INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
Online ISSN 1841-9844, ISSN-L 1841-9836, Volume: 18, Issue: 2, Month: April, Year: 2023
Article Number: 5241, https://doi.org/10.15837/ijccc.2023.2.5241

Association mining-based method for enterprise's technological innovation intelligent decision making under big data

Q. Zhang, G. Geng, Q. Tu

Qianqian Zhang
School of Information
Beijing Wuzi University, China
No 1 Fuhe Street, Tongzhou District, Beijing, 101149, China
zhangqianqian@bwu.edu.cn

Guining Geng
360 Digital Security Technology Group Co., Ltd.
No 2 Building, No 6 Yard, Jiuxianqiao Road, Chaoyang District, Beijing 100015, China
Gengguining@360.cn

Qun Tu*
School of Economics and Management
Beijing University of Chemical Technology, China
No.15, Beisanhuandong Road, Chaoyang District, Beijing 100029, China
*Corresponding author: tuqun@buct.edu.cn

Abstract

Technological innovation is vital for the survival and development of enterprises. In the era of intelligent information interconnection and knowledge-driven economy, there is a growing interest in how to manage high-volume data, unlock its potential value, and provide intelligent analysis and decision-making support for enterprise's technological innovation. This paper proposes an improved knowledge association analysis method based on the semantic concept model. This approach enables the discovery of potential correlations and interaction modes between the influencing factors of enterprise's technological innovation, and provides a useful reference for decision-making by combining the analysis with the enterprise's own situation.

Keywords: Intelligent decision, association rule mining, enterprises technological innovation, FP-Growth algorithm.

1 Introduction

Technological innovation is the driving force behind growth and progress in enterprises. In today's fiercely competitive business landscape, implementing a technological innovation strategy and mastering core technologies are inevitable choices for businesses. In recent years, the Chinese central government has issued a series of policies aimed at promoting technological innovation among enterprises. These policies have established clear requirements for enhancing the basic innovation capacity of enterprises and have identified key areas and directions for technological innovation capabilities development. As the value of enterprise technological innovation gains greater recognition from the state and government, more and more attention is being paid to the decision-making processes involved. Accurate analysis of a company's technological innovation ability can help identify problems, analyze root causes, and identify effective countermeasures. Such analysis can provide decision-making guidance and direction for the development of a company's technological innovation.

With the advent of big data, research on enterprise technological innovation decision-making has shifted from traditional manual analysis methods to intelligent decision-making methods. While many scholars have already begun utilizing big data technology in the field of enterprise research, such as optimal allocation management of corporate human resources [33], data mining-based decision support systems to enhance marketing strategies [27], and enterprise resource planning [38], data mining technology has become an integral part of the big data application process. It can extract valuable, nontrivial patterns or knowledge from a large amount of incomplete, noisy, fuzzy, and random data. Big data-driven technology now enables the use of a large amount of unstructured textual data that enterprises had previously ignored. However, most research has focused on structured data, overlooking the use of unstructured data. The challenge now is to deal with the massive amount of ignored textual data generated by enterprises, unlock its potential value, and provide auxiliary decision-making for technological innovation [30].

This paper investigates the potential correlation among the influencing factors of a company's technological innovation, based on various forms of data accumulated during the development process. To achieve this, we employ an improved FP-Growth knowledge association rule mining method. By doing so, we can identify the interaction mode and importance of the factors affecting the technological innovation decision-making of enterprises, providing intelligent decision-making reference to improve technological innovation capability.

The paper is organized as follows: Section 2 presents the research background, Section 3 describes the implementation process of the research methodology, Section 4 presents the results and discussion, and the final section concludes the paper.

2 Literature review

2.1 Technological innovation conceptual background

The concept of enterprise technological innovation originated from Schumpeter's "innovation theory" [45], which believed that innovation is a leading engine of growth, economic development, and social evolution [43]. With the deepening of research, scholars have discussed a lot about the concept of technological innovation capability of enterprises. The Organization for Economic Co-operation and Development (OECD) defined technological innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations [5]. Diaconu [13] proposed that most technological innovation of enterprises is complex and cumulative. Enterprises should effectively combine information, human, financial and material resources and need a perfect function distribution system to carry out enterprise innovation activities. Kline and Rosenberg believed [26] that enterprise's technological innovation exists in the entire product life cycle of the enterprise and improve the economic benefits of the enterprise through frequent changes. Hall and BagchiSen [21] proposed thatnot all enterprises need intensive R&D activities. Enterprises with relatively low R&D intensity can focus on strategic innovation or market innovation, which can also improve innovation performance. Lokshin *et al.* [35] introduced the concept of marketing and organizational innovation, emphasizing the importance of combining different types of resources and reconfiguring various functions to improve enterprises' technological innovation. Barton [4]proposed that management system, technical system, professional staff and corporate values constitute the technological innovation capability of an enterprise. However, there is a lack of integration in his views. Burgelman [8] believed that technological innovation is the sum of a series of characteristics, including the availability of resources and allocation, structural and cultural conditions, the ability to understand industry development, and strategic management capabilities, *etc.* However, its definition focuses on the strategic management perspective of the enterprise. In general, enterprise's technological innovation is a process, not only in a certain production cycle or stage but also in every production link of an enterprise. Enterprises' technological innovation reflects the strength of comprehensive ability, integrates all aspects of capability, and is a complex, creative and open-ended system with numerous influencing factors. Yet given its characteristics, the technological innovation process is often thought of as random, irregular, or chaotic [10],[17]. Therefore, the research on the technological innovation capability of enterprises has not been able to form a systematic and complete theory, and it is difficult for enterprises to succeed without guidance in the decision-making of technological innovation.

2.2 Intelligent decision-making method based on data mining

The birth of big data has changed the way of data storage, processing and analysis for enterprises. The application of big data allows a large amount of noisy and abandoned data to utilize, providing unique insight for enterprises on market analysis, process analysis, risk management and providing accurate decision-making information. Big data analytics is becoming increasingly popular for enterprise's technological innovation decision-making.

For market analysis, many researchers utilize big data technology to capture rich and plentiful data on the consumer in real time and extract consumer activity from big data to develop enterprise marketing strategies [16][15]. Hartmann *et al.*[20] also proposed a derived taxonomy of data-driven business model to help enterprises in start-ups create new business mode, and provide a business perspective by big data analysis. Customer churn prediction is also an important research topic for enterprise's decision-making. Many researches utilize big data analysis to predict customers who are most likely subject to churn in various fields, such as the financial industry and telecom operators based on the unstructured data from web pages, website visits and phone conversation logs [49][31].

There are many scholars who focus on big data application and analysis in operations or supply-chain management, for example, customer behavior analysis [6][12][36], trend analysis [50][40][9], and demand prediction [46][39][41][34]. Big Data Analytics has become the most popular technology in enterprises' process analysis. It can deliver the best possible solution to decision-makers for efficiently handling the problems related to huge data [37].

In addition, for the credit risk assessment, Du *et al.* [14] utilized the BP neural network algorithm and genetic algorithm to build an early warning model of Internet credit risk based on massive data. Li [32] established a SME venture financing risk assessment model and built a risk evaluation index system according to the characteristics of the enterprise production organization, process characteristics, and the development of the socioeconomic and technical environment. It provides risk assessment and risk control for enterprises. Except for the application of big data in enterprises' credit risk assessment, there are many researches on fraud detection, for example, Zhou *et al.* [54] put forward a distributed deep learning model based on Convolutional Neural Network (CNN) for financial fraud behaviors detection in a supply chain, the application of Apache Spark and Hadoop accelerate the processing speed of large dataset.

2.3 The application of association rules mining method (ARM)

ARM is also a representative method for enterprises' intelligent management. The researches applied the ARM to each link of the supply chain. Guo *et al.* [19] proposed an intelligent decision support system (DSS) based on the association rule method for the manufacturing industry to support decision-making. Wang and Jin [52] developed an intelligent logistics system based on the association rules data mining method to help decision-makers solve problems in logistics. Sakanai *et al.* [44] proposed a method to identify the operational risk in the supply chain with association rule mining algorithm based on the historical data of enterprises. The ARM method is also widely applied in enterprises' quality management, such as product quality assessment [24], and manufacturing operation process improvement[25]. Regarding financial management, Yao [53] utilized the data mining algorithm to process massive financial accounting data and analyze the financial risk index coefficient of the enterprise by the association rules algorithm. Shang *et al.* [47] also propose a method based on association rule mining to select more representative financial risk indicators for enterprises. In terms of inventory management, Agarwal [1] imported the association rule mining and clustering into the inventory management of enterprises and the cross-selling effect is brought into the classification of inventories. Agarwal [2] also proposed an inventory model with Multi-level association rule mining to determine the optimum order quantity by frequent items discovering. In addition, ARM also can provide an analysis to enterprises marketing management. Hosseinioun *et al.* [22] constructed a knowledge-driven decision support system based on association rules mining to improve the process of decision-making and management of market resources. Shelke [48] Analysed the product based on transactional data with association rules mining and provide decision support for product sales and customer consumption. In addition, ARM also can provide intelligent decision-making for other fields, such as agriculture [23][51], garment industry [28], education industry [18][3], medical industry [29][7], transportation [11], etc.

Although the big data technology, especially ARM helps enterprises provide intelligent decision-making in market management, risk control, etc., and even extends to other fields. Since the complexity of influencing factors in the field of enterprise technology innovation, there is still no method system to provide intelligent decision-making for enterprises in technological innovation and to provide guidance for the development direction for enterprises.

3 Research methodology

This section presents an improved analysis of Knowledge Association using the Semantic Concept model (KASC). The KASC model comprises four parts, as illustrated in Figure 1. Upon preprocessing the text documents, we implemented the Frequent Pattern Growth algorithm to create a Single Linked item header table (SLFP-Growth) and generate association rules. Subsequently, we proposed a semantic interestingness rule filtering method based on the domain ontology semantic concept model to refine the large number of rules. Finally, we provide decision-making advice for enterprises based on the association rules.

Traditionally, association rule mining methods use interestingness as a metric to assess the usefulness and significance of association patterns. However, subjective measurement methods based on prior domain knowledge tend to rely heavily on the user's background knowledge and expected goals, limiting the scope of association results [42]. In contrast, the KASC model leverages the rich semantic knowledge and hierarchical structure of the domain ontology, eliminating the knowledge gap that often arises in the mining and pruning process of traditional association rule methods. The general steps of the KASC model are outlined in Figure 1, and we discuss these steps in the following subsection.

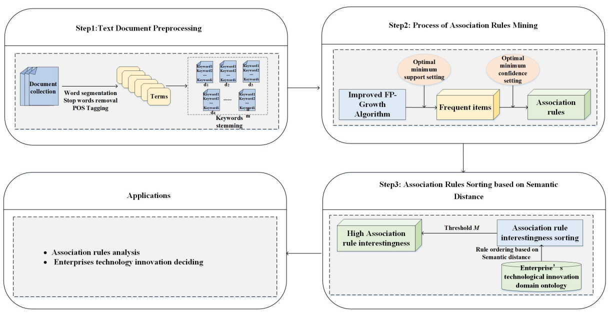

Figure 1: The process of knowledge association analysis based on semantic concept model

3.1 Text Document Preprocessing

The Text document preprocessing is the first step of the KASC, and the process includes four steps, word segmentation, POS selection, stop-word filtering and feature extraction. The Process of text preprocessing is shown in Figure 2.

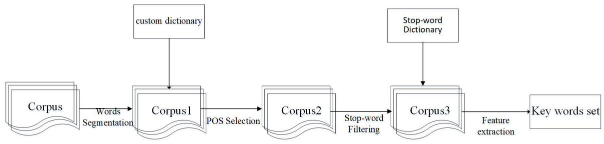

Figure 2: Process of text preprocessing

3.1.1 Chinese Segmentation

Firstly, based on the Jieba Tokenfilter, this paper realizes the word segmentation of enterprise's technological innovation text collection. However, the segmentation result will appear as an ambiguous segmentation problem since a Chinese phrase is wrongly divided into many words. For example, "enterprise technological innovation" was divided into three small-grained words such as "enterprise", "technological", and "innovation". Then, we acquire and optimize the custom dictionary, then apply the dictionary to correct ambiguous segmentation. The custom dictionary defines many special words in the field of enterprise technological innovation, such as "enterprise technological innovation", "product innovation", "innovation mechanism", etc., which can help to improve the segmentation effect.

3.1.2 POS Selection

This paper utilizes the automatic part-of-speech tagging with Jieba. It selects the nouns of the text collection which are the most representative important for semantic information in the field of enterprise's technological innovation. Hence, selecting the nouns and words similar to nouns as the research object, such as the verb with noun function, the adjective with noun function, *etc.*

3.1.3 Stop-word Filtering

This paper removes the useless words from the text collection of enterprise technological innovation. We built a stop-word dictionary which contains many meaningless words, such as modal particles. The stop-word filtering can help to reduce the size of the indexing structure considerably.

3.1.4 Feature extraction

This paper utilizes the term frequency (TF) to rank the frequency of words in the text collection according to their importance. We count the number of occurrences of each term in the document, filter the word whose occurrences are less than the threshold θ and obtain the key words set. The calculation formulas of TF are present as the following formula. The term frequency $tf(t_i, d_j)$ represents the number of occurrences of t_i in a document d_j.

$$tf(t_i, d_j) = \frac{n_{ij}}{\sum_k n_{kj}},$$

3.2 SLFP-Growth Algorithm

The traditional Frequent Pattern Growth (FP-Growth) algorithm is shown in Figure 3. It needs to scan the database first to get the support counts of all frequent itemsets, delete the items lower than the minimum support threshold, and sort them in descending order of support. Then create the FP pattern tree and item header table according to the order of frequent itemsets in the database. After establishing the FP tree, mining the conditional pattern base from the bottom of the item header table and the frequent itemsets is obtained by recursively mining from the conditional pattern base. Although the FP-Growth algorithm has a faster operation speed than other association algorithms, it requires a lot of time to generate conditional pattern trees and traverse mining patterns and requires a large storage space. Therefore, this paper combines the Single Linked item header table with the Frequent Pattern Growth algorithm (SLFP-Growth), which including transaction names, count statistics, node links, etc. We store frequent items that satisfy the minimum support threshold in the table, and then mining frequent itemsets by traversing the item header table. The proposed SLFP-Growth algorithm does not need to generate and traverse the FP condition tree like the traditional method, which saves computation time and memory consumption.

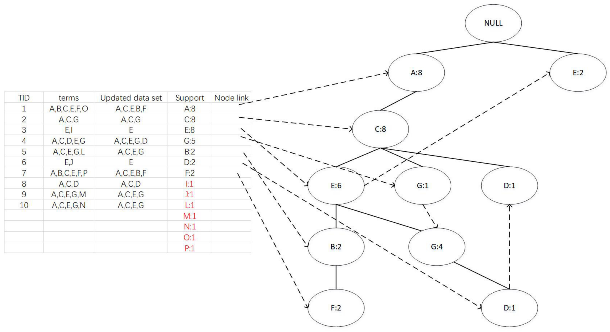

Figure 3: The item header table with first data inserting

3.2.1 The steps of the improved SLFP-Growth Algorithm

The improved SLFP-Growth Algorithm mainly includes two steps:

1) Scan the database first to get the support counts of all frequent itemsets, delete the items in the original dataset that are less than the minimum support threshold, and sort the itemsets in the dataset in descending order of support.

2) Scan the sorted database again and insert the database items recursively into the item header table.

The steps of the improved SLFP-Growth Algorithm are described as follows.

Algorithm 1 SLFP-Growth Algorithm.

Input: preprocessed dataset $D = \{d_i | j = 1, 2, \ldots, m\}$, the dataset contains N terms $C = \{c_i | i = 1, 2, \ldots n\}$, domain ontology O, minimum support *minsup*;

Output: frequent pattern sets and association rules;

Scan the preprocessed text dataset and calculate the support for all 1 item sets I_1;
Filter and select $I_1 \geq minsup$
Sort and reorder the text dataset in descending order according to I_1 element support;
Scan the reordered text dataset, read the itemsets in each text in the dataset and save them in the item header table;
for $i = 1; i < m; i++$ **do** Scan the text database, p points to frequent itemsets;// i is the text reading sequence, p is the node link to the frequent itemset, m is the total text;
end for
while $p \neq Null$ **do**,
end while
if $p \rightarrow next == Null$, **then**, end;
elseScan frequent items
end if
if frequent items already exist in the item header table **then**, $count + 1$;
elseGenerate new node and insert to the item header table,$count = 1$;
end if
Filter the frequent itemsets that satisfy the minimum support, construct the possible association rules by recursive iteration for each frequent itemset, and calculate the rule confidence and filter out the rules satisfying the minimum confidence.
if $support \geq minsup$ **then return** *frequentset*
end if
if $conf \geq minconf$ **then return** *frequentPatterns*
end if

Table 1: The text database of enterprise's technological innovation

Text set	Keywords
Doc1	Industry Type, Core business, Technological innovation, R&D expenditures Sales revenue
Doc2	Company name, Industry Type, Core business, R&D expenditures, Sales revenue
Doc3	Company name, Core business
Doc4	Company name, Industry Type, Technological innovation
Doc5	Industry Type, Core business, Technological innovation, R&D expenditures, Sales revenue

Table 2: Updated text database based on frequent item support

TID	Items	Support	Reordered dataset
1	Industry Type, Core business, Technological innovation, R&D expenditures, Sales revenue	Core business:4	Core business, Industry Type, R&D expenditures, Sales revenue, Technological innovation
2	Company name, Industry Type, Core business, R&D expenditures, Sales revenue	Industry Type:4	Core business, Industry Type, R&D expenditures, Company name, Sales revenue
3	Company name, Core business	R&D expenditures:3	Core business, Company name
4	Company name, Industry Type, Technological innovation	Company name:3	Industry Type, Company name, Technological innovation
5	Industry Type, Core business, Technological innovation, R&D expenditures, Sales revenue	Sales revenue:3 Technological innovation:3	Core business, Industry Type, R&D expenditures, Sales revenue, Technological innovation

3.2.2 An example of SLFP-Growth algorithm realization

The following is an example we utilized part of data in the same database to describe the SLFP-Growth Algorithm in detail for demonstration. Table 1 shows the key itemsets of the original textual database after text preprocessing. Each document is equivalent to a transaction, and the collection of all keywords in the documents is equivalent to the itemsets in the transaction database. Scan the items in the database and count the support of frequent. Since the minimum support threshold is 2, the itemsets in the example all meet the minimum threshold for retention. Then sort the itemsets in descending order according to the support counts, as shown in Table 2.

Create the item header table and insert each itemset of reordered text database in turn according to the transaction name, support count, and node link, as shown in Figure 4 to Figure8. Delete the frequent items with support less than 2 according to the item header table, and mine the frequent item set, the final result of frequent itemsets as shown in Table 3.

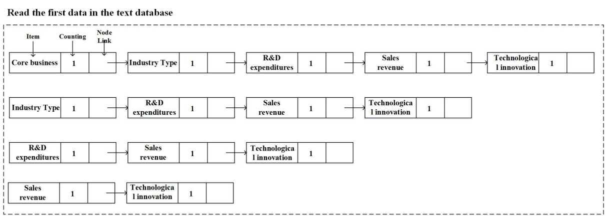

Figure 4: The item header table with first data inserting

3.3 Association rules ranking method based on semantic concept model

Domain ontology has rich professional background knowledge, and with the help of a large number of current formal knowledge ontology structures, the implicit relations between concepts can be discovered. We propose a semantic interestingness rule filtering method that combines the similarity measure between domain ontology concepts and the traditional interestingness measure method to filter a large number of rules generated by association rule mining methods. The proposed method

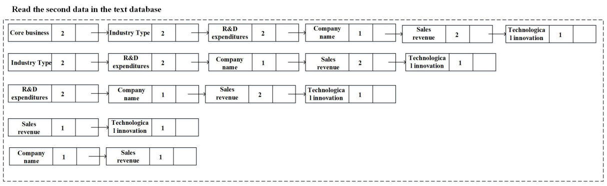

Figure 5: The item header table with second data inserting

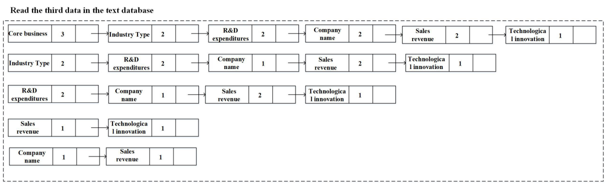

Figure 6: The item header table with third data inserting

ranks the generated association rules based on the conceptual distance of the domain ontology hierarchy. In the hierarchy of domain ontology structure, the shorter the semantic distance between concepts, the greater the semantic similarity between concepts, and the more related the two concepts are. Instead, the greater the semantic distance between concepts, the less related the concepts, and the more interesting the discovered rules will be.

The Figure 9 shows part of enterprise technological innovation domain ontology. If the semantic distance between concept C_1 and concept C_2 is smaller than the semantic distance between concept C_1 and concept C_{41} , the interestingness of association rules generated between concepts C_1 and C_2 will be less than that generated by concept C_1 and C_{41}. Therefore, the proposed association rule ranking method based on domain ontology semantic conceptual distance can rank the generated association rules by interest and extract the most interesting and relevant rules.

3.3.1 The realization of association rules ranking method

We propose a semantic conceptual model based on domain ontology to calculate the semantic distance and semantic similarity between concepts. The concept semantic distance calculation is shown as follows. There are three conditions: (1) when the concept nodes c_i and c_j are the same concept, the semantic distance is 0; (2) when there is a direct path between concept nodes c_i and c_j, the semantic distance is the path weight value between the two concepts; (3) when there is an indirect path between concept nodes c_i and c_j, the semantic distance is sum of the path weights connecting the two concept nodes.

$$Dist(c_i, c_j) = \begin{cases} 0; & c_i \equiv c_j \\ w[sub(c_i, c_j)]; & c_i \to c_j \\ \sum\limits_{c \in sPath(c_i, c_j)} wc[sub(c_i, c_j)]; & \text{others} \end{cases}$$

The calculation of path weight for each node connected to each other in the domain ontology is shown in as follows, where K is a predefined factor,$K \geq 1$ represents the rate of the weight decreases

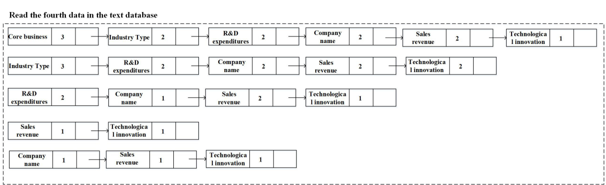

Figure 7: The item header table with fourth data inserting

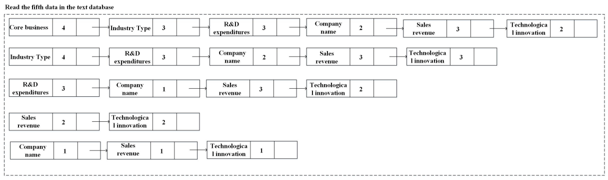

Figure 8: The item header table with fifth data inserting

Table 3: Frequent itemsets

Itemset name	Frequent itemsets
Core business	{Core business:4}, {Core business, Industry Type:3}, {Core business, R&D expenditures:3}, {Core business, Company name:2}, {Core business, Sales revenue:3}, {Core business, Technological innovation:2}, {Core business, Industry Type, R&D expenditures:3}, {Core business, Industry Type, Company name:2}, {Core business, Industry Type, Sales revenue:3}, {Core business, Industry Type, Technological innovation:2}, {Core business, R&D expenditures, Company name:2}, {Core business, R&D expenditures, Sales revenue:3}, {Core business, R&D expenditures, Technological innovation:2}, {Core business, Company name, Sales revenue:2}, {Core business, Company name, Technological innovation:2}, {Core business, Sales revenue, Technological innovation:2}, {Core business, Industry Type, R&D expenditures, Company name:2}, {Core business, Industry Type, R&D expenditures, Sales revenue:2}, {Core business, Industry Type, R&D expenditures, Technological innovation:2}, {Core business, R&D expenditures, Company name, Sales revenue:2}, {Core business, R&D expenditures, Company name, Technological innovation:2}, {Core business, Company name, Sales revenue, Technological innovation:2}, {Core business, Industry Type, R&D expenditures, Company name, Sales revenue:2}, {Core business, Industry Type, R&D expenditures, Company name, Technological innovation:2}, {Core business, R&D expenditures, Company name, Sales revenue, Technological innovation:2}, {Core business, Industry Type, R&D expenditures, Company name, Sales revenue, Technological innovation:2},
Industry Type	{Industry Type:4}, {Industry Type, R&D expenditures:3}, {Industry Type, Company name:2}, {Industry Type, Sales revenue:3}, {Industry Type, Technological innovation:3}, {Industry Type, R&D expenditures, Company name:2}, {Industry Type, R&D expenditures, Sales revenue:3}, {Industry Type, R&D expenditures, Technological innovation:3}, {Industry Type, Company name, Sales revenue: 3}, {Industry Type, Sales revenue, Technological innovation:3}, {Industry Type, R&D expenditures, Company name, Sales revenue: 2}, {Industry Type, R&D expenditures, Company name, Technological innovation:2}, {Industry Type, R&D expenditures, Company name, Sales revenue, Technological innovation:2}
R&D expenditures	{ R&D expenditures:3}, {R&D expenditures, Sales revenue:3}, {R&D expenditures, Technological innovation:2}, {R&D expenditures, Sales revenue, Technological innovation:2}
Sales revenue	{Sales revenue: 2}, {Sales revenue, Technological innovation:2}

with the ontology hierarchy.

$$w[sub(c_i, c_j)] = \frac{1}{2K^{depth(c_j)}} + 1$$

The following formula represents the calculation method of concept semantic similarity of domain ontology, where λ is the influence factor of semantic distance on semantic similarity, $0 < \lambda \leq 1$.

$$Sim(c_i, c_j) = \frac{1}{1 + \lambda dist(c_i, c_j)}$$

To determine the semantic interestingness of association rules, the measurement method based on the semantic distance of the domain ontology concept is shown as follows. Where the association rules R are consist of $\{c_1, c_2, \ldots, c_n\}$, $Dist(c_i, c_j)$ represents the conceptual semantic distance between two items, k indicates the number of output rules. When the association rules are sorted by semantic interest, the number of generated association rules can be selected, and the association rules with high interestingness are obtained.

$$SemIntere = \frac{\sum_{1 \leq i,j \leq n} Dist(c_i, c_j)}{\sum_{k=1}^{n-1} k}$$

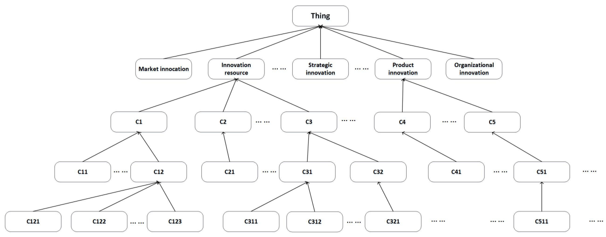

Figure 9: The part of structure of enterprises' technological innovation domain ontology

Algorithm 2 The realization of association rules ranking method

Input: ontology O,frequent pattern set N;

Output: association rules;

1: Loading domain ontology O;

2: for i=1, j=1 $Dist(c_i, c_j) = \sum_{c \in sPath(c_i,c_j)} \frac{1}{2K^{depth(c_j)}} + 1$ //Calculating the semantic distance between itemset based on domain ontology;

3: $SemIntere = \frac{\sum_{1 \leq i,j \leq n} Dist(c_i,c_j)}{\sum_{k=1}^{n-1} k}$; //Calculating semantic interest based on itemset semantic distance;

4: Sort rules in descending order based on semantic interest, take Top M association rules;

5: End. obtained M association rules

4 Results and Discussion

This paper collects the information related to technological innovation of more than 400 enterprises in Beijing, and conducts an empirical study with these enterprises as an example. According to the KASC method proposed in this paper, including data collection and preprocessing, association rule mining, association rule filtering, we obtain the key influencing factors of technological innovation decision-making of enterprises in Beijing and the potential correlation between the influencing factors.

4.1 Experimental Datasets and Parameter Setting

The experimental data are provided by the Beijing Municipal Commission of Economic Informatization and mainly consist of the enterprise's background (see Table 4), the development of enterprise technological innovation activities, enterprise innovation projects, enterprise organizational structure, enterprise main products and services, enterprise profitability. After data preprocessing, there are 867 valid texts, and the overall data size is about 20M. The experimental operating environment is the Windows 10 system, 2.70 GHz core processor, 8.0 GB memory, and Python 3.6.2.

4.2 Evaluation Measures

In order to verify the performance and efficiency of the proposed KASC method, we compare the Apriori algorithm, the FP-Growth algorithm and the improved KASC algorithm in terms of the operation time, memory usage and the number of generated rules with the same dataset in different minimum support setting. The experimental results are as follows.

We compare the performance of the Apriori algorithm, the FP-Growth algorithm and the SLFP-Growth Algorithm in terms of operation time and memory usage by setting different minimum support. The different minimum support setting and the performance with three algorithms is shown in Table

Table 4: Frequent itemsets

Area of focus	Format	Number
Enterprise profiles	.doc	388
Enterprise technical and financial reports	.xlsx	212
Enterprises products	.txt	131
Enterprises rewards	.pdf	136

Table 5: Algorithm performance comparison

Minimum support	Apriori algorithm		FP-Growth algorithm		KASC algorithm	
	Operation time (s)	Memory usage (Mb)	Operation time (s)	Memory usage (Mb)	Operation time (s)	Memory usage (Mb)
0.1	110	4070	108	4557	93	3797
0.2	12	1655	11	1654	9	1378
0.23	0.47	200	0.47	199	0.33	155
0.25	0.07	156	0.05	155	0.03	129
0.27	0.05	153	0.04	154	0.02	128
0.3	0.03	153	0.04	153	0.02	128

Table 6: The number of rules generated under different support

Minimum support	Minimum confidence	Number of rules
0.1	1.0	3514642
0.2	0.8	1417087
0.23	0.8	58481
0.25	0.8	2544
0.27	0.8	14
0.3	0.8	1

5. It can be seen from the Figure 10, The FP-Growth algorithm is slightly faster than the Apriori algorithm, and the KASC algorithm has the fastest operation time among the three algorithms. The comparation of memory usage as shown in Figure 11, the FP-Growth algorithm has the largest memory usage, followed by the Apriori algorithm, and the KASC algorithm takes the least amount of memory. Therefore, the performance of KASC algorithm is better than the traditional Apriori algorithm and the FP-Growth method.

As can be seen in Table 6, the number of association rules generated by the three algorithms are the same, and the higher of the thresholds of minimum support and minimum confidence, the less association rules are generated. Increasing the minimum support will significantly reduce the number of generated rules, however, blindly increase the thresholds may lead to the useful information is ignored. For example, when the minimum support is 0.27 and 0.3, and the minimum confidence is 0.8, the number of generated rules is only 14 and 1. On the other hand, if the threshold of the parameter is set too low, the algorithm will generate a large number of association rules. For example, when the minimum support is 0.1 and 0.2, and the minimum confidence is 1.0 and 0.8, the generated association rules are all in the millions, and it is difficult to extract useful and interesting association rules among them. Therefore, in order to obtain an appropriate number of association rules, we set the threshold of minimum support is 0.25, the minimum confidence is 0.8, and the number of generated association rules is 2544.

We rank the generated association rules based on the domain ontology semantic distance, and select the most interesting rules according to the threshold of sematic interest . The value range of is [0-1]. When the value of closer to 1, which represents the higher interest in the generated association rules, and the fewer generated number of association rules. Therefore, in order to select association

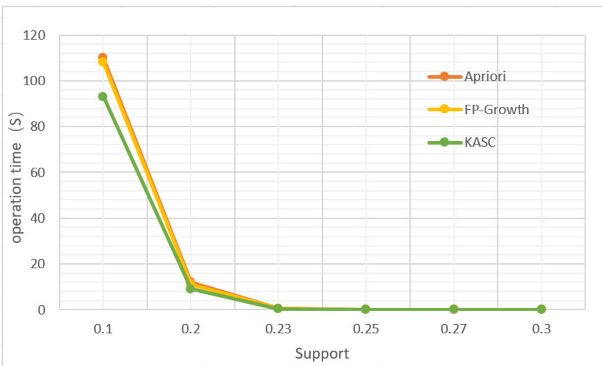

Figure 10: Comparison of computing time of three algorithms under different support degrees

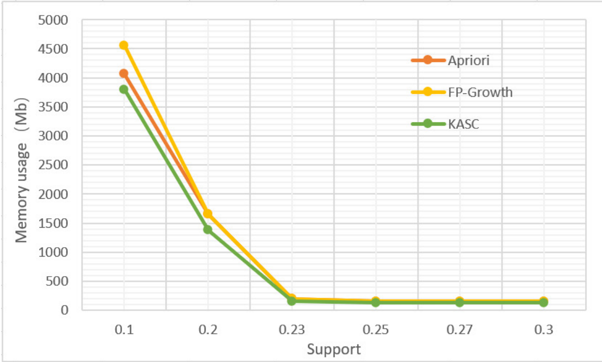

Figure 11: Comparison of memory usage of three algorithms under different support degrees

rules with high interest, we set the threshold of 0.5 and filter out association rules when . At last, the number of generated association rules is 1338.

4.3 Result Analysis and Discussion

4.3.1 Enterprise technological innovation decision making knowledge association result visualization

The structure of the enterprise's technological innovation domain ontology is shown in Figure 12. We utilize the KASC algorithm based on the domain ontology to mining the association rules for enterprise technological innovation decision making and the result is shown in Figure 13,Figure 14, and Figure 15. The Scatter plots can display the entire generated association rules as shown in Figure 13 and can identify thresholds includes of support, confidence, and lift. The association graph as shown in Figure 14 can display all the generated association rules and display the relationship between the nodes. The heat map can display part of information of association rules and confidence. The color corresponds to the confidence level. As shown in Figure 15, the more orange and lighter the color, the higher the confidence value.

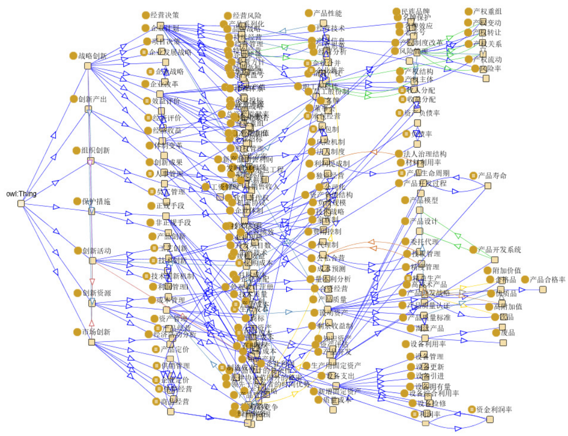

Figure 12: The structure of ontology concepts in the field of enterprises' technological innovation

4.3.2 Enterprise technological innovation decision making knowledge association result analysis

It can be seen from Figure 13, Figure 14, and Figure 15, the influencing factors related to enterprise technological innovation are interrelated and interact with each other. We analyze all generated association rules, and shown top 19 association rules with high semantic interest in Table 7 which can give more detailed information. The first association rule in the table shows the influence of invention patents and technical research on enterprises technological innovation. Invention patents belong

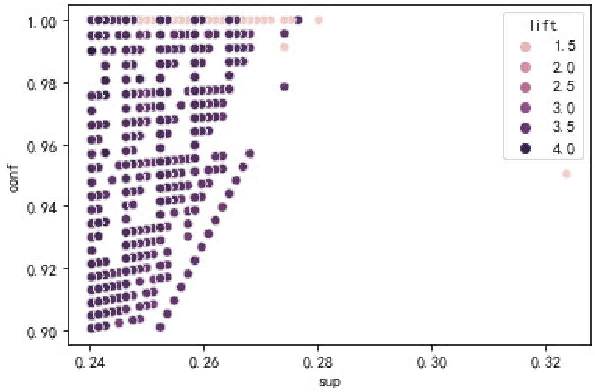

Figure 13: Association rule scatter plot

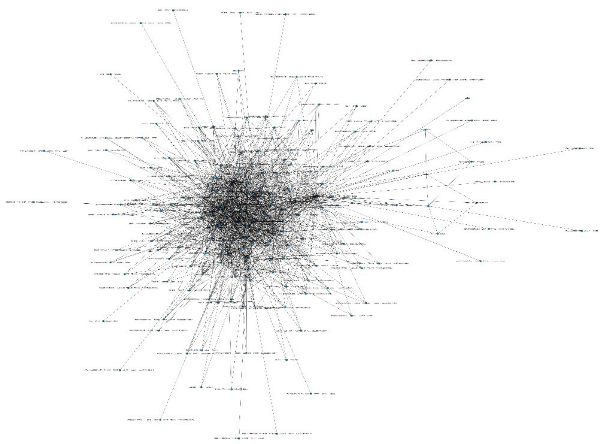

Figure 14: The relationship of node in association rule

to innovation output, and technical research belongs to manufacturing capability, which reflects the relationship between innovation output, manufacturing capacity and technological innovation of enterprises. Manufacturing capacity and innovation output will affect the decision-making of enterprises in technological innovation. The second association rule indicates the impact of new product design and research and development (R&D) on the technological innovation of enterprises. New product design and R&D belong to product manufacturing capabilities, that is, manufacturing capabilities will directly affect the decision-making of technological innovation of enterprises. The third association rule display the core product development cycle and the number of technology development projects has impact on new product and sales revenue. The core product development cycle and the number of technology development projects belong to the influencing factor of manufacturing capacity and technological output, the new product and sales revenue belong to the influencing factor of innovation revenue. Therefore, manufacturing capacity and technological output have a direct impact on the innovation revenue of enterprises.

We also found potential associations between many factors that affect technological innovation decisions of enterprises through the knowledge association mining method, such as the role and impact of intellectual property on sales revenue. The intellectual property belongs to the influence factor of protection measures, and sales revenue belongs to the innovation income factor. The protection measures of intellectual property have impact on the sales revenue of enterprises. The fifth association rule reflects the relationship between the application of new materials, technological innovation and sales revenue. The application of new materials belongs to the impact factor of product integration innovation, and the decision on the application of product integration innovation in enterprise technology will directly affect sales revenue. The sixth rule shows the role of university-industry cooperation (UIC) on enterprise technology and product R&D. UIC is an influencing factor of innovation strat-

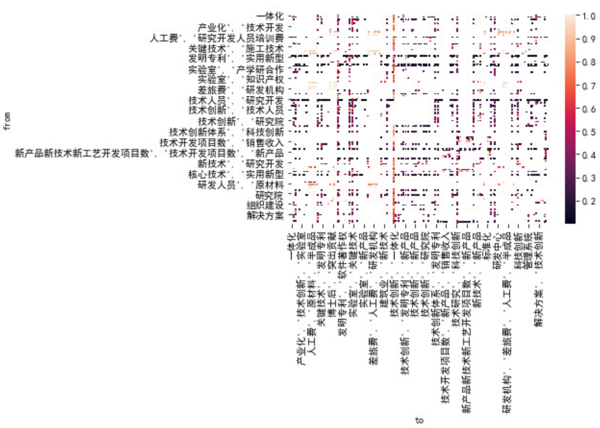

Figure 15: Heat map of partial association rules

egy. Core technologies and product R&D reflect the product manufacturing capabilities. Therefore, innovation strategy has an impact on the technological R&D and product manufacturing capability of enterprises. In addition, R&D personnel belong to innovation resources, and product design belongs to manufacturing capabilities. Therefore, R&D personnel have impact on the product manufacturing capabilities of enterprises. Since new products belong to manufacturing capabilities, and market share belongs to market analysis capabilities. Therefore, enterprise market innovation is influenced by the product manufacturing capabilities of enterprises.

Utility models and invention patents belong to technical output, while product design belongs to manufacturing capacity. The technical output of innovation has an impact on the manufacturing of enterprises and the technological innovation decision-making of enterprises. The management system belongs to the organizational management mechanism, while R&D belongs to manufacturing capacity. Therefore, the setting of the organizational management mechanism plays an important role in the manufacturing capacity and technological innovation decision-making of enterprises. The use of funds belongs to the funding guarantee mechanism, while resource management belongs to resource allocation. Hence, the funding guarantee mechanism in the mechanism innovation has an impact on the resource allocation ability in the innovation strategy. Intellectual property belongs to protection measures, and invention patents belong to innovation output. Intellectual property protection has a certain impact on enterprise innovation output.

Additionally, industrialization is an innovative strategy, and the application of intellectual property has a significant impact on the strategic layout of enterprises' industrialization innovation. Research and development (R&D) expenditure is considered an input of innovation resources, and the sales of an enterprise's main products are considered as innovation output. Therefore, the input of innovation resources is directly proportional to the innovation output. The relationship between innovation resource input and innovation output is also reflected in the R&D expenditure, sales revenue of the enterprise's main products, and the total industrial output value. Technology introduction, on the other hand, belongs to non-R&D input. Therefore, " technology import, product manufacture technology development, Industrial output" represents the relationship between innovation resources, manufacturing capacity, and innovation output of enterprises. Brand influence is related to quality and brand building, while marketing pertains to market innovation. Thus, quality and brand building in manufacturing capability have a certain impact on enterprise market innovation. Incentive mechanism belongs to mechanism innovation, and talent management is considered as resource allocation ability in the innovation strategy. Hence, mechanism innovation has a direct impact on innovation strategy. Knowledge sharing and enterprise culture are both part of the innovation strategy, and organizational management belongs to mechanism innovation. Therefore, the innovation strategy significantly influences the mechanism innovation.

Table 7: Association rules with high semantic interest

No	Association rules	Semintere
1	Invention patent, technical research → technological innovation	0.98
2	New product design,R&D → technological innovation	0.96
3	Core product development cycle,Number of technology development projects → New product,Sales revenue	0.96
4	intellectual property → Sales revenue	0.94
5	new material,technological innovation → Sales revenue	0.94
6	UIC → core techniques,product development	0.93
7	R&D personnel → product design	0.93
8	New product → market share	0.92
9	Utility model,Invention patent → Product design,technological innovation	0.92
10	management system → R&D,Technology innovation system	0.91
11	use of funds → resource management	0.88
12	intellectual property → Invention patent,laboratory	0.88
13	Intellectual property → Industrialization,technological innovation	0.87
14	R&D expenditure → Sales revenue, main products	0.86
15	R&D expenditure,Sales revenue, main products → Industrial output	0.84
16	technology import,product manufacture → technology development,Industrial output	0.83
17	brand influence → Marketing	0.82
18	incentive mechanism → talent management	0.79
19	knowledge sharing,enterprise culture → organizational management	0.76

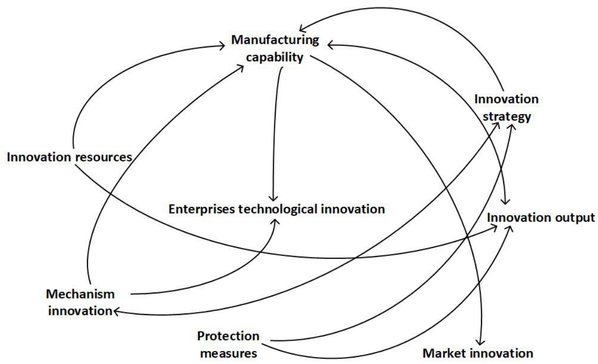

Figure 16: The potential correlation between the influencing factors of enterprises' technological innovation capability

4.3.3 Discussion

Based on the association rules with high semantic interest presented in Table 7, we can analyze the semantic interpretation that corresponds to each association rule and explore the potential relationships between the influencing factors that affect enterprise technological innovation decision-making. There are seven main factors that affect technological innovation: innovation resources, manufacturing capacity, innovation strategy, mechanism innovation, market innovation, protection measures, and innovation output. The potential correlations between these factors can be roughly depicted in Figure 16. From Figure 16, we can observe the modes of interaction and influence between the influencing factors that affect enterprise technological innovation, which are mainly manifested in the following aspects:

(1) Direct impact of factors on enterprise technological innovation. Mechanism innovation and innovation resources have a greater impact on enterprise technological innovation, while manufacturing capacity also plays a significant role. There exists a positive correlation among innovation resources, manufacturing capabilities, and enterprise technological innovation. The more resources an enterprise invests in technological innovation and the stronger its product manufacturing capability, the greater

the impact on its technological innovation. This is because technological innovation requires not only a substantial initial capital investment, but also a large number of high-quality and innovative R&D personnel, as well as efficient human resource management methods, strong financial support, and production capacity. Therefore, these factors become important guarantees for improving the technological innovation of enterprises.

(2) Potential cross-action and influence modes among influencing factors. There are potential interactions among mechanism innovation, innovation strategy, protection measures, innovation output, and enterprise technological innovation. For example, the interaction mode between mechanism innovation, innovation strategy, manufacturing capability, and technological innovation capability explains how effective enterprise organization management mechanisms, talent incentive mechanisms, and integrated resource allocation have an important impact on an enterprise's manufacturing and technological innovation capability. In addition, protection measures also have a potential impact on innovation strategy and innovation output. Intellectual property protection effectively promotes the progress of enterprise technological innovation, protects the rights of enterprises, and supports the output of innovation achievements. It also plays a role in coordinating and allocating enterprise resources, which is conducive to the success probability of high-quality technology development.

Based on the analysis above of the interaction and influence mode between the influencing factors of enterprises' technological innovation, it is clear that the technological innovation and development of enterprises require not only increased investment in R&D and leveraging of internal and external resources, but also improved organizational management and marketing capabilities to increase the likelihood of successfully developing innovative technological products. Additionally, external support is necessary, such as a resource integration platform for industry-university-research cooperation and government measures for intellectual property protection to improve the effective acquisition of social capital and utilization of knowledge in technological innovation.

5 Conclusion

In this paper, we propose an improved knowledge association analysis based on the semantic concept model (KASC). Our method combines the Single Linked item header table with the Frequent Pattern Growth (SLFP-Growth) algorithm to generate knowledge association rules. We also use the constructed enterprise technology innovation domain ontology and the semantic distance calculation method to rank the association rules.

Our proposed approach addresses three key issues. Firstly, the performance of the SLFP-Growth algorithm is superior to the traditional Apriori algorithm and FP-Growth algorithm in terms of operation time and memory usage on the same textual dataset. This solves the issue of the traditional algorithm's time and space complexity, and our SLFP-Growth algorithm is simpler and more efficient. Secondly, the proposed KASC model leverages the rich semantic knowledge and hierarchical structure of the domain ontology, eliminating the knowledge gap that often arises in the mining and pruning process of traditional association rule methods. Thirdly, based on the technological innovation data provided by 400 enterprises in Beijing, we use our proposed KASC method to discover the potential correlation and interaction modes between the influencing factors of enterprises' technological innovation. The intelligent analysis results can provide reference for enterprises on technological innovation decision-making.

In the future, we suggest continuing this research in several directions. Firstly, other methods such as text clustering methods should be integrated into the evaluation index system construction to provide enterprises with technological innovation decision-making. Secondly, future research may consider using a general ontology that can be applied to more fields.

Funding

This research was supported by the Youth Research Fund Project of Beijing Wuzi University (2022XJQN19) and The Edge computing security technology and product projects for 5G converged application security guarantee (TC220H054)

Author contributions

Qianqian Zhang: Conceptualization, Methodology, Formal analysis, Writing-Original Draft. Guining Geng: Project administration, Funding acquisition. Qun Tu: Software, Writing-Review and Editing.

Conflict 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.

References

[1] Agarwal, R.(2017). Decision making with association rule mining and clustering in supply chains *International Journal of Data and Network Science*, 1(1),11-18,2017.

[2] Agarwal, R.; Pareek, S.; Sarkar, B.; Mittal, M. (2018). Ordering policy using multi-level association rule mining *International Journal of Information Systems and Supply Chain Management*, 11(4),84-101,2018.

[3] Alangari, N.;Alturki, R. (2020). Association rule mining in higher education: A case study of computer science students *Smart Infrastructure and Applications: Foundations for Smarter Cities and Societies*, 311-328,2020.

[4] Barton, D.L.(1992). capabilities and core rigidities: A paradox in managing new product development *Strategic management journal*, 13(S1),111-125,1992.

[5] Bloch, C.(2007). Assessing recent developments in innovation measurement: the third edition of the Oslo Manual *Science and Public Policy*, 34(1),23-34,2007.

[6] Boone,T.;Ganeshan,R.;Jain, A.;Sanders, N.R.(2019). Forecasting sales in the supply chain: Consumer analytics in the big data era. *International Journal of Forecasting*, 35(1),170-180,2019.

[7] Borah, A.; Nath, B.(2018). Identifying risk factors for adverse diseases using dynamic rare association rule mining, *Expert systems with applications*, 113,233-2632018,2018.

[8] Burgelman,R.A.;Christensen,C.M.;Wheelwright,S.C.(1998). *Management of technology and innovation*, McGraw-Hill/Irwin, 2008.

[9] Cetindamar, D.;Shdifat, B.; Erfani,E.(2022). Understanding big data analytics capability and sustainable supply chains, *Information Systems Management*, 39(1),19-33,2022.

[10] Chen, J.;Adamson, C.(2015). Innovation: Integration of random variation and creative synthesis, *Academy of Management Review*, 40(3),461-464,2015.

[11] Das, S.;Sun, X.;Goel, S.;Sun, M.;Rahman, A.;Dutta, A.(2022). Flooding related traffic crashes: findings from association rules *Journal of Transportation Safety & Security*, 14(1),111-129,2022.

[12] Davidaviciene, V.;Markus, O.;Davidavicius, S.(2020). Identification of the opportunities to improve customer's experience in e-commerce, *Journal of logistics, informatics and service science*, 42-57,2020.

[13] Diaconu, M.(2011). Technological Innovation: Concept, Process, Typology and Implications in the Economy, *Theoretical & Applied Economics*, 18(10),2011.

[14] Du, G.;Liu, Z.;Lu, H.(2021). Application of innovative risk early warning mode under big data technology in Internet credit financial risk assessment, *Journal of Computational and Applied Mathematics*, 386,113260,2021.

[15] Ducange, P.; Pecori, R.; Mezzina, P.(2018). A glimpse on big data analytics in the framework of marketing strategies, *Soft Computing*, 22(1),325-342,2018.

[16] Erevelles, S.;Fukawa, N.;Swayne, L.(2016). Big Data consumer analytics and the transformation of marketing, *Journal of business research*, 69(2),897-904,2016.

[17] Frishammar, J.; Florén, H.; Wincent, J.(2010). Beyond managing uncertainty: Insights from studying equivocality in the fuzzy front end of product and process innovation projects, *IEEE Transactions on Engineering Management*, 58(3),551-563,2010.

[18] Guleria, P.;Sood, M.(2020). Intelligent Data Analysis Using Hadoop Cluster–Inspired MapReduce Framework and Association Rule Mining on Educational Domain, *Intelligent Data Analysis: From Data Gathering to Data Comprehension*, 137-156,2020.

[19] Guo, Y.;Wang, N.;Xu, Z.Y.;Wu, K. (2020). The internet of things-based decision support system for information processing in intelligent manufacturing using data mining technology, *Mechanical Systems and Signal Processing*, 142,106630,2020.

[20] Hartmann, P.M.; Zaki, M.; Feldmann, N.;Neely, A.(2016). Capturing value from big data–a taxonomy of data-driven business models used by start-up firms, *International Journal of Operations & Production Management*, 36(10),1382-1406,2016.

[21] Hall, L.A.;Bagchi-Sen, S.(2007). An analysis of firm-level innovation strategies in the US biotechnology industry, *Technovation*, 27(1-2), 4-14, 2007.

[22] Hosseinioun, P.; Shakeri, H.; Ghorbanirostam, G.(2016). Knowledge-Driven decision support system based on knowledge warehouse and data mining by improving apriori algorithm with fuzzy logic, International Journal of Computer and Information Engineering, 10(3),528-533,2016.

[23] Issad, H.A.; Aoudjit, R.; Rodrigues, J.J.P.C.(2019). A comprehensive review of Data Mining techniques in smart agriculture, *Engineering in Agriculture, Environment and Food*, 12(4),511-525,2019.

[24] Kamsu-Foguem, B.; Rigal, F.; Mauget, F.(2013). Mining association rules for the quality improvement of the production process, *Expert systems with applications*, 40(4),1034-1045,2013.

[25] Kao, H.A.; Hsieh, Y.S.; Chen,C.H.;Lee, J. (2017). Quality prediction modeling for multistage manufacturing based on classification and association rule mining *MATEC Web of Conferences* 123,00029,2017.

[26] Kline, S.J.;Rosenberg, N.(2010). An overview of innovation, *Studies on science and the innovation process: Selected works of Nathan Rosenberg*, 173-203,2010.

[27] Kumar,T.S.(2020). Data mining based marketing decision support system using hybrid machine learning algorithm, *Journal of Artificial Intelligence*, 2(03),185-193,2020.

[28] Lee, C.K.H.; Choy, K.L.;Ho, G. T.; Chin, K. S.; Law, K. M.; Tse, Y. K.(2013). A hybrid OLAP-association rule mining based quality management system for extracting defect patterns in the garment industry, *Expert Systems with Applications*, 40(7),2435-2446,2013.

[29] Li, X.;Wang, Y.;Li, D.(2019). Medical data stream distribution pattern association rule mining algorithm based on density estimation *IEEE Access*, 7,141319-141329,2019.

[30] Li, C.; Chen, Y.; Shang, Y.(2022). A review of industrial big data for decision making in intelligent manufacturing, *Engineering Science and Technology*, 29,101021,2022.

[31] Li, J.; Pan, S.; Huang, L.(2019). A machine learning based method for customer behavior prediction, *Tehnički vjesnik*, 26(6),1670-1676,2019.

[32] Li, J.(2022). Venture financing risk assessment and risk control algorithm for small and medium-sized enterprises in the era of big data, *Journal of Intelligent Systems*, 31(1),611-622,2022.

[33] Liu, P.;Wang, Q.;Liu, W.(2021). Enterprise human resource management platform based on FPGA and data mining, *Microprocessors and Microsystems*, 80, 103330, 2021.

[34] Lin, H.;Sun, H.(2022). Short-Term Demand Forecasting Methods for Public Bicycles Under Big Data Environment, *Innovative Computing: Proceedings of the 4th International Conference on Innovative Computing*, 1039-1046,2022.

[35] Lokshin, B.;Van Gils, A.;Bauer, E.(2009). Crafting firm competencies to improve innovative performance, *European Management Journal*, 27(3),187-196,2009.

[36] Ma, D.;Hu, J.;Yao, F.(2021). Big data empowering low-carbon smart tourism study on low-carbon tourism O2O supply chain considering consumer behaviors and corporate altruistic preferences, *Computers & Industrial Engineering*, 153,107061,2021.

[37] Maheshwari, S.;Gautam, P.;Jaggi, C. K.(2021). Role of Big Data Analytics in supply chain management: current trends and future perspectives, *International Journal of Production Research*, 59(6),1875-1900,2021.

[38] Mesbahi, N.;Kazar, O.; Benharzallah, S.;Zoubeidi, M.;Bourekkache, S.(2015). Multi-agents approach for data Mining based K-Means for improving the decision process in the ERP systems, *International Journal of Decision Support System Technology*, 7(2),1-14,2015.

[39] Nazifa, T.H.;Ramachandran, K.K.(2019). Information sharing in supply chain management: a case study between the cooperative partners in manufacturing industry, *Journal of System and Management Sciences*, 9(1),19-47,2019.

[40] Ogbuke, N.J.; Yusuf, Y.Y.;Dharma, K.;Mercangoz, B.A.(2022). Big data supply chain analytics: ethical, privacy and security challenges posed to business, industries and society, *Production Planning & Control*, 33(2-3),123-137,2022.

[41] Orsic, J.;Rosi, B.;Jereb, B.(2019). Measuring sustainable performance among logistic service providers in supply chains, *Tehnicki vjesnik*, 26(5),1478-1485,2019.

[42] Paul, R.;Groza, T.;Hunter, J.;Zankl, A.(2014). Semantic interestingness measures for discovering association rules in the skeletal dysplasia domain, *Journal of biomedical semantics*, 5(1),1-13,2014.

[43] Pietronudo,M.C.;Croidieu, G.;Schiavone, F.A.(2022). solution looking for problems? A systematic literature review of the rationalizing influence of artificial intelligence on decision-making in innovation management, *Technological Forecasting and Social Change*, 182,121828,2022.

[44] Salamai, A.;Saberi, M.;Hussain. O;Chang, E.(2018). Risk identification-based association rule mining for supply chain big data, *Security, Privacy, and Anonymity in Computation, Communication, and Storage: 11th International Conference and Satellite Workshops, SpaCCS 2018*, 219-228,2018.

[45] Schumpeter, J.A. (2013). *Capitalism, socialism and democracy*, routledge, 2013.

[46] Seyedan, M.;Mafakheri, F.(2020). Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities, *Journal of Big Data*, 7(1),1-22,2020.

[47] Shang, H.;Lu, D.;Zhou, Q.(2021). Early warning of enterprise finance risk of big data mining in internet of things based on fuzzy association rules, *Neural Computing and Applications*, 33,3901-3909,2021.

[48] Shelke, R.R.;Dharaskar, R.V.;Thakare,V.M.(2017). Data mining for supermarket sale analysis using association rule, *International Journal of Trend in Scientific Research and Development*, 1(4),179-183,2017.

[49] Shirazi, F.;Mohammadi, M.(2019). A big data analytics model for customer churn prediction in the retiree segment, *International Journal of Information Management*, 48,238-253,2019.

[50] Tiwari,S.;Wee, H.M.;Daryanto,Y.(2018). Big data analytics in supply chain management between 2010 and 2016: Insights to industries, *Computers & Industrial Engineering*, 115,319-330,2018.

[51] Thakkar,R.G.;Kayasth,M.;Desai,H.(2014). Rule based and association rule mining on agriculture dataset, *International Journal of Innovative Research in Computer and Communication Engineering*, 2(11),6381-6384,2014.

[52] Wang,G.J.;Jin,S.G.(2015). Design and development of intelligent logistics system based on data mining and association rules technology, *dvanced Materials Research*, 1078,392-396,2015.

[53] Yao,L.(2019). Financial accounting intelligence management of internet of things enterprises based on data mining algorithm, *Journal of Intelligent & Fuzzy Systems*, 37(5),5915-5923,2019.

[54] Zhou, H.;Sun, G.;Fu, S.;Fan, X.;Jiang, W.;Hu, S.;Li,L.(2020). A distributed approach of big data mining for financial fraud detection in a supply chain, *Comput Mater Continua*, 64(2),1091-1105,2020.

Cite this paper as:

Zhang, Q.; Geng, G.; Tu, Q. (2023). Association mining-based method for enterprise's technological innovation intelligent decision making under big data, *International Journal of Computers Communications & Control*, 18(2), 5241, 2023.

https://doi.org/10.15837/ijccc.2023.2.5241