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Associated Patterns in Open-Ended Concept Maps within E-Learning

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ABSTRACT

A concept map is a diagram that visualizes the structure of individual cognitive knowledge. An approach to creating a concept map structure that allows users to contribute concepts and linkages that express their understanding freely is known as an "open-ended concept map." It has been demonstrated that an open-ended concept map accurately depicts student knowledge structures and reveals student differences. However, manually analyzing an open-ended map is difficult, time-consuming, and includes many propositions, especially in a big classroom. Educational data mining could be used to further process and analyze a collection of concept maps. However, many works attempted to employ data mining in order to produce concept maps structure from text documents rather than examining the knowledge representation. This study aimed to identify hidden students' knowledge representation combination patterns using association rules analysis. The dataset used in this study consisted of 27 open-concept maps created by university students. This study found interesting patterns that reveal students' knowledge in understanding the material given by the teacher.

I. Introduction

Concept maps are widely known as graphical tools that facilitate the representation of individual cognitive knowledge. It has been demonstrated that concept maps are beneficial for instruction, learning, and evaluation [1][2]. The concept map comprises concepts or nodes, connecting or linking lines, connecting or linking words, and organized concept maps that can be created by the students or directly provided by the instructor [3]. Even though the concept map elements only consist of concepts and links, they can capture individual knowledge accurately [2][4]. A learner may benefit from concept maps if they want to memorize material meaningfully and develop more casually valuable reading comprehension skills.

In a concept map, ideas are depicted as nodes, and connections between concepts are established using linking labels to construct propositions [5]. Propositions could be statements about some real object or things in the universe that either happen naturally or are artificially created [6][7]. It provides a concept map's logical and meaningful structure by emphasizing how concepts are connected each other. The concept map's essential components are propositions, which are the concept map's small semantic units. As a result, it might be seen as an essential part of cognitive knowledge [8][9]. The proposition represents the declarative knowledge the unit used to shape meaningful information.

Two basic methods for creating concept maps are closed-ended and open-ended [1][2]. In open-ended concept map construction, individuals can generate and add their concepts and relationships without any predetermined structure or constraints. This approach allows for creativity and flexibility, as learners can explore diverse connections and expand the concept map based on their unique understanding and insights. On the other hand, closed-ended concept map construction follows a predefined structure or template with specific concepts and relationships already provided [10]. This style provides a more guided and structured learning experience, focusing on specific concepts and

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relationships the instructor or curriculum deems essential. While closed-ended concept maps may be more efficient in conveying specific knowledge or following a particular learning objective, open-ended concept maps foster critical thinking, creativity, and a deeper exploration of the subject matter [6].

Compared to the closed-ended strategy, the open-ended approach presents more significant evaluation challenges. Judging students' open-ended idea maps may involve rubrics and expert assessment [11][12]. However, rubrics have their limitations, particularly regarding different open-ended learners' concept maps. The rubric takes time and does not allow for a thorough assessment of learners' knowledge structure [12]. It is challenging for teachers to identify specific student mental model patterns because of the variety of concept maps. The data mining technique is one method that could be used to manage and analyze concept maps automatically.

Data mining, commonly called knowledge discovery in data (KDD), is the systematic exploration and analysis of extensive datasets to unveil patterns and extract valuable insights. Data mining is synonymous with extracting information from large datasets to discover significant hidden knowledge patterns. Unlike text mining which extracts patterns from natural language texts, data mining extracts patterns from structured databases [13]. Educational Data Mining (EDM) is a widespread use of data mining in education. It has been demonstrated to have numerous advantages. EDM is an emerging multidisciplinary field of research that focuses on providing methods for examining data generated in an educational context [14][15]. It uses computational approaches to examine educational data in studying education topics. EDM focuses on creating tools for examining the special forms of data present in educational settings to improve understanding and learning environments.

Numerous research has previously examined the effects of data mining techniques on maintaining concept maps. For instance, a valuable study [16] described a process known as Concept Map Mining (CMM) that involves autonomously creating concept maps from a text. CMM is a process for automatically or partially creating concept maps from the source text. Another relevant study attempted to generate concept maps automatically by utilizing input in text documents and applying association rules mining [17]. Still related to making semi-automatic concept maps, a recent study offers easy concept map making on English reading materials and shows satisfactory results [18]. Instead of reviewing the concept map that the learners created, CMM strives to build a concept map that offers reliable information about the student's comprehension. Concept maps from source documents could be automatically or partially created using CMM.

Although several studies on mining concept maps have been carried out, only a few have analyzed the knowledge structure. The current study processed open-ended maps structure and examined students' comprehension of study topics using data mining techniques. Previous studies that resemble this study have been conducted by Yoo and Cho [12]. They used association analysis and sub-graph mining tasks to investigate students' understanding quickly and accurately. In practice, they provided a predefined concept map and asked learners to draw by hand.

Furthermore, the student hand-drawn concept maps were digitized and processed using a data mining approach. On the other hand, the prior strategy was designed for closed-ended concept maps that refer to students' understanding instead of open-ended concept maps. This study investigated the application of association rules analysis to uncover crucial hidden information that quickly represents students' understanding of a Database topic.

II. Method

In this study, utilizing data mining operations on open-ended (or low-directed) concept maps to swiftly determine learners' knowledge is called "mining concept maps." In particular, the concept maps data was subjected to the association rules analysis methodology to uncover significant hidden information. However, open-ended concept maps created by students could not be as interpreted as closed-ended ones, which have provided components to be reconstructed. Figure 1 shows the general process required in open-ended concept map mining activities.

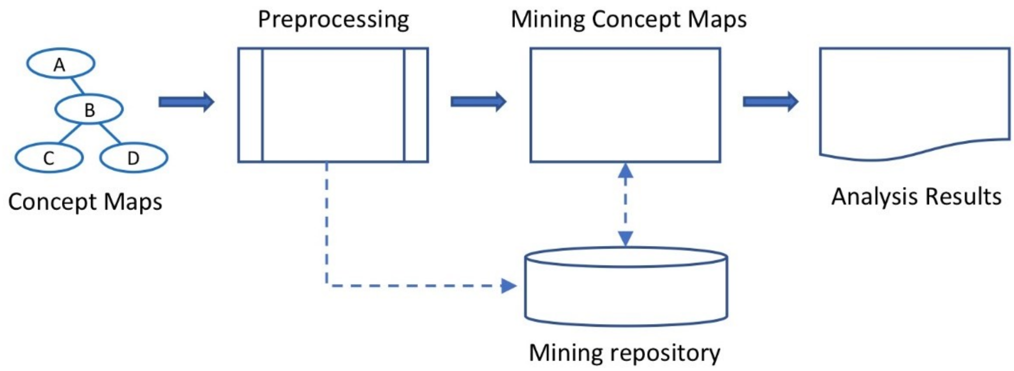

Fig. 1. General mining concept maps process

The association rule is an appropriate data mining operation for assessing the degree of correlation between different database variables [19]. By identifying particular patterns, it seeks to find regularity in the data. Finding crucial connections between the elements in each transaction is the core task of association rules. The relationship may show how strong a rule is inside the group. Depending on the characteristics and data requirements, most association rules are solved using a priori algorithms [20].

A. *Dataset and Preprocessing*

The data source used in this study was a dataset generated from open-ended concept maps created by 27 university students. Learning was carried out by utilizing a web-based e-learning system. In relational database material, students were asked to demonstrate their comprehension after the teacher delivers the lecture material. Furthermore, student concept maps were stored in the database as a corpus concept map. The concept map extraction stage produces a dataset of 27 open-ended concept maps describing students' knowledge of relational database topics.

Preprocessing was done before carrying out the main activity, as is typical for data mining activities in general. Preparing the data is a crucial phase in the data mining process and a crucial effort. Data preparation and form-fitting transformation are both included. The techniques used in the data preparation stage are designed to enhance the dataset or data used in the modeling step. In order to ensure that the modeling step can produce the best results consistent with expectations, a preprocessing approach, cleaning process, and data selection will be carried out at this point.

The primary objectives of preprocessing include normalizing data, lowering data size, determining how the data connect, removing outliers, and extracting features from the data [21]. The preprocessing phase was applied to the concept pairings that make up the relationships on the concept maps. It creates a useful and effective framework from the unprocessed ideas and propositions data. The set of propositions on the concept maps created by the students was first processed during this step. Initial processing involves cleaning up the data, tokenization, and reading and analyzing concept maps from the data source [22].

B. *Association Rules Mining*

The stages of association rules mining in this study are shown in Figure 2. Preparation is the initial stage in open-ended concept map mining to prepare data for further analysis. Concept recognition involves the identification of potential candidates for key ideas in a student's knowledge structure. The student's knowledge structure is recognized and retrieved from the relational database system. The frequent one itemset method was used to ascertain the emergence of concepts in each student's knowledge. The group's organizational structure was analyzed since the concept is a special component in each learner's knowledge. Additionally, the concept identification function results could be verified to find out which concepts students understand through the developed knowledge structure. The support value for a single itemset X is computed by dividing the count of operations that contain X by the total number of operations and is given by the formula Support (X) = PX / P total.

Relationships refer to statements explaining how two particular labels relate ideas. During the relationship's detection phase, each concept wholly linked to another idea is acknowledged as a sub-concept map. Association rules or collections of frequently occurring elements illustrate the relationships. For instance, the frequent itemset of terms "A – B" shows that there was a close connection between the terms "A" and "B" in the learning content.

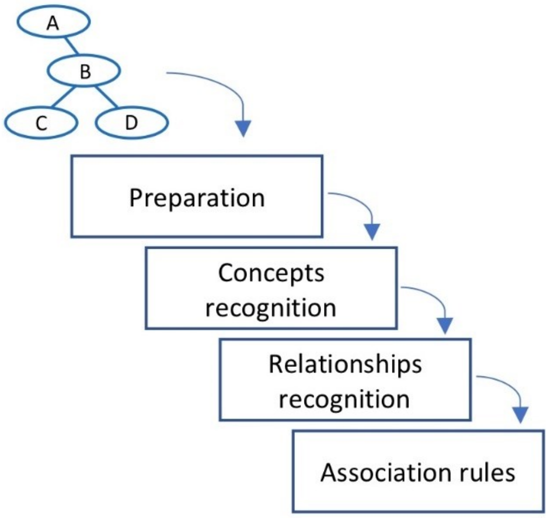

Fig. 2. The flow of association rules analysis

The association rules phase reveals fascinating connections or links among various data points [2][23]. It shows characteristics that have a high likelihood of coexisting in a dataset. The primary aim of association rules is to discover patterns that demonstrate the simultaneous occurrence of features within a database. An association rule is a formula that says X => Y, where X and Y are two sets of items. It suggests that database transactions containing X are more likely to have Y [19]. For instance, the item sets (a, b) => (c, d) together appear in 5 out of 10 learners' concept maps. Thus, it can be said that 50% of the learners have the same understanding of topics (a, b) and (c, d) in the learning materials.

Support and confidence criteria are frequently used to evaluate the validity of association analysis results [24][25][26]. The lower the minimum support value, the more items appear in the frequent itemset [27][28][29]. A low minimum support value will also increase the frequency of itemset at a higher level. Conversely, the higher the minimum support value, the fewer items that appear will have an impact. Therefore, improving the recognition of special patterns by raising the support value is possible.

Support is commonly expressed in probability notation as support (X => Y) = P (X Y) for a two-item set. The equation indicates the frequency of the rule inside transactions. The confidence value was further tested using associative rules after receiving a frequent high value. Confidence (X => Y) = P (Y | X) is the formula for a directional connection. It displays the proportion of transactions that contain both X and Y. This study examined frequent association idea map mining using the Apriori method.

III. Results and Discussion

The preparation phase which was carried out on a dataset of 27 open-ended concept maps resulted in 505 concepts and 283 propositions. Next, the association rules mining stage begins by uncovering the frequent itemset of concepts in class groups consisting of 27 learners. This analysis was based on a unique collection of concepts defined by each group member. The goal of this operation was to find the concepts in the group that has the highest frequency. The results of the formation of frequent 1-itemset combinations with a minimum support value of 40% are shown in Table 1. The results of the frequent 1-itemset concepts show the ideas most expressed by students in relational database material.

Table 1. Concepts Frequent itemset

Concepts	Frequency	Support (%)
relational database	22	81
relation	22	81
attribute	22	81
tuple	22	81
domain	21	78
cardinality	20	74
two-dimensional table	17	70
degrees	14	52
super key	13	48
row and column	13	48
candidate key	12	44
primary key	12	44
simple	12	44
term	12	44

Table 1 explains that the concepts "relational database", "relational", "attribute", and "tuple" are the most frequently occurring ideas with a frequency value of 22 (support 81%). This value states that as many as 22 learners jointly define these ideas on their concept map. When viewed from the substance of the relational database material, these ideas have a close relationship with the topic of the material. Nevertheless, further analyses must be conducted to uncover other, more obvious association patterns.

In the open-ended concept map, the concept is an essential element representing an individual's original idea. However, concept analysis cannot reveal essential and hidden information on concept maps. This condition is very different from the market basket case, which considers terms as independent data to be analyzed directly. In the case of concept maps, the appearance of concepts *a* and *b* in some concept maps does not necessarily indicate them as important terms unless they are related. The concept will not have any meaning when it is not associated with other concepts to form a proposition. Therefore, an analysis that focuses on the propositions the learners have created is required.

Further investigation was done to identify patterns of frequent relationships that represented learners' knowledge of the propositions that have been made. Table 2 lists the relationships with a minimum support level of 20%. With the results of the frequent itemset of concepts, the pattern of frequent relationships appears to be consistent.

Relationships "two-dimensional table – row and column" appear 10 times with a support value of 37%. These results state that some 10 learners define the proposition "two-dimensional table – row and column" on their concept map. Referring to the results of the concept frequent itemset, the concept of "two-dimensional table" has a frequency value of 17 (support 70%), while "row and column" weights 13 (support 48%). This condition confirms that the proposition "two-dimensional table – row and column" is formed from concepts often appearing in concept map collections. Thus, the relation "two-dimensional table – row and column" became the dominant proposition representing learners' understanding of learning materials.

Table 2. Relationships frequent itemset

Relationships	Frequency	Support (%)
two-dimensional table -- row and column	10	37
term -- relation	8	30
term -- attribute	8	30
term -- tuple	8	30
relational database -- profit	7	26
term -- domain	7	26
relational database -- term	7	26
relational key -- super key	6	22
term -- degrees	6	22
relational key -- candidate key	6	22
relational database -- relational key	6	22

Further analysis is carried out on the frequent itemset relationships formed by identifying concept pairs. This research aims to reveal whether the concept pairs in the proposition are considered concepts in the frequent itemset list of concepts with at least 40% support. Table 3 shows the concepts marked in bold, indicating that they are in the list of frequent itemset concepts.

The identification results of Table 3 emphasize again that the propositions formed by learners consist of concepts with a high emergence value. Almost all concepts are found in frequent items concepts with a minimum support value of 40%, except for the "profit" and "relational key" concepts. Even so, the emergence value of the concept of "profit" was 9 times (support 33%) and the concept of "relational key" was 10 times (support 37%).

Table 3. Relationships frequent itemset

Relationships	In concepts frequent itemset	
	Concept 1	Concept 2
two-dimensional table -- row and column	yes	yes
term -- relation	yes	yes
term -- attribute	yes	yes
term -- tuple	yes	yes
relational database -- profit	yes	no
term -- domain	yes	yes
relational database -- term	yes	yes
relational key -- super key	no	yes
term -- degrees	yes	yes
relational key -- candidate key	no	yes
relational database -- relational key	yes	no

Further analysis is to combine the support and confidence value parameters to get the association rules patterns. Table 4 depicts the results of the investigation of the concept association rules by applying the minimum support and confidence of 50% and 90%, respectively. The minimum support was set at 50% because a lower value would result in more patterns. To obtain fascinating patterns with a manageable number of numbers, some researchers advise using a minimum value of 90% confidence [30]. Too many patterns make extracting valuable insights into the dataset difficult.

Table 4. Concepts association rules

Association rules	Min-Support (%)	Min-Confidence (%)
degrees => domain	50	100
degrees => relation	50	100
degrees => attribute	50	100
degrees => tuple	50	100
degrees => relational database	50	100
attribute => tuple	50	96
tuple => attribute	50	96
domain => attribute	50	96
domain => tuple	50	96
cardinality => domain	50	95
cardinality => relation	50	95
cardinality => attribute	50	95
cardinality => tuple	50	95
relation => attribute	50	91
relation => tuple	50	91
attribute => domain	50	91
attribute => relation	50	91
tuple => domain	50	91
tuple => relation	50	91
domain => relation	50	91

The frequent sub-concept maps were examined to see if any new hidden patterns might emerge. Frequent sub-concept maps illustrate the link between propositions a and b on idea maps. Further analysis was conducted using association rules to find patterns in the propositions formed. Two settings were applied to the pattern search for relationships. The first used minimum support of 30% and 100% confidence, and the second applied a minimum support of 20% and 90% confidence. This processing stage was based on the fact that no relationship patterns were found when the support value was more than 30%. Table 5 shows the results of association rules analysis on propositions with relational database material.

Table 5. Propositions association rules

Association rules	Min-Support (%)	Min-Confidence (%)
term -- attribute => term -- relation	30	100
term -- attribute => term -- tuple	30	100
term -- relation => term -- attribute	30	100
term -- relation => term -- tuple	30	100
term -- tuple => term -- relation	30	100
term -- tuple => term -- attribute	30	100
profit -- simple => term -- relation	20	90
profit -- simple => term -- attribute	20	90
profit -- simple => term -- tuple	20	90
profit -- simple => term -- domain	20	90
profit -- simple => term -- degrees	20	90
term -- attribute => term -- relation	20	90
term -- attribute => term -- tuple	20	90
term -- relation => term -- attribute	20	90
term -- relation => term -- tuple	20	90
term -- tuple => term -- relation	20	90
term -- tuple => term -- attribute	20	90
term -- domain => term -- relation	20	90
term -- domain => term -- attribute	20	90
term -- domain => term -- tuple	20	90
term -- degrees => term -- relation	20	90
term -- degrees => term -- attribute	20	90
term -- degrees => term -- tuple	20	90
term -- degrees => term -- domain	20	90
term -- cardinality => term -- relation	20	90
term -- cardinality => term -- attribute	20	90
term -- cardinality => term -- tuple	20	90
term -- cardinality => term -- domain	20	90

Data mining approaches may be useful for revealing hidden information in the context of education, in line with prior studies [31]. This study revealed that data mining techniques made it possible to determine how well students understood an open-ended concept map construction. In particular, teachers might immediately identify recurring ideas, common connections, and relationships analysis developed by students through association rules.

Analysis of association rules applied to a collection of open-ended concept maps reveals new concept and proposition formation patterns. Teachers can use the results of these findings to understand learners' knowledge in capturing material. Furthermore, teachers gain important insights regarding the association of forming concepts and propositions in electronic learning activities using concept maps.

A weight is given for each concept on the concept maps to determine its frequency. Frequent itemset of concepts makes it easier for teachers to identify original ideas related to learning materials. After exposing the frequent itemset of relationships in the context of the concept map, the teacher benefited greatly because it highlighted that relationships are illustrations of propositions on the concept map [1][2]. Weight was assigned to each instance of a proposition in the concept map to make clear its function. Finally, teachers could record their students' understanding patterns by creating association rules. This information is significant because it reveals what they believe after learning new information.

This study also identified several issues that need to be considered to improve the operation of association rules. Since the concept map was formed with an open-ended approach, there are possibly several terms that have the same meaning but are written differently, for example, "two-dimensional table," “2-dimensional table”, and “2D table”. As a result, manual spelling correction was required to obtain the correct expression. Additionally, a semantic similarity approach might be suggested to produce more accurate results.

IV. Conclusion

The current study uses data mining techniques to uncover hidden data in e-learning built on open-ended concept maps. The association rule analysis using the Apriori algorithm was used to identify the pattern of association knowledge among students studying relational databases. This study discovered that data mining methods can potentially interpret sizable collections of open-ended concept maps effectively. The analysis's findings showed that forming patterns of association rules and frequent item sets for concepts, relationships, and relationships between concepts could reveal the learners' level of understanding. Association analysis quickly uncovers valuable insight compared to laborious and time-consuming manual processing. The extent to which the students comprehend the information the teacher has presented can also be determined using the discovered associative rules.

Some restrictions on this study should be considered. In order to get more trustworthy results, the experiment's use of a relatively small number of concept maps as data sets needed to be expanded. Second, the Apriori algorithm, which is typically less effective when dealing with large data sets, was used in this study. So, it is possible to test other algorithms like FP-Growth, hash-based, or Generalized Rules Induction. Additionally, association rules analysis that merely expresses the percentage of proposition combinations was the focus of the current study. Applying other operations, such as comparing concept maps made by students and teachers, is fascinating.

Declarations

Author contribution

All authors contributed equally as the main contributor of this paper. All authors read and approved the final paper.

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Conflict of interest

The authors declare no known conflict of financial interest or personal relationships that could have appeared to influence the work reported in this paper.

Additional information

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References

[1] T. Hirashima, "Reconstructional concept map: Automatic Assessment and reciprocal reconstruction," Int. J. Innov. Creat. Chang., vol. 5, no. 5, pp. 669–682, 2019.
[2] D. D. Prasetya, A. Pinandito, Y. Hayashi, and T. Hirashima, "Analysis of quality of knowledge structure and students' perceptions in extension concept mapping," Res. Pract. Technol. Enhanc. Learn., vol. 17, no. 1, p. 14, Dec. 2022.
[3] K. E. de Ries, H. Schaap, A.-M. M. J. A. P. van Loon, M. M. H. Kral, and P. C. Meijer, "A literature review of open-ended concept maps as a research instrument to study knowledge and learning," Qual. Quant., vol. 56, no. 1, pp. 73–107, Feb. 2022.
[4] A. Whitelock-Wainwright, N. Laan, D. Wen, and D. Gašević, "Exploring student information problem solving behaviour using fine-grained concept map and search tool data," Comput. Educ., vol. 145, p. 103731, Feb. 2020.
[5] A. J. Cañas and J. D. Novak, "Concept Mapping Using CmapTools to Enhance Meaningful Learning," in Advanced Information and Knowledge Processing, 2014, pp. 23–45.
[6] J. D. Novak and A. J. Cañas, "The Theory Underlying Concept Maps and How to Construct Them," Tech. Rep. IHMC C. 2006-01, no. May, pp. 1–31, 2006.
[7] D. D. Prasetya, T. Hirashima, and Y. Hayashi, "Comparing Two Extended Concept Mapping Approaches to Investigate the Distribution of Students' Achievements," IEICE Trans. Inf. Syst., vol. E104.D, no. 2, pp. 337–340, Feb. 2021.
[8] V. Aleven et al., "Example-Tracing Tutors: Intelligent Tutor Development for Non-programmers," Int. J. Artif. Intell. Educ., vol. 26, no. 1, pp. 224–269, Mar. 2016.
[9] J. Pailai, W. Wunnasri, K. Yoshida, Y. Hayashi, and T. Hirashima, "The practical use of Kit-Build concept map on formative assessment," Res. Pract. Technol. Enhanc. Learn., vol. 12, no. 1, p. 20, Dec. 2017.

[10] A. Cañas, E. Martínez-Ortigosa, B. Prieto, B. Pino, and A. Prieto, “SWAD, an Open Learning Management System: Results and Challenges.,” in EdMedia+ Innovate Learning, 2019, pp. 1496–1509.
[11] E. M. Taricani and R. B. Clariana, “A Technique for Automatically Scoring Open-Ended Concept Maps,” Educ. Technol. Res. Dev., vol. 54, no. 1, pp. 65–82, Feb. 2006.
[12] J. S. Yoo and M.-H. Cho, “Mining Concept Maps to Understand University Students’ Learning,” 2012.
[13] S. Inzalkar and J. Sharma, “A survey on text mining-techniques and application,” Int. J. Res. Sci. Eng., vol. 24, pp. 1–14, 2015.
[14] C. Romero and S. Ventura, “Educational data mining and learning analytics: An updated survey,” WIREs Data Min. Knowl. Discov., vol. 10, no. 3, May 2020.
[15] R. S. Baker, “Challenges for the future of educational data mining: The Baker learning analytics prizes,” J. Educ. Data Min., vol. 11, no. 1, pp. 1–17, 2019.
[16] J. J. Villalon and R. A. Calvo, “Concept Map Mining: A Definition and a Framework for Its Evaluation,” in 2008 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, Dec. 2008, pp. 357–360.
[17] Z. Shao, Y. Li, X. Wang, X. Zhao, and Y. Guo, “Research on a new automatic generation algorithm of concept map based on text analysis and association rules mining,” J. Ambient Intell. Humaniz. Comput., vol. 11, no. 2, pp. 539–551, Feb. 2020.
[18] A. Pinandito, D. D. Prasetya, Y. Hayashi, and T. Hirashima, “Design and development of semi-automatic concept map authoring support tool,” Res. Pract. Technol. Enhanc. Learn., vol. 16, no. 1, p. 8, Dec. 2021.
[19] A. Ait-Mlouk, F. Gharnati, and T. Agouti, “An improved approach for association rule mining using a multi-criteria decision support system: a case study in road safety,” Eur. Transp. Res. Rev., vol. 9, no. 3, p. 40, Sep. 2017.
[20] K. Li et al., “Impact factors analysis on the probability characterized effects of time of use demand response tariffs using association rule mining method,” Energy Convers. Manag., vol. 197, p. 111891, Oct. 2019.
[21] S. A. Alasadi and W. S. Bhaya, “Review of data preprocessing techniques in data mining,” J. Eng. Appl. Sci., vol. 12, no. 16, pp. 4102–4107, 2017.
[22] R. Nacheva, L. Todoranova, S. Sulova, and B. Penchev, “Concept Map Mining Approach Based on the Mental Models Retrieval,” TEM J., vol. 8, no. 4, p. 1484, 2019.
[23] M. Karabatak, M. C. Ince, and A. Sengur, “Wavelet domain association rules for efficient texture classification,” Appl. Soft Comput., vol. 11, no. 1, pp. 32–38, Jan. 2011.
[24] R. Agrawal, T. Imieliński, and A. Swami, “Mining association rules between sets of items in large databases,” in Proceedings of the 1993 ACM SIGMOD international conference on Management of data - SIGMOD ’93, 1993, pp. 207–216.
[25] T. M. Alam et al., “A novel framework for prognostic factors identification of malignant mesothelioma through association rule mining,” Biomed. Signal Process. Control, vol. 68, p. 102726, Jul. 2021.
[26] M. Kaushik, R. Sharma, S. A. Peious, M. Shahin, S. Ben Yahia, and D. Draheim, “A Systematic Assessment of Numerical Association Rule Mining Methods,” SN Comput. Sci., vol. 2, no. 5, p. 348, Sep. 2021.
[27] L. H. Son et al., “ARM–AMO: An efficient association rule mining algorithm based on animal migration optimization,” Knowledge-Based Syst., vol. 154, pp. 68–80, Aug. 2018.
[28] Y. Kurnia, Y. Isharianto, Y. C. Giap, A. Hermawan, and Riki, “Study of application of data mining market basket analysis for knowing sales pattern (association of items) at the O! Fish restaurant using apriori algorithm,” in Journal of Physics: Conference Series, Mar. 2019, vol. 1175, p. 012047.
[29] T. Osadchiy, I. Poliakov, P. Olivier, M. Rowland, and E. Foster, “Recommender system based on pairwise association rules,” Expert Syst. Appl., vol. 115, pp. 535–542, Jan. 2019.
[30] I. H. Witten, E. Frank, M. A. Hall, C. J. Pal, and M. DATA, “Practical machine learning tools and techniques,” in Data Mining, 2005, vol. 2, no. 4.
[31] Y. Xu, “Research of association rules algorithm in data mining,” Int. J. Database Theory Appl., vol. 9, no. 6, pp. 119–130, 2016.