was evaluated based on Equations (8) and (9), resulting in positive and consistent outcomes. Therefore, the new solution obtained using the cross-domain knowledge in the recommended patent schemes meets the radical innovative design index, thus validating the effectiveness of the proposed method.

5. Discussion and Conclusions

This paper focuses on proposing a process management method for cross-domain knowledge development. Although previous studies have demonstrated that cross-domain knowledge is essential in motivating radical innovative designs, how to accurately search and screen cross-domain knowledge is still a problem. The method will help firms effectively utilize cross-domain knowledge to promote radical innovative design when facing problems and ultimately improve the success rate of RI. The following is a discussion of the contributions and limitations of this paper and opportunities for future research.

5.1. Contributions

The limitations of relying on the similarity of patent data among firms to determine whether knowledge transfer is appropriate are twofold. From the introduction perspective, only those large firms with a sufficient number of patents or that emphasize intellectual property protection can search for firms that are at a moderate TD from them for knowledge transfer according to their technological spatial distribution. SMEs, which occupy less market share, are eager to realize RI by introducing cross-domain knowledge to improve their influence in the market. However, due to the lack of their patent data, it is difficult for them to use the TD between them and other firms as a reference basis for knowledge transfer. This is very dangerous for firms aiming at RI because it is a double-edged sword with a high return accompanied by a high risk, and once it fails, the firm will pay a considerable price.

Similarly, the knowledge discovered using the previous methods also comes from large firms, which ignores the value of the knowledge and technology contained in SMEs. This is incompatible with the view of RI, which is first and foremost about breaking down fixed perceptions, finding as much cross-domain knowledge as possible, and then prioritizing from there. This idea only applies to assisting knowledge transfer between large firms and will limit radical innovative design.

The method proposed in this paper searches a large amount of patent knowledge based on FOS from the perspective of solving the product problem and realizing the target function. After categorizing the patent knowledge into problem and target domains, the TD between them is calculated to help firms choose the appropriate cross-domain knowledge. The method breaks the limitation of patent data to firms and can inspire radical innovative design. The case study in Section 4 validates the effectiveness of the proposed method by designing a stovetop cleaning device.

In addition, the measurement of TD is an effective tool for screening assist cross-domain knowledge. However, relying only on a certain level of IPC to represent patent vectors and measure TD is not sufficient as a reference basis for knowledge transfer. In this paper, the first and second levels of the IPC system are utilized to represent patent vectors respectively. TD_1 and TD_2, obtained based on the min-complementary distance, are used to compose the TD range between knowledge domains, and the best knowledge domain is determined by calculating the overlap between each TD range and the optimal TD range. It can provide a more accurate reference for enterprise knowledge transfer.

5.2. Limitations and Future Study Opportunities

First, different firms may obtain the same or similar cross-domain knowledge by applying the method proposed in this paper when facing the same problem. From a macro perspective, this is contrary to the trend of product diversification nowadays. Therefore, subsequent research can seek a method that applies to most firms and takes into account the firm's strategic development direction to inspire radical innovative design.

Second, the IPC system's first level of categorization is too coarse, which downplays the differences between different or similar knowledge domains. The second level of categorization is so fine-grained that it ignores the links between similar knowledge domains. Even if the two levels of classification numbers are used comprehensively to measure TD, there is still a certain degree of ambiguity. Subsequent research should explore a categorization that can distinguish knowledge domains relatively accurately and be used to measure TD.

Third, this method requires multiple searches, categorizations, and counting of patent schemes, and future attention should be given to developing software that incorporates artificial intelligence to extract the data automatically and complete the calculations.

Furthermore, the patent data involved in case study are all sourced from CNIPA. To further improve the comprehensiveness of the method, cross-domain knowledge should be extracted from all patent databases worldwide. It requires us to use more languages for technical retrieval and extraction.

In the end, the optimal TD for knowledge and technology transfer for RI in different domains has yet to be examined.

Author Contributions: Conceptualization, F.Y. and X.J.; Methodology, F.Y. and X.J.; Formal analysis, X.J. and J.L.; Data curation, X.J. and X.Z.; Writing—original draft, X.J.; Writing—review and editing, F.Y.; Visualization, X.Z. and J.L.; Supervision, F.Y.; Funding acquisition, F.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This paper was sponsored by the National Innovation Method Fund of China (No. 2020IM030200-2) and the National Natural Science Foundation of China (No. 51805142).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available in Patsnap at: https://analytics.zhihuiya.com (accessed on 1 January 2024).

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A1. Function classes, basic functions, and synonyms.

Class	Basic	Synonyms
Branch	Separate	Switch, Divide, Release, Detach, Disconnect, Disassemble, Subtract, Cut, Polish, Sand, Drill, Lathe
	Refine	Purify, Strain, Filter, Percolate, Clear
	Distribute	Diverge, Scatter, Disperse, Diffuse, Empty, Absorb, Dampen, Dispel, Resist, Dissipate
Channel	Import	Input, Receive, Allow, Form Entrance, Capture
	Export	Discharge, Eject, Dispose, Remove
	Transfer	Lift, Move, Conduct, Convey
	Guide	Direct, Straighten, Steer, Turn, Spin, Constrain, Unlock
Connect	Couple	Join, Assemble, Attach
	Mix	Combine, Blend, Add, Pack, Coalesce
Control Magnitude	Actuate	Start, Initiate
	Regulate	Control, Allow, Prevent, Enable/Disable, Limit, Interrupt, Valve
	Change	Increase, Decrease, Amplify, Reduce, Magnify, Normalize, Multiply, Scale, Rectify, Adjust, Compact, Crush, Shape, Compress, Pierce
Convert	Convert	Transform, Liquefy, Solidify, Evaporate, Condense, Integrate, Differentiate, Process
Provision	Store	Contain, Collect, Reserve, Capture
	Supply	Fill, Provide, Replenish, Expose
	Extract	
Signal	Sense	Perceive, Recognize, Discern, Check, Locate
	Indicate	Mark
	Display	
	Measure	Calculate
Support	Stop	Insulate, Protect, Prevent, Shield, Inhibit
	Stabilize	Steady
	Secure	Attach, Mount, Lock, Fasten, Hold
	Position	Orient, Align, Locate

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