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Applying Natural Language Processing and TRIZ Evolutionary Trends to Patent Recommendations for Product Design

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Featured Application: The research may be applied to computer-aided innovation system to assist product design process.

Abstract: Traditional TRIZ theory provides methods and processes for systematic analysis on engineering problems, which can improve the efficiency of solving problems. However, the effect of solving problems is not necessarily guaranteed, and depends on the user's profession and experience. Therefore, this study proposes a methodology to apply evolutionary benefits in the 37 trend lines developed by TRIZ researchers to assist in intelligently screening relevant patents applicable to the content of the product design. In such a way, the efficiency of problem solving and product design quality may be improved more effectively. First, the patent database is used as the training dataset, words and sentences in the patent documents are analyzed through natural language processing to obtain keywords that may be related to evolutionary benefits. Using word vectors trained by Doc2vec, the semantic similarity can be calculated to obtain the similarity relationship between patent text and evolutionary benefit. Secondly, the goals of the product development project may make be related to the evolutionary benefits, and then applicable patent recommendations can be provided. The proposed methodology may achieve the purpose of intelligent design assistance to enhance the product development process and problem-solving.

Keywords: natural language processing; patent analysis; TRIZ evolutionary trends; evolutionary benefits

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1. Introduction

Nowadays, human beings have entered an era of massive applications of big data and artificial intelligence (AI). People use AI technology in various fields to provide better work efficiency and quality of life. Thus, data is indispensable and has become the foundation for training AI models. Through continuous training, artificial intelligence can be made smarter to meet various needs. Text Mining is based on unstructured and highly complex texts to find information that was more difficult to obtain in structured data in the past [1]. With the vigorous development of machine learning in recent years as well as the improvement of computing power, it is possible to perform computational analysis on huge amounts of text more efficiently. Natural Language Processing (NLP), combined with linguistics, information science and artificial intelligence, helps to deconstruct unstructured documents and compare with analysis, thereby interpreting the semantics and sentence structure of natural language from features. The NLP in a statistical approach gives good results in practice simply because, by learning with copious real data, they utilize the most common cases: the more abundant and representative the data, the more they improve. They also degrade more gracefully with unfamiliar/erroneous data [2].

This study is based on the 37 evolutionary trends referred from TRIZ researcher Darrell Mann. In a traditional approach, the application of the 37 evolutionary trends on a specific problem still relies on human judgment. These evolutionary trends are general principles, and some of the evolutionary stages are conceptual and consist of many subjective factors in their application. Sometimes it is not an easy task to select which evolutionary trends to apply. There are more than 100 evolutionary stages of 37 evolutionary trends, and the evolutionary benefits of each stage have the same benefits and different characteristics as well. Most of the results rely on reference materials through human judgement, and some connections are not obvious and difficult to judge during the process. Therefore, we propose a recommendation methodology that relieves subjective judgment to provide designers with more effective usage.

2. Materials and Methods

2.1. Theory of Inventive Problem Solving-TRIZ

TRIZ is the abbreviation of the Russian saying "theory of inventive problem solving". It was developed by the former Soviet scientist G. Altshuller and his team, who studied hundreds of thousands of patents to conclude several methods including *Problem Formulation*, *Functional Analysis*, *Contradiction Matrix*, *40 Inventive Principles*, *Trends*, *Substance-Field*, *Ideal Final Result (IFR)*, *Effects* and *Algorithm of Inventive Problem Solving (ARIZ)*, etc.

Trends of Evolution is one of the important tools in TRIZ theory. It means that a system slowly evolves from the most primitive starting point to the best ideal result. Altshuller found that the evolutionary process of different technical systems is not untraceable, but requires a pattern to evolve. Its technological system evolution can be divided into eight patterns, as described below [3]:

- Stages of evolution of a technological system
- Evolution toward increased ideality
- Non-uniform development of system elements
- Evolution toward increased dynamism and controllability
- Increased complexity followed by simplification
- Evolution with matching and mismatching elements
- Evolution toward micro-levels and increased use of fields
- Evolution toward decreased human involvement

Furthermore, Darrell Mann compiled a set of 37 evolutionary trends from these eight patterns, and the evolution is divided into three fields: Time, Space, and Interface, as shown in Table 1 [4].

The evolutionary trend is composed of several evolutionary stages, and each evolutionary stage has evolutionary reasons (reasons for jumps). These evolutionary reasons can be identified as the benefits and which are brought by the system evolution. Taking *space segmentation* as an example, there are five evolutionary stages as shown in Figure 1. The direction of system evolution is from left to right. The evolving benefits from "monolithic solid" to "hollow structure" are to reduce weight, reduce the use of materials, increase moment of inertia, etc. For instance, a basketball shoe, which has a single solid sole in the early design, is redesigned by adding a hollow air cushion to acquire the evolutionary benefits mentioned above, and then it can achieve certain improvements.

Table 1. The 37 trend lines of evolution.

	Trend Lines			
	Numbering	**Trend Name**	**Numbering**	**Trend Name**
Space-related	S1	Smart Materials	S8	Increasing Asymmetry
	S2	Space Segmentation	S9	Boundary Breakdown-Space
	S3	Surface Segmentation	S10	Geometric Evolution (Linear)
	S4	Object Segmentation	S11	Geometric Evolution (Volumetric)
	S5	Macro to Nano Scale Space	S12	Nesting-Down
	S6	Webs and Fibers	S13	Dynamization
	S7	Decreasing Density		

Table 1. *Cont.*

	Trend Lines			
	Numbering	**Trend Name**	**Numbering**	**Trend Name**
Interface-related	I14	Mono-Bi-Poly(Similar)-Interface	I23	Market Evolution
	I15	Mono-Bi-Poly(Various)-Interface	I24	Design Point
	I16	Mono-Bi-Poly(Inc. diff.)-Interface	I25	Degrees of Freedom
	I17	Nesting-Up	I26	Boundary Breakdown-interface
	I18	Reduced Damping	I27	Trimming
	I19	Senses Interaction	I28	Controllability
	I20	Color Interaction	I29	Human Involvement
	I21	Transparency	I30	Design Methodology
	I22	Customer Purchase Focus	I31	Reducing Energy Conversions
Time-related	T32	Action Co-ordination	T35	Mono-Bi-Poly(Similar-Time)
	T33	Rhythm Co-ordination	T36	Mono-Bi-Poly(Various-Time)
	T34	Non-linearity	T37	Macro to Nano Scale-Time

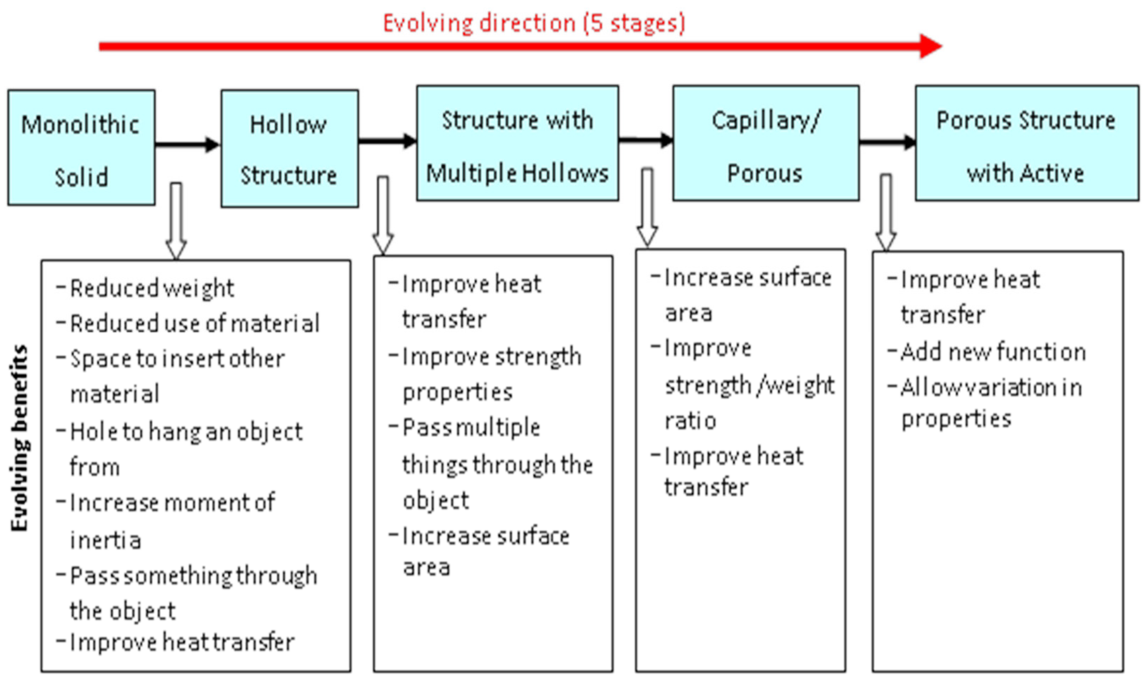


Figure 1. The *Space Segmentation* trend (S2) and its evolving benefits.

2.2. Natural Language Processing

Natural Language Processing (NLP) belongs to the combination of artificial intelligence and linguistics. It mainly uses mathematical models and algorithms to allow computers to recognize and understand human language. Early natural language processing technology is based on statistical concepts to train models. Converting a large amount of text into a dictionary-like format allows the computer to calculate the probability of encountering words and sentences. Recently, NLP has been widely combined with deep learning. The most famous one is BERT, which is a model developed by google based on Transformer [5].

Sentiment analysis (SA) is the use of NLP, text analysis and computational linguistics to systematically recognize personal opinions and emotional conditions. A common application of which is to collect the voice of customers for marketing purpose, such as product reviews and survey. Zhang presented a ranking product model based on sentiment analysis combined with an intuitionistic fuzzy TODIM method. Using the online review data to help customers make purchasing decisions, the proposed method considers consumers' subjective needs and different sentiment orientations (positive, neutral, and negative) for each product feature [6]. Based on BERT fine-tuning, Sun et al. [7] converted "Aspect-Based Sentiment Analysis (ABSA)" from a single sentence classification task to a sentence-pair classification task by constructing auxiliary sentences, so that the final recommendation effect is greater than the classification effect using SA only.

Sheu and Hong used statistical methods to construct a computer-aided effect recognition system to optimize the quality of the recommendation system to match the specific topic. Combined with the accumulation of the knowledge of many experts, the system can put forward the priority of problem solving according to the principle of "similar problems have similar solutions", and achieve higher efficiency for the solution recommendation system [8]. However, the texts used in the contents of a patent are more technology-oriented than sentiment-oriented. Regarding patent recommendation for product design, SAO structure analysis combined with dependency syntax analysis is more suitably adopted as described below.

2.2.1. Text Preprocessing

Text preprocessing is a very important step. This step is a method of sorting out the text and extracting text features. It is mainly divided into: tokenization, stemming, lemmatization, and filtering. Allahyari mentioned that a large amount of text cannot be effectively processed by a computer, and meaningful text and information must be extracted through preprocessing [9]. The steps involved in text and processing will be mentioned below.

1. Tokenization: To cut the text of a paragraph into a single word, symbol and number, as shown below: Before: In Canada, all indications point to an economy growing at a much faster pace than it had in the final three months of last year and the beginning of 2019. After: /In/ /Canada/ /,/ /all/ /indications/ /point/ /to/ /an/ /economy/ /growing/ /at/ /a/ /much/ /faster/ /pace/ /than/ /it/ /had/ /in/ /the/ /final/ /three/ /months/ /of/ /last/ /year/ /and/ /the/ /beginning/ /of/ /2019/ /./
2. Stemming: To reduce the number of words by extracting the root and stem of a single word, so as to achieve the effect of simplification, as shown below. Before: /indications/, /growing/, /beginning/ After: /indic/, /grow/, /beginn/
3. Lemmatization: Since English words have the problem of tense and form, the words in the text must be standardized as prototypes. Unlike stemming, lemmatization attempts to select the correct lemma depending on the context or basing on a dictionary that the algorithm can consult to. For example, the word "was" has "is" as its lemma. However, the previous example after lemmatization is shown below. Before: /indications/, /faster/, /had/, /beginning/ After: /indicate/, /fast/, /have/, /begin/
4. Filtering: To filter and delete words that appear too trivial and meaningless in the text, this step is also called stop-word removal (stop-word), because when processing a large amount of text, too many stop words may cause computer performance burden issues. Before: In Canada, all indications point to an economy growing at a much faster pace than it had in the final three months of last year and the beginning of 2019. After: /canada/ /indication / /point / /economy/ /grow / /fast / /pace / /final / /three/ /month / /year / /begin / /2019 /

2.2.2. SAO-Based Content Analysis

SAO (Subject-Action-Object) structure is composed of subject (noun phrase), action (verb phrase) and object (noun phrase), and its main function is to analyze the keywords in the sentence. For example, "sensor detects signal", in this sentence "sensor" is the subject, "detection" is the verb, and "signal" is the object. From the SAO analysis, it can be judged that the word "detect" provides the correlation between "sensor" and "signal". "Sensor" is the main body of "detect" and "signal", and "signal" is the object "detected" by "sensor". Simply put, the AO "detect signal" is a problem, and the S "sensor" is the method or tool to solve the "detect signal". S and O can be expressed as components, and A can be expressed as the function or relationship between the two components. Cascini [10] mentioned that the SAO structure is usually used to represent technical functions, and this structure clearly indicates the related words between various functions, effects, solutions, and technical concepts that appear in the patent document.

2.2.3. Dependency Parsing

Dependency parsing is also a significant part of natural language processing technique. Its function is to identify the correlation between words in different sentences, which is called dependency. Usually, the dependency is described in a binary form with two words as a group. The advantage is that the subject, verb, and object may be presented in different orders in different sentences. It can effectively find the dependencies between words. Dependency syntactic analysis is mainly divided into clause relationship and modification relationship. The clause relationship is usually related to the predicate. The predicate also means that the main semantics in the sentence may be a verb, called ROOT, and the modification relationship is to classify modifiers to modify subject. From Figure 2, it can be clearly understood that all the arrows of the word "jumped" are called ROOT, and ROOT cannot be pointed by any arrow. From "jumped" as the starting point, the word corresponding to nsubj is found to be "fox", and "fox" is the subject, which is a clause relationship. Another word corresponding to prep is "over" and "with", "over" and "with" are preposition modifiers, which are modifier relationships.

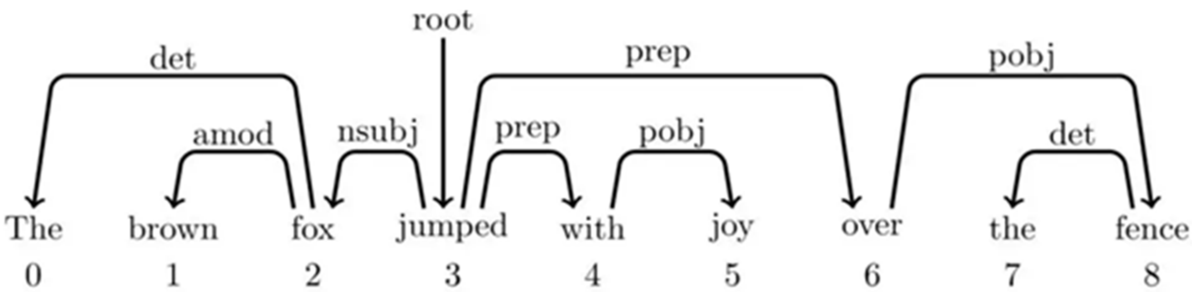


Figure 2. The example of dependency relationship.

2.3. Semantic Similarity

Semantic similarity is the most important part of natural language processing. However, the determination of the similarity between words is quite subjective, and it is quite difficult for computers to judge the semantic similarity. Based on the category of machine learning, we can understand that semantic similarity is the contextual interaction within the training text. If it is possible to replace each other in different contexts without changing the syntactic-semantic structure of the text, the similarity between the two will be higher, otherwise the similarity will be lower. Semantic similarity has been achieved in various fields, such as: text retrieval, information retrieval, text classification, machine translation, text recommendation, etc.

The function of cosine similarity is to use the cosine of the angle between two vectors to determine the similarity. The calculation method is described as Equation (1), which depicts the smaller the angle, the more similar, and the larger the angle, the lower the similarity. As the cosine value of the 0 degree angle is 1, it means that the A and B are completely similar. If A and B are in the opposite direction, i.e., totally dissimilar, the cosine value will be −1. So, the range of similarity is between −1 and 1.

$$sim(A,\ B) = cos\theta = \frac{A \cdot B}{\|A\| \cdot \|B\|} \tag{1}$$

The Doc2vec model, proposed by Mikolov and Le [11], is an improved version based on the shortcomings of Word2vec. The weakness of Word2vec is that the sequence of words in the text and the contextual relationship are lost, and the semantics are also ignored, even if the distance between words with the same semantics in the vector is far away [12], which cause the similarity is low. In other words, Word2vec can only express the relationship between words, but cannot compare the relationship between paragraphs. Therefore, Doc2vec considers the order of words and adds paragraph vectors to improve the accuracy of semantic similarity.

2.4. Methodology

The methodology of this research is based on the TRIZ evolutionary trends and Doc2vec model for similarity analysis. Through similarity comparison to find out the correlation with evolutionary benefits, we then recommend patents related to the product design for references. According to SAO structure, the research contents are mainly divided into the construction of evolutionary benefits keywords dictionary, the extraction of patent text keywords, and the calculation of semantic similarity.

2.4.1. Construction of Evolutionary Benefits Keywords Dictionary

As mentioned, each trend line is composed of several evolutionary stages, and there are evolutionary reasons (reasons for jumps) between each evolutionary stage. The evolutionary benefits of trends are usually presented in the form of binary relations, and the structures are usually "adjective" + "noun" or "verb" + "noun". For example, in *space segmentation*, the evolving benefits from the second stage to the third stage are shown in Table 2. Based on the above description, we will then define an evolutionary benefits keywords dictionary, as shown in Table 3, including the expansion of synonyms to increase the vocabulary of the dictionary, which is used to evaluate the relevance of patent text keywords.

Table 2. Evolutionary benefits of the *Space Segmentation* trend (partially presented).

Trend Line	Evolutionary Stage	Evolving Benefits
Space Segmentation (S2)	Structure with multiple hollow (S2.3) [1]	Improve surface area Improve strength/weight ratio Improve heat transfer
	Capillary/porous (S2.4)	

[1] S2.3 means the 3th evolutionary stage of trend line S2.

Table 3. Example of synonym expansion for evolutionary benefits dictionary.

Evolving Benefit (Reasons for Jump)	keyword 1	Keyword 2
Improve surface area	improve, increase, better, enhance, raise	surface area, area, surface

2.4.2. Extraction of SAO Structure Keywords of Patent Text by Dependency Parsing

The extraction of SAO structure keywords from patent texts is carried out through the Python package Spacy. Spacy is a natural language processing library developed by the Explosion AI team. It is mainly used for word segmentation, part-of-speech restoration, part-of-speech tagging, dependency analysis, etc. The steps are explained as follows:

1. Import patent text: The import of data is the first step of natural language processing. Through the Pandas package, the patent as shown in Figure 3 can be imported into the compiler for subsequent analysis.
2. Dependency parsing analysis: Since the evolutionary benefit is based on the word structure of the binary relation, the SAO structure keywords of the binary relation are extracted from the patent text by using Spacy to perform dependency parsing. The dependencies "amod" adjective modifiers and "dobj" direct objects are extracted through Spacy, which are related to the SAO structure. Figure 4 is partially demonstrated the output as shown below.

```
In [20]: df['patent'][0]

Out[20]: "Methods, systems, and apparatus, including medium-encoded computer program products, for improving 3D printing systems and t
echniques include, in one aspect, a system including: three dimensional (3D) printer hardware; and at least one computer comm
unicatively coupled with the 3D printer hardware, the at least one computer programed to receive 3D print type inputs for an
object to be 3D printed and create a 3D print profile including parameters for 3D printing the object using the 3D printer ha
rdware by matching the 3D print type inputs against a database.BACKGROUND This specification relates to three dimensional (3
D) printing systems and techniques, also known as, additive manufacturing. The selection of 3D print parameters across all 3D
printing techniques, for example extrusion temperature for Fused Deposition Modelling (FDM) or exposure pattern for Stereolit
hography (SLA), is often critical to the success or failure of a print. 3D print parameters are typically specific to the 3D
printing technique, 3D geometry, material and application and therefore can vary greatly from user to user. Nonoptimized 3D p
rint parameters can lead to 3D prints taking longer than necessary and producing lower quality parts than the 3D printer is c
apable of. In addition, it can lead to an increased instance of failures, machine downtime and machine maintenance. This cont
ributes to increased running costs through material wastage and extra maintenance hours and a reduction in throughput due to
machine downtime and unproductive print hours. SUMMARY This specification describes technologies relating to 3D printing syst
ems and techniques, also known as, additive manufacturing. In general, one or more aspects of the subject matter described in
this specification can be embodied in one or more methods that include: receiving three dimensional (3D) print type inputs fo
r an object to be 3D printed; creating a 3D print profile including parameters for 3D printing the object using 3D printer ha
rdware by matching the 3D print type inputs against a database; and outputting the 3D print profile for use in 3D printing th
e object using the 3D printer hardware. The receiving can include receiving the 3D print type inputs including user selected
critical features of a 3D model of the object and material properties of the object to be 3D printed. The method can include
```

Figure 3. Patent text.

```
In [11]: #Depoendency
         doc = nlp(df['patent'][0])
         for token in doc:
             if token.dep_ =='dobj' or token.dep_ =='amod':
                 print("Current word:{:20} Releted word:{:20} Dependency:{:20}".format(token.text,token.head.text,token.dep_))
                 #print(token.head.text)

Current word:encoded        Releted word:products       Dependency:amod
Current word:3D             Releted word:systems        Dependency:amod
Current word:systems        Releted word:improving      Dependency:dobj
Current word:system         Releted word:include        Dependency:dobj
Current word:dimensional    Releted word:hardware       Dependency:amod
Current word:3D             Releted word:type           Dependency:amod
Current word:inputs         Releted word:receive        Dependency:dobj
Current word:profile        Releted word:create         Dependency:dobj
Current word:object         Releted word:printing       Dependency:dobj
Current word:hardware       Releted word:using          Dependency:dobj
Current word:3D             Releted word:type           Dependency:amod
Current word:type           Releted word:matching       Dependency:dobj
Current word:dimensional    Releted word:3D             Dependency:amod
Current word:additive       Releted word:manufacturing  Dependency:amod
Current word:3D             Releted word:parameters     Dependency:amod
Current word:3D             Releted word:parameters     Dependency:amod
Current word:3D             Releted word:technique      Dependency:amod
Current word:Nonoptimized   Releted word:parameters     Dependency:amod
Current word:3D             Releted word:prints         Dependency:amod
```

Figure 4. Dependency parsing of patent texts.

2.4.3. Semantic Similarity Calculation

This research applied the Doc2vec model to calculate the semantic similarity. The calculation method uses the SAO structure of the patent text and the evolutionary benefits keywords dictionary to compare the similarity. We define Pt as the patent text keyword and Eb as the evolutionary benefit keyword, and then rewrite Equation (1) to into Equation (2) as shown below.

$$sim\left(Pt_i, Eb_j\right) = cos\theta = \frac{Pt_i \cdot Eb_j}{||Pt_i|| \cdot ||Eb_j||} \tag{2}$$

As shown in Figure 5, the method is to compare the similarity between the text keyword 1 from the patent and the evolutionary benefits keywords dictionary keyword 1, as well as the text keyword 2 from the patent and the evolutionary benefits keywords dictionary keyword 2.

Text keywords 1 and 2 themselves are words with connected relations, and the similarity calculation with evolution benefit keywords needs to sum up the semantic similarity of the two as expressed in Equation (3). $Pt_{(1)i}$ is the ith word of the patent text keyword 1, and $Eb_{(1)j}$ is the jth word of the evolutionary benefit keyword 1. $Pt_{(2)i}$ is the ith word of the patent text keyword 2, and $Eb_{(2)j}$ is the jth word of the evolutionary benefit keyword 2. Therefore, the sum of the similarity calculation for $sim\left(Pt_i, Eb_j\right)$ are between −2 and 2. We illustrate the relative relationship of the similarity calculation in Figure 6.

$$sim\left(Pt_i, Eb_j\right) = cos\theta = \left(\frac{Pt_{(1)i} \cdot Eb_{(1)j}}{\left|\left|Pt_{(1)i}\right|\right| \cdot \left|\left|Eb_{(1)j}\right|\right|}\right) + \left(\frac{Pt_{(2)i} \cdot Eb_{(2)j}}{\left|\left|Pt_{(2)i}\right|\right| \cdot \left|\left|Eb_{(2)j}\right|\right|}\right) \quad (3)$$

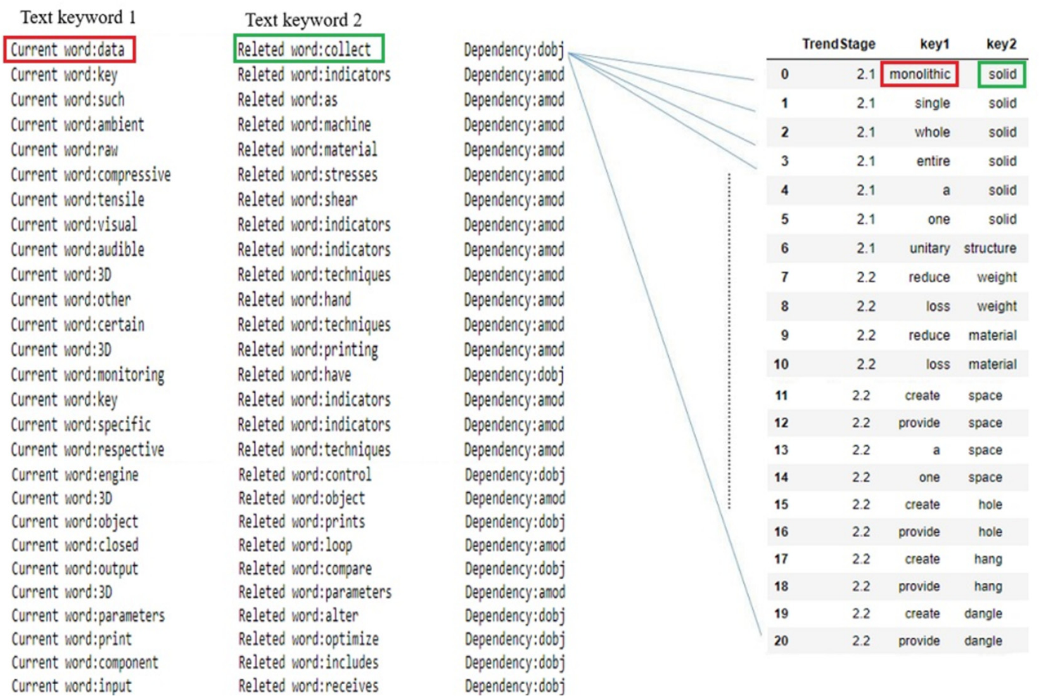


Figure 5. Calculation illustration between patent text keywords and dictionary keywords.

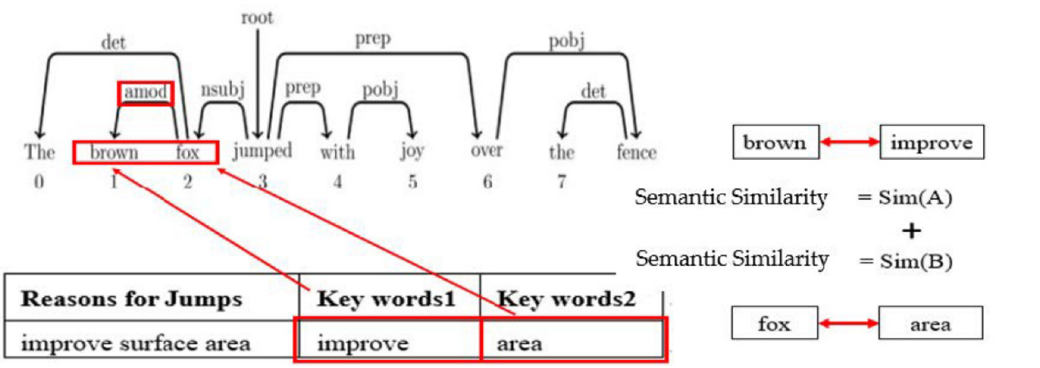


Figure 6. Illustration of the similarity calculation between corresponding text keywords and dictionary keywords.

Once the similarity value reaches a certain threshold, it can be determined that the evolutionary benefit is related to the patent text, thereby recommending relevant patents. After experiments and analysis, this study defines that the threshold is 1.55, which means that the patent text is related to the evolutionary benefits. Conversely, less than 1.55 is considered irrelevant. The flowchart of the above-mentioned is shown in Figure 7.

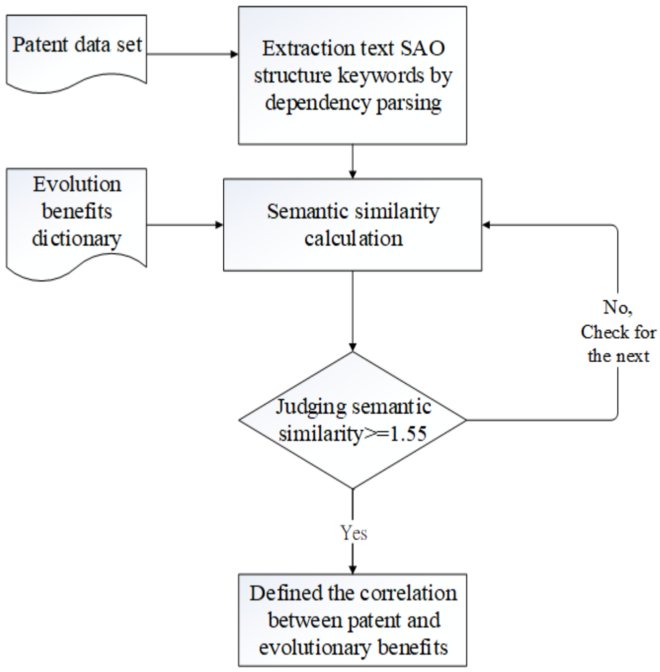
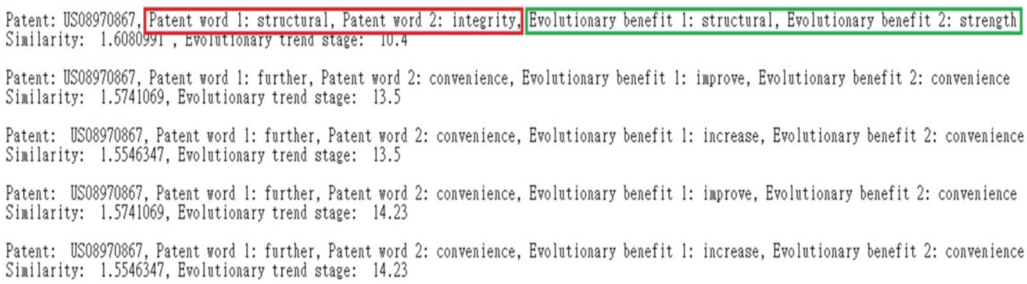


Figure 7. Flowchart of evolution benefits and patent text analysis.

3. Results with Case Study

Thirty patents for 3D printing and peripherals were selected for this experiment. It is assumed that the user tries to improve the problem of 3D printing, and defines the problem as "continuous printing", "automatic calibration", and "fault detection". We first select several evolutionary trends that may be applicable to improve the above problems: space segmentation (S2), boundary breakdown-space (S9), geometric evolution-linear (S10), nesting structure-downward (S12), dynamization (S13), action coordination (T32), mono-bi-poly(various)-interface (I15), controllability (I28) and human involvement (I29). Through the correlation between the evolutionary benefits of the above evolutionary trends and patents, it is used as a reference for recommending patents.

Taking the patent *US08970867*: *Secure management of 3D print media* as an example, the texts based on the dependency analysis of the patent text include "structural integrity", "further convenience", "other device", "based system", "system forms", "system access". As shown in Figure 8, for example, "structural integrity" is related to evolutionary benefit "structural strength", which show in the evolving stage of geometric evolution (S10). Therefore, the patent *US08970867* can be used as a reference for patent recommendation for product design that geometric evolution (S10) is applied.


Patent: US08970867, Patent word 1: structural, Patent word 2: integrity, Evolutionary benefit 1: structural, Evolutionary benefit 2: strength
Similarity: 1.6080991 , Evolutionary trend stage: 10.4

Patent: US08970867, Patent word 1: further, Patent word 2: convenience, Evolutionary benefit 1: improve, Evolutionary benefit 2: convenience
Similarity: 1.5741069, Evolutionary trend stage: 13.5

Patent: US08970867, Patent word 1: further, Patent word 2: convenience, Evolutionary benefit 1: increase, Evolutionary benefit 2: convenience
Similarity: 1.5546347, Evolutionary trend stage: 13.5

Patent: US08970867, Patent word 1: further, Patent word 2: convenience, Evolutionary benefit 1: improve, Evolutionary benefit 2: convenience
Similarity: 1.5741069, Evolutionary trend stage: 14.23

Patent: US08970867, Patent word 1: further, Patent word 2: convenience, Evolutionary benefit 1: increase, Evolutionary benefit 2: convenience
Similarity: 1.5546347, Evolutionary trend stage: 14.23

Figure 8. Result of similarity calculation greater than 1.55 (partial).

In addition, we use the patent *US10073424: Intelligent 3D printing through optimization of 3D print parameters* as another example to observe the result and explain its rationality. Through the similarity comparison with the keyword thesaurus of evolutionary benefits, the text keywords identified based on the semantic similarity above 1.55 are “lower parts”, “single object”, “fluid dynamics”, “higher quality”, “system causes”, “operation adjust”, “total failure”, “single device”, “single processor”, “optical device”, “solid device”, and the above words correspond to several evolutionary benefits, as partially shown in Table 4 below. For example, with “lower parts”, the corresponding evolutionary benefits are “reduced packaging” and “reduced number of systems”, and which are set in the evolutionary trend I15 Mono-Bi-Poly (various). Therefore, we may correlate S10073424 with I15, and the rest are inferred accordingly.

Table 4. The result of similarity comparison for patent US10073424.

Patent	Identified Keywords	Relevant Evolutionary Benefits
US10073424	lower parts	reduced packaging reduced number of systems
	fluid dynamics	improve flow distribution
	higher quality	improve strength properties improve surface area improve compatibility with real world effects improve structural strength increased material strength increased component flexibility increase reliability increase efficiency improve safety increased accuracy
	system causes	increase ability to change system characteristics
	operation adjust	increase operation flexibility
	total failure	reduced error/catastrophic failure

As summarized in Table 5, the correlation between the thirty patents and the selected evolutionary trends can be obtained through the similarity comparison of evolutionary benefits. Among these thirty patents, patent recommendation can be provided based on the trend lines that are applied. In such a way, users may utilize these relevant patents to help improve their product design.

Table 5. Recommendations of the correlation between patents and evolutionary trends.

Evolutionary Trends	Recommend Patents
S2	US10073424, US05424801, US06900814, US04708502
S9	US10073424, US05028950, US09782934
S10	US10073424, US04232324, US05028950, US05408294, US05572633, US05625435, US05786909, US05801811, US05801812, US05825466, US05838360, US06226093, US05500712, US06602378, US09595037, US05542768
S12	US09782934
S13	US10073424, US05400096, US05408294, US05625435, US05786909, US09595037, US08970867, US06602378, US05838360, US09782934, US06037963
T32	US10073424, US04903069, US05028950, US05400096, US05412449, US05424801, US05691805, US05786909, US05838360, US06602378, US09595037
I15	US10073424, US05583971, US05657111, US05838360, US06900814, US09595037, US09782934, US04759647, US06037963, US04708502, US08970867
I28	US10073424, US05786909
I29	US10073424, US05424801, US05691805, US05786909, US05838360, US06602378, US09782934
Undefined	US05717844, US05744291, US05850278

4. Conclusions

This research proposes a patent recommendation method based on natural language processing technique, which is integrated with evolutionary trends in TRIZ. The results of the research are summarized as follows:

- Instead of judging merely by personal experience, a novel approach was developed to improve the application of evolutionary trends in TRIZ. This approach is not only systematic but also intelligent.
- Through evolutionary trends and their evolving benefits, the related patents could be then recommended to assist in product design for needs of improvement.
- Three-dimensional printing was used as an example to explain the methodology and demonstrate the feasibility of the methodology.

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