Concept Map Mining Approach Based on the Mental Models Retrieval

Radka Nacheva, Latinka Todoranova,
Snezhana Sulova, Bonimir Penchev

*Department of Informatics, University of Economics – Varna,
9002 Varna, 77 Knyaz Boris I, Blvd., Bulgaria*

Abstract **– Studying the mental models of software users is not a new topic in the scientific literature, but we could point out that it is also not sufficiently researched. Still there is no universal method which could be used for exploration and visual presentation of mental models. Therefore, the aim of the current article is to propose an approach for concept map mining based on retrieving users' mental models. To achieve this, a combination of text mining techniques and concept map software is used in the research article.**

Keywords **– mental models, conceptual models, concept map mining, text mining, human–computer interaction.**

1. Introduction

Software cost, size and schedule forecasting are very complex tasks which require the prediction [1] of many variables. One of the challenges in software development is the creation of an adequate conceptual model representing the software's essence at a high level of abstraction. This model describes mainly the tasks and functions planned for development. When creating the conceptual model it is important to verify and evaluate its consistency according to the user expectations. On the other hand, designing a user interface and developing software functionality based on the users' mental model helps for the creation of simple, intuitive and easy-to-understand products.

DOI: 10.18421/TEM84-54
https://dx.doi.org/10.18421/TEM84-54

Corresponding author: Radka Nacheva,
University of Economics – Varna, Varna, Bulgaria
Email: *r.nacheva@ue-varna.bg*

Received: 20 August 2019.
Revised: 12 October 2019.
Accepted: 18 October 2019.
Published: 30 November 2019.

Moreover, the study of mental models can be accomplished at every stage of the software development, but has been proven that it could be accomplished most effectively in its early stages. Thus, the conceptual model of the software will largely meet user expectations, which in turn could also reduce the costs for future changes caused by the mismatch between the mental models of the developers and those of the users. The high uncertainty and the series of price collapses of some items lead to caution among managers [23]. With web applications one must be careful when choosing the right approach towards any task [22] and the right database management system - MySQL, MS SQL Server and MongoDB [24].

On this basis, **the aim of the current article** is to propose an approach for concept map mining based on retrieving users' mental models. In order to prove the approach, we have studied user expectations for developing a web-based platform which will be used as a guide for people who pursue career development in the field of computer science. The target group includes computer science students and people who intend to change their desired career path in the mentioned field.

2. Mental Models and Their Importance in HCI

A group of authors [2] define mental models as "a logical, temporal and algorithmic structure that stores models of controlling objects, controlling algorithms, influence of external impacts and that has the ability to generate new knowledge". Other researchers [3] define them much simplier, pointing out that they are "cognitive representations of external reality". According to the same scientific paper [3], individuals construct mental models by relying on their unique perceptions, understanding of the world, and life experience. Thagard's opinion [4] is that mental models are structures that determine "many important aspects of human reasoning, including deduction, induction, problem solving, language understanding, and human-machine interaction". On the other hand, Carley and Palmquist [5] make the following assumptions about mental models: a) they are dynamic structures that are considered "working models"; b) when creating mental models it is also important to take into account the circumstances in which they are going to be built.

It could be pointed out that the study of mental models in the context of human-computer interaction is essential for the creation of user-oriented designs that enhance human-machine communication. When interacting with the software interface, the users' approach is often irrational and is mainly driven by their current mental state. As Indi Young notes, mental models are used while studying people's motivation and thought processes, along with the emotional and philosophical landscape in which they are operating. [6]

In the process of interaction with the software, users apply the accumulated knowledge from the usage of similar system-specific software products. In our opinion, the intuitiveness of the human-machine interface, which can be realized by applying real world and design conventions, plays a significant role in the formation of correct mental models. This ensures continuity between the knowledge from different human areas, which in turn facilitates users when perceiving innovations in the field of software interface. Also, we consider that the construction of mental models is strongly dependent on the amount of cognitive resource that users put into the interaction with the products. If the interface is as simple and intuitive as possible, they do not consume additional cognitive resources when performing their tasks. In order to form adequate mental models, the human-machine interface should minimize the thought processes and the involvement of working memory[1].

This often leads to the usage of a combination of different methods, which study the mental models in software development. Examples for such methods are Thinking-aloud protocol, Question-asking protocol, Coaching method, Field observation, Interviews, Focus groups, Contextual inquiry, Surveys. In practice, the study of mental models can also take place in brainstorming sessions. The choice of a particular method is guided by different factors such as budget, duration, the ability to obtain quantitative and/or qualitative data, the ability to conduct the method remotely, etc.

When carrying out some of the methods for studying users' mental models two factors are often taken into account: a) the decision making process while they work with the software, and b) their behavior built in different environments, based on the accumulated knowledge and the specifics of their perceptions. Mental models can be represented by concept maps, mind maps, conceptual diagrams, visual metaphors [20], content maps or charts of similarity [6]. For example, concept maps and mind maps represent the extracted information in the form of terms and relationships between them, often organized in a hierarchical form. Conceptual diagrams in turn require more detailed information of user's expectations, organized into categories and subcategories. They are similar to the class diagrams in UML used by the developers to represent the organization of object-oriented programs.

In our previous study [14], we suggested a hierarchical representation of mental models based on Maslow's pyramid. "We integrate only the idea of using such a diagram with color distinction and categorization, but not with the terminology proposed in Maslow's motivational theory. The model represents ideas generated during a brainstorming session." [14]

Depending on the method used to study the mental models, different visual tools would be used in order to represent users' ideas about the functioning of the software. The choice of a particular visual tool also depends on the needs of the development team.

3. Concept Map Mining: Approaches and Tools

Concept maps support the development of conceptual models of the software user interface and provide guidance on the expected functionality. Thanks to them the so called "design gap" is reduced, which represents the discrepancy between users' knowledge and designers' decisions about the conceptual model of the user interface.

Concept maps (CMs) were introduced by the education theorist Novak in the 1970s in order to assist the process of adopting a new learning material. Today, they find application not only in education but also in many other fields. They are presented as visual maps of concepts for a given domain, also reflecting the links between these concepts in the form of one-way or two-way arrows with added verbs. In [15] concept maps are defined as "a triplet CM = {C; R; G} where C is a set of concepts C = {c1; c2; … ; cn}, R is a set of relations between concepts R = {r1; r2; … ; rk} and G = {g1; g2; … ; gm} is a sorted set of generalization levels". In [16] are described as semantic maps, that are a means of visualization of subject knowledge. "Concept maps stimulate the generation of ideas, and help improving one's own creativity" [17].

The concept map mining (CMM) process is defined in [18] as a "search for common propositions (a triple concept - relationship - concept) and

[1] This is the ability of the human brain to store a limited amount of information as long as it is used. It can be said that this type of memory combines short-term memory with knowledge derived from long-term memory to support processes such as decision-making or calculations.

misconceptions". CMM is based on Natural Language Processing techniques that are used to create concept maps by extracting concepts from text or from a set of documents with the goal of doing this automatically. A lexicon is often used in order to compare the extracted words with the ones recorded in it.

In their research Villalon and Calvo propose a CMM approach that is implemented in the following stages [18]:

- Concept identification using grammar trees;
- Cascading relationship identification;
- Concept and relationship summarization.

This approach includes basic steps used to create concept maps, but it does not take into account the details of the data or text mining techniques that are applied in order to be identified the individual terms and the relationships between them. Moreover, it can be considered theoretical since there is no data presented for its validation.

In [21], CMM is considered as a process based on standard text miming techniques. When extracting text from documents this process is carried out in the following steps:

- preparation phase – the text enriched with semantic information is stored and the rest of it is removed;
- tokenization phase – "document is divided into sentences, and every sentence into tokens";
- linguistic pre-processing – it is carried out in iterations and "the stop words without information value are removed";
- concept recognition phase - concepts candidates are chosen from a set of tokens;
- relationships recognition phase - relationships candidates are the words semantically connected to extracted concepts;
- summarization phase - the most important propositions are chosen based on their statistical significance.

This approach proposes the usage of a dictionary that contains the most important terms in the problem area, so that machine learning methods can be applied to extract text from documents. The authors note that the stop words should only be removed after understanding whether they are building elements in multiword phrases.

[16] defines CMM as the process by which the specifics of CM must be taken into account: „concept maps are more subjective, they depend on the point of view of their creator". The authors base their work on the approach presented in [18]. They propose:

- extraction of concepts – these are words which are strongly attached to the domain as terms;
- extract relations between concepts – the phase should be concentrated on links between terms, i.e. it is used a term-term matrix. For this, it should be found pairwise distances between terms which have been presented by vectors-lines in the initial term-document matrix;
- summary - extracted concepts and relations must be plotted on a concept map.

The common thing about the aforementioned approaches is that they offer the basic stages of concept map formation: concept identification, relationship identification and summarization. Some of them integrate part of the text preprocessing that is really typical for the text mining (TM) approaches. However, they do not take into account the methods that can be used to obtain data connected with the mental models of the users for a certain software. We consider that in order to apply the CMM process to the needs of a software development and, in particular, to study the opinions and expectations of the users, it is necessary that this process is conducted in more coordinated way. This means giving it formal guidance. For example, the process may be considered in the context of a certain standard in order to ensure the quality of the final result.

The CMM process could be supported by different software tools which would automate it. Most of these tools differ mainly in their ability to automate the CMM process. Examples of some concept maps tools are: CmapTools, VUE (Visual Understanding Environment), Mindomo and Leximancer. The first three can be used to create CM using only processed and analyzed text. Leximancer supports a fully automated CMM process and it is a commercial product with a 7-day trial period, unlike the others. Mindomo is also available as a cloud application which in turn could facilitate collaborative work. CmapTools also enables teamwork by offering shared cloud space after creating the user account. Unlike Leximancer, the other software tools do not offer support for importing files that can be used to extract concepts and relationship candidates, and they are not based on Natural Language Processing techniques.

All four tools support basic concept map creation capabilities like concepts creation and named relationships. In addition, they offer export into different files formats, most often xml, pdf, html.

There are a lot of concept map software products, but the aforementioned are the most commonly used, especially for scientific purposes. The choice of a particular product depends mainly on the needs of the study. Each of them can be combined with data mining products such as RapidMiner or KNIME in order to fully process the unstructured data derived from the user responses given while applying one of the methods for studying mental models. For example, this can be observed when processing the text of interviews or questionnaires.

4. Research Methodology

In the current research we propose an approach towards concept map mining, which is based on the study on users' mental models. The concept map mining process can take a formal direction if it is applied to be proven in practice approach, such as the process approach. It aims to assist companies in the process of creating user-oriented interfaces in a coordinated manner, with clearly defined input parameters, constraints and output artifacts. According to [19], it should provide "lower value and faster creation of new products; lower, fixed and predictable costs; an opportunity to dynamically improve the organization's activities."

The input data for the business process presented in fig. 1 are the software requirements of the project.

The constraints that affect the execution of the process relate to the users – their technical knowledge and their current physical and mental state.

As *an output artifact* of the process a concept map that will be used as a basis for predicting user interfaces is expected to be created.

The stages in which the concept map mining process is carried out are presented in fig. 1. They are:

1) Conducting a survey aimed at checking the attitude of potential users to the intended functions. The purpose is to compare the expectations of the designers and the users. A questionnaire divided in three sections is used.
2) Conducting an analysis of the survey results by using statistical methods.
3) Conducting concept map mining – creating a generalized conceptual model by using text mining based on the results of the survey.
4) Refining the conceptual model according to the requirements of the developed software and the suggestions from the development team.

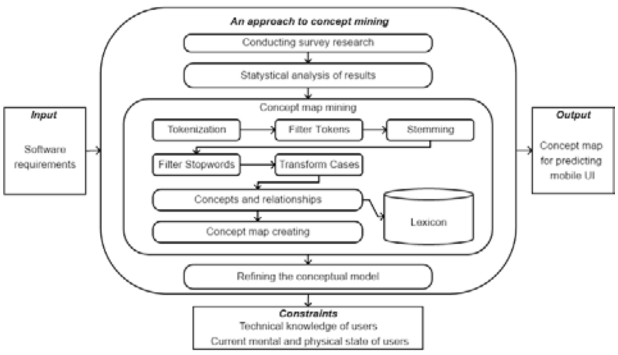

Figure 1. Stages of the proposed approach to concept map mining
(Source: Own elaboration)

The preparation of the **first stage** begins with a study of the subject area, a study of the software with similar functionality and an analysis of the requirements of the potential users. Nowadays, the most effective way to check the attitudes, opinions and expectations for future users regarding the particular product or service is to conduct a survey. In scientific literature there are numerous studies on how to create a survey.

The recommendations are mainly related to determining the purpose of the survey and how to ask the questions [7], [8]. Oracle researchers identify the following 7 best practices for formulating survey questions [9]:

- the questions should be directly related to the purpose of the survey and the purpose in turn should always be clear enough in order to deliver reliable results;
- the questions should be short because the respondents are reluctant to answer long and incomprehensible questions. A good practice is to group questions that use the same answers;
- the questions should be clearly asked, avoiding misleading or hypothetical questions, such as: "Would you not like ...";
- consider the wording and the precision of the language in order to avoid unusual words and combined sentences;
- the questions with several possible answers, should be formulated well enough, in order not to disappoint the respondents that their option is not included;
- the answers of the closed questions should be clear enough, and when a grade scale is used the meanings of each grade should be clear enough;
- the survey should include open-ended questions because they provide valuable feedback from the respondents. Although these types of questions are more difficult to process, in some cases they are appropriate for use because they help to identify important issues in the study area.

Based on the aforementioned recommendations for the purpose of our research, we propose the use of a questionnaire in order to retrieve users' mental models and subsequently verify their compliance with the mental models of the development team. The questions are divided into groups, each with a specific purpose. The groups are:

- Personal profile – this is the data that will be used for the implementation of the statistical analysis;
- Expectations about the platform – closed-ended questions are used in order to describe the concept of the platform design, and text input fields in order to describe the expectations about the application functionality;

- Special needs – these are questions for people with special needs. They are used in order to define whether the respondent has disabilities and what functionalities should be added in order to facilitate the future use of the platform.

In **the second stage** of the approach a statistical analysis of the results is carried out. The goal is to differentiate the respondents by gender and age, for example, in order to evaluate which functionality will be useful for each user group.

The third stage of the approach is to derive concepts from the survey participants' answers. On this basis a concept map with links between the different concepts should be automatically created. For the effective implementation of the current stage we propose the usage of tools from the field of Machine Learning and Text Mining. The use of Text Mining is required in order to accurately analyze the answers of the users to the open-ended questions.

For the analysis and discovery of data models, we suggest the usage of Data Mining technologies, and in particular Machine Learning techniques. Arthur Lee Samuel first identifies machine learning as a field of study that gives computers the ability to learn without being explicitly programmed [10]. The types of machine learning depending on the nature of the feedback are: Supervised Machine Learning and Unsupervised Machine Learning. For the purposes of this study, the methods of Supervised Machine Learning are mainly used. They are characterized with an input example and desired output parameters given by a "teacher". Examples of such classification methods are: decision tree, linear classification, rule classification, probability classifications.

In order to accurately analyze the answers of the users to the open-ended questions, the use of word processing is also required. This is a scientific problem that is studied by many researchers. In scientific literature, the processing of text arrays is known as Text Mining, (TM) [11], [12]. The typical TM tasks are: text categorization, clustering, concept extraction, grammatical taxonomy, attitude and relationship analysis, document annotation, and modeling of relationships between entities [13]. We consider that in our study the most useful task will be concept extraction, because it will be used to understand users' attitudes and perceptions of the software design.

In general, the current stage requires the implementation of a large set of algorithms, which are highly dependent on the nature of the analyzed data. For this reason, we consider that at this stage of the approach it is not possible for us to define certain algorithms that will be valid for each project. The use of methods such as Simple Linear Regression and Multiple Linear Regression methods are appropriate to find the dependencies between the offered functionalities. Depending on the specific needs of the developers, it is often appropriate to apply methods such as Logistic Regression, K Nearest Neighbors, and clustering methods such as K Means.

The processing of the documents is usually based on Natural Language Processing techniques. In order to convert the text into word vectors, we propose the processing to be divided into the following sub-stages:

- Tokenization – it is used to divide the text into its main units - the words and it is not used for text recognition;
- Filter Tokens – it is used to filter the words according to their length. The parameters of this sub-stage set the minimum and maximum word lengths. The purpose is usually to remove the shortest words consisting of 2-3 letters;
- Stemming – it is used to reduce the number of words. With the help of a dictionary for the respective language, the derivatives of a certain word are removed and only the base of the word is left;
- Stopwords – it is used to remove unnecessary words. These are the words that are not important for the post-processing because they carry little information about the content of the text. This stage helps to increase processing speed because it reduces the amount of text;
- Transform Cases – it is used to convert the case of the letters in the text.

In addition, the extracted and processed concepts are compared with the supported lexicon and two more steps are taken:

- Creating concepts and their relationships – a lexicon is used which helps identify the concepts and the words that are semantically related to them;
- Concept map creating – through CM or CMM software a concept map is developed by using the derived concepts and their relationships.

5. Results

The proposed approach has been tested by developing a web-based platform which will be used as a guide for people who pursue career development in web design. The planned main functionalities of the application are presented in fig. 4. They are chosen on the basis of the requirements on the product being developed, as well as on the basis of competitive software of the same class. The purpose of the developers is to offer basic features that largely meet user requirements, and at the same time turn the application into an innovative product.

The first stage, according to the approach suggested in the previous section, is **to conduct a survey**. The questions were organized into groups as mentioned earlier in the approach description. We added additional questions related to the attitude of potential users to certain elements of the user interface.

In **the second stage** of the approach we performed a **statistical analysis**. The online survey was distributed through the Internet and has reached 102 potential users. It was answered by 74 respondents, which represents 72.5% of all the potential respondents. After learning about the features offered by the application and after evaluating their importance, the respondents answered whether or not they would be satisfied with an application that is based on them. The users had the opportunity to answer in free form, and express their personal opinions on the survey questions.

The distribution of the respondents by age group and gender is presented in fig. 2 and fig. 3.

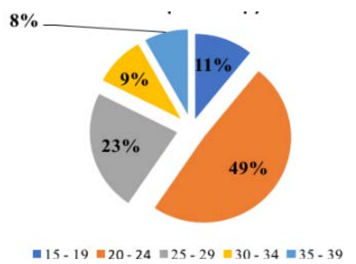

Figure 2. Distribution of the respondents by age group (Source: Own elaboration)

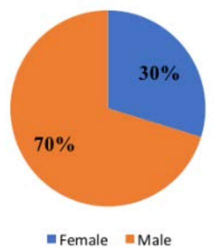

Figure 3. Distribution of the respondents by gender (Source: Own elaboration)

The ratings given by the users to the significance of the proposed functionalities are averaged and are presented in fig. 4. As fig. 4 shows, the values obtained are above 5.5 out of 10, which demonstrate that the users highly appreciate the proposed features.

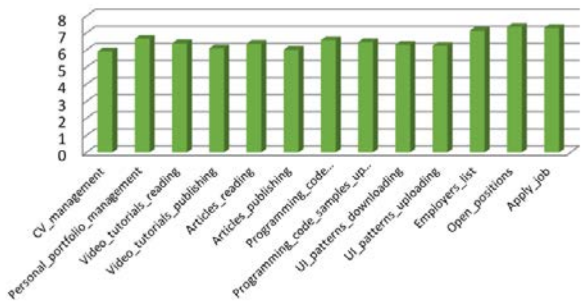

Figure 4. Average grade of the significance of the proposed functionalities (Source: Own elaboration)

In order to determine the dependencies between the proposed functionalities we have conducted an analysis using the Simple Linear Regression method. The results show an extremely strong relationship between the pairs of functionalities, which is expected due to their general nature (e.g., Video tutorials reading and Video tutorials publishing, Employers list and Open job positions). By applying Multiple Linear Regression, we have also found dependencies among the other functionalities, i.e. users who value one of the features also give a high rating to the others and vice versa. The applied classification methods (Logistic Regression, K Nearest Neighbors) and clustering (K Means) do not produce significant results due to the specificity of the collected data. However, in many other cases they would be extremely useful.

Regarding the questions about the need for additional user interface capabilities, users mostly give a negative answer (fig. 5).

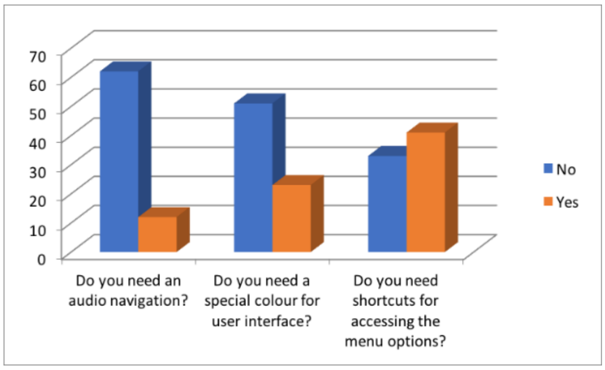

Figure 5. Average grade of the significance of the proposed interface improvements (Source: Own elaboration)

Over 80% of the respondents are satisfied with the proposed functionalities. At the same time, the analysis shows that the suggested improvements to the interface are not relevant to the respondents. It is enough for them that interface is simple and intuitive.

Therefore, it is of utmost importance to develop innovative functionality that has significant competitive advantages.

The third stage is related to the processing of the text answers in the survey and the subsequent creation of the concept map. In accordance with the approach proposed in the previous section, we used the conventional Text Mining techniques, in which text pre-processing is essential. It includes the steps shown in fig. 1, through which each recorded answer that looks like an unstructured text is presented as a vector of words. They in turn can be easily processed and analyzed. We have prepared a lexicon beforehand, which we used to train the applied algorithm. The words and phrases are 100 in number. For example, we used the following words and their derivatives: web design, web developer, web development, video tutorials, programming, jobs, search, etc.

The software used to analyze the unstructured survey data is RapidMiner. The application has a special tool for word processing and is one of the most used analytical software tools [13].

As a result of the processing we got the answer of each open-ended question presented as a vector of words. When creating the word vector in RapidMiner, we used the term frequency evaluation method TF-IDF (Term Frequency - Inverse Document Frequency), which shows statistically how important a word is for a document or corpus collection. TF-IDF increases its value in proportion to the number of occurrences of the word, but the frequency of the word in the corpus as a whole is also taken into account because some words tend to appear more often.

The open-ended questions are very essential to the study because they help users describe their expectations for the platform connected with career development in web design. We used a pre-prepared lexicon in order to identify them. Respondents most often describe the user interface with the terms: simple, response, complete, intuitive, and friendly. The words "course, compare, groups, tutorials, rate, find" describe the additional functionality that users expect and are not offered in the requirements (fig. 5). Users suggest logging into the platform through password, username, email or social media. The most commonly used platform for career development is LinkedIn.

The analysis of the answers of the open-ended questions shows that, in general, the proposed functionalities (fig. 4) are in line with users' expectations for the career development platform. What would enrich it is the capability to evaluate video lessons and job positions, for example, as well as searching for job positions and content training. Similarly, there would be the expectations for any web based platform, regardless of the field of activity.

Using the extracted user expectations for the platform we have prepared a CM - a summary model of all respondents. We have used the free software CmapTools. In fig. 6 a part of the CM diagram is presented.

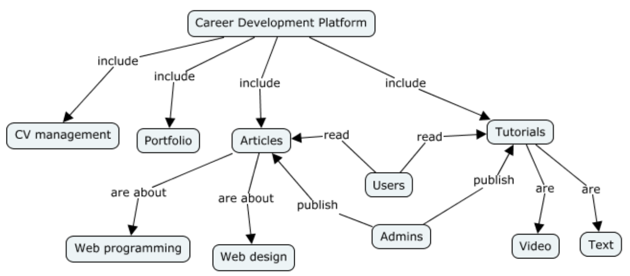

Figure 6. Partial model of the user expectations for a web-based career development platform (Source: Own elaboration)

6. Conclusion

The results of the conducted experiment show that in order to create accurate and complete concept maps, it is necessary to use a lexicon that is specific to the study area. Researchers do not always have a pre-prepared lexicon, which makes the process of concept maps mining significantly time-consuming in terms of building a dictionary of appropriate terms. As indicated by [16], it must be taken into account that some of the unnecessary stop words may be involved in the words that make up the lexicon. Therefore, the knowledge of the subject area is of great importance for creating correct models.

References

[1]. Hihn J. et. al. (1993). *Mental Models of Software Forecasting*. Jet Propulsion Laboratory, California Institute of Technology, 1-26.

[2]. Getsov P., Hubenova Z. & Popov V. (2009). Exploring human beings as a control system in a virtual reality environment. (in Bulgarian), *Proceedings of the Fifth Scientific Conference with International Participation Space, Ecology, Nanotechnology, Safety*, Sofia: Bulgaria, 96-103.

[3]. Jones N. A. et. al. (2011). Mental models: an interdisciplinary synthesis of theory and methods, *Ecology and Society, 16*(1), 46.

[4]. Thagard P. (2010). How Brains Make Mental Models. In: Magnani L., Carnielli W., Pizzi C. (eds) *Model-Based Reasoning in Science and Technology. Studies in Computational Intelligence*, Berlin: Springer, 314, 447-461.

[5]. Carley K. & Palmquist M. (1992). Extracting, Representing, and Analyzing Mental Models. *Social Forces*,*70*(3), 601-36.

[6]. Young I. (2008). *Mental Models: Aligning Design Strategy with Human Behavior*, Rosenfeld Media.

[7]. Krosnick J. et. al. (2012). *The Future of Survey Research:Challenges and Opportunities*. National Science Foundation, 1-163.

[8]. Lietz, P. (2008). Questionnaire design in attitude and opinion research: current state of an art, *Forschergruppe Priorisierung in der Medizin, & Jacobs University*, Bremen: Jacobs Univ., FOR 655.

[9]. Oracle. (2012). *Best Practices for Improving Survey Participation: An Oracle Best Practice Guide*. Oracle, 1-25.

[10]. Samuel A. (1995). Some studies in machine learning using the game of checkers. *Computation & intelligence, American Association for Artificial Intelligence Menlo Park*, 391-414.

[11]. Feldman R. & Sanger J. (2007). *The text mining handbook. Advanced Approaches in Analyzing Unstructured Data*. Cambridge: Cambridge University Press.

[12]. Kumar E. (2011). *Natural Language Processing*. New Delhi: I. K. International Pvt.

[13]. Peña-Ayala, A. (Ed.). (2013). *Educational data mining: applications and trends* (Vol. 524). Springer.

[14]. Nacheva R. (2015). The Importance of Users' Mental Models for Developing Usable Human-Machine Interfaces. *Scientific papers at the University of Rousse,* 54(6.1), 132-135.

[15]. Villalon J. & Calvo R. A. (2009). Concept extraction from student essays, towards concept map mining. *Proceedings of the Ninth IEEE International Conference on Advanced Learning Technologies, ICALT '09*, 221–225.

[16]. Nugumanova, A., Mansurova, M., Alimzhanov, E., Zyryanov, D., & Apayev, K. (2015, July). Automatic generation of concept maps based on collection of teaching materials. In *Proceedings of 4th International Conference on Data Management Technologies and Applications* (pp. 248-254). SCITEPRESS-Science and Technology Publications, Lda.

[17]. Katagall, R., Dadde, R., Goudar, R. H., & Rao, S. (2015). Concept mapping in education and semantic knowledge representation: An illustrative survey. *Procedia Computer Science*, *48*, 638-643.

[18]. Villalon J. J. & Calvo R. A. (2008). Concept Map Mining: A Definition and a Framework for Its Evaluation. Sydney, NSW: *IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology*, 357-360.

[19]. Filipova, N. (2013). Conceptual architecture of business process management systems. *Izvestiya*, (2), 43-54.

[20]. Eppler, M. J. (2006). A comparison between concept maps, mind maps, conceptual diagrams, and visual metaphors as complementary tools for knowledge construction and sharing. *Information visualization*, *5*(3), 202-210.

[21]. Zubrinic K., Kalpic D. & Milicevic M. (2012). The automatic creation of concept maps from documents written using morphologically rich languages. *Expert Systems with Applications*, *39*(16), 12709–12718.

[22]. Bankov B. (2019). Software Evaluation of PHP MVC Web Applications. *19 International Multidisciplinary Scientific Geoconference SGEM 2019*, *19*(2.1), 603-610.

[23]. Vasilev J. & Stoyanova M. (2019). Information Sharing with Upstream Partners of Supply Chains. *19 International Multidisciplinary Scientific Geoconference SGEM 2019*, *Geoinformatics a. Remote Sensing*, *19*(2.1), 329-336.

[24]. Kuyumdzhiev I. (2019). Comparing Backup and Restore Efficiency In MySQl, MS SQL Server And MongoDB. *19 International Multidisciplinary Scientific Geoconference SGEM 2019, Geoinformatics a. Remote Sensing*, *19*(2.1), 167-175.