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Emotionally Colored Information and Decision Support Systems

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***Abstract*— The article discusses the relevance of detecting, formalizing and accounting tasks for emotionally colored information in intelligent decision support systems. The approaches to the application of Affective Computing in the tasks of processing and interpreting emotionally colored information are analyzed. The task is to take into account emotions in decision support systems for different areas of the service sector. An example of taking into account emotionally colored information in the management of the services provision at an enterprise in the health and beauty industry is given.**

Keywords*— *emotions, affects, affective computing, artificial intelligence, decision support system, beauty and health industry

I. INTRODUCTION

Emotions – are the feelings, coloring the perception and thinking. They exist everywhere and in every moment of life. Emotions stimulate our brains around 3000 times faster than our rational thinking does. In decision-making processes, the rational thinking is responsible for achieving our goals, but at the end but often it is emotions that lead to decisions.

The processing and interpretation of emotionally colored information is also a key element in many areas of IT research, such as: human-computer interaction, user profiling and personalization, e-learning, marketing, analysis of opinions and sentiments of service customers, etc.

Affective Computing (AC) – is a field of research related to formalization, modeling and accounting of human affects and emotions in computer science. AC are aimed to the introduction of a higher level of computational intelligence into information systems, which allows to emulate human affects and emotions.

The actual task is to improve management efficiency and decision making based on processing emotionally colored information in the intelligent decision support systems by using Affective Computing technologies.

This article is devoted to the emotionally colored information role in decision support systems. Here the well-known experience of emotion accounting information systems is given. The examples of emotion colored information accounting in different applications is also considered here. And the tools that can be used to solve decision making support problems, for example, in the beauty and health industry.

II. HISTORY OF THE QUESTION

Science Direct's databases of scientific publications contain more than ten thousand publications on this topic. Consider the history of the affective computing concepts' development. And how researchers came to the detection and accounting of emotions and applied them in information systems.

The founder of the term Affective Computing is Rosalind Picard. The information in our brain is emotionally predetermined, and we often make decisions simply under the influence of one or another emotional impulse. That is the reason why Picard, in her book Affective Computing [1], introduced the idea of constructing machines that would be directly related to human emotions and even capable of influence them. She considers the challenges which researchers have to deal in this area. The problems associated with affects in human-computer interaction are also thoroughly discussed [2].

There are two components in human communication: explicit and implicit. First one sends information which can be about anything or about nothing. The second one sends messages about the speaker itself. Both linguistics and technology have put great effort to understand the first, explicit channel. But the second is still not understood well enough. Understanding of speaker's emotions – is primary task related to the second component of communication process. To model this process is necessary to develop methods for processing and analyzing information and to combine psychological and linguistic emotions analysis. There is a consideration of the main issues of developing a hybrid system for recognizing human emotions based on faces and voices information [3].

There are represents the researches of the four emotions: sadness, joy, anger, and fear. The 3D video sensory technology of skeletal movements was used to analyze them. The numerical experiments were carried by using various machine learning methods. The quality of data classification ranges from 84% to 92% [4].

Many autors analysis of the development of computational capabilities for the creation of cognitive algorithms which is capable to detect a human attention and emotions. They criticizes the technologies and evaluates their suitability for use in real-world applications today [5].

To date, the Emotion Detected and Recognition Systems (EDRS) market has an average annual growth of 27.4 per cent and will reach $ 29.1 billion by 2022. (figure 1). According to marketandmarkets.com, the efficient computing market will grow from $ 12.2 billion in 2016 to $ 54 billion by 2021 at an average annual rate of 34.7 percent. (figure 2).

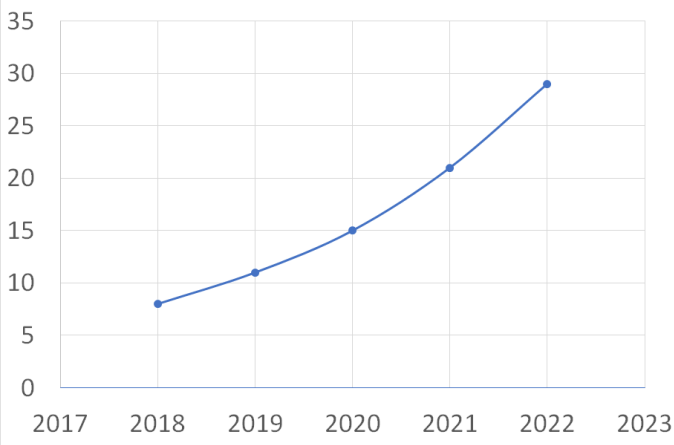

Fig. 1. Emotion Detected and Recognition Systems (EDRS) market

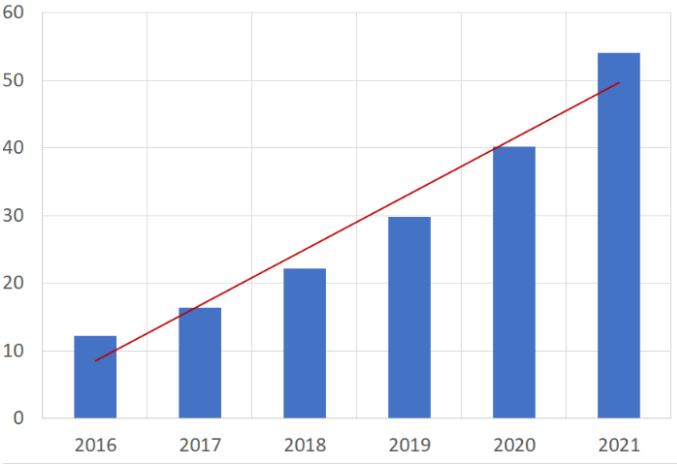

Fig. 2. Affective computing market

Leading IT giants are heavily investing in affective computing because they see the benefits from the emotion accounting in information systems.

III. Problem Statement

It is necessary to use emotional information to develop the decision support systems in complex systems (like economic, social, healthcare, etc.), if it can help to improve the efficiency of decisions making. Using the example of an enterprise in the health and beauty industry let's consider the concept of building a decision support system by using emotionally colored information and the well-known affective computing approaches.

To solve this problem, it is necessary to systematize the known affective computing solutions and answer the following questions: in which subject areas it works, what tools can be used and what needs to be done to improve the efficiency of decision-making by accounting emotionally colored information.

IV. Analysis of the Experience of Emotional Colored Information Use

There is a relationship between affective computation and sentiment analysis [6]. Emotion processing is essential for the polarity detection task. There is a consideration of the possibility of automatically capturing customer mood towards marketing campaigns, product preferences, etc. Affective computing and sentiment analysis use a human-computer interaction, an information retrieval, and a multimodal signal processing to extract people's emotions from large amounts of data on the Internet.

The video game industry could not ignore the processing and accounting of emotionally colored information in the development their game content. Because an affect plays a key role in the user experience in both entertainment and "serious" games. This area focuses on the perception and recognition of players' emotions, and for adaptation of the game reaction to these emotions [7]. And there are significant efforts that was made to create "emotional behavior" in playable characters and player avatars to enhance their realism and believability.

There is a problem of adjusting user behavior from suboptimal cognitive and affective states to states that increase their productivity [8]. To achieve that you have to understand what the desired and initial states of the user are. A closed system in which considers both cognitive and affective states of users in real time is useful for developing adaptive environments. That environments can respond to a user's emotions and motivations in real time. The authors use the Virtual Reality Stroop Problem (VRST) Virtual Reality Cognitive Performance Assessment (VRCPAT) to determine the optimal level of arousal that can serve as a target for an affective / cognitive state. The research results also represent that the support vector method gives high indicators of the quality of the users' psychophysiological reactions classification with different levels of arousal.

The application of the analysis of emotionally colored information in the education sphere can increase the efficiency of learning. In this area considered how affect can significantly influence education / learning [9]. In this understanding of a student's emotions throughout the learning process is a critical moment to understanding student motivation. Affective computing technologies can help to objectively identify and measure a learner's affective status while learning in real time. This study intends to classify and summarize these measurements to understand their relations with learning efficiency.

Computer vision can be applied to recognize the affects of students [10]. This allows the teachers to adapt their behavior not only to the cognitive level of the student, but also to his emotional state. There are considerations of modern researches in the field of recognition of facial expressions and gestures. It happens in the context of intelligent learning to build affective intelligent learning systems.

There are various representative adversarial learning algorithms aimed at solving various problems associated with AI emotional systems [11]. The researchers also highlight several potential areas for future research, hoping to foster the development of adversarial learning for effective computation and analysis of community sentiment.

Ways of applying detection and intervention methods in affective computing in adaptive e-learning systems are described [12]. Improving the effectiveness of personalized support in online educational institutions is achieved by considering the influence of emotions and personality on the learning process. A review of 26 studies is analyzed, which presents current trends in identifying the affective states of students and providing appropriate affective support in various educational conditions.

Collaborative Learning (CL) can be a powerful method of increasing productivity by sharing knowledge between learners. Research has shown that not only individual processes are important, but also general group processes. This means that group-level regulation is critical to training success. The problem is that the "general" processes in CL are invisible, making it nearly impossible for researchers to study and understand them, for students to recognize them, and for teachers to support them. Applying interdisciplinary collaboration between learning domains, affective computing and machine learning increases the productivity of understanding and facilitates CL [13].

There is a relationship between the emotional state of a job seeker and his success chances on applying [14]. Recently, research in behavioral economics has shown that people make systematic mistakes in decision making. In most cases job seekers fail in predictable ways not because of their lack of knowledge, practice, or desire. It happened because they are limited in the decisions making way. The research is aimed at supporting decision-making in effective recruiting, based on accounting the emotions, applicants' cognitive abilities and psychophysical states of stress.

Emotion rating is also very important in medical applications: psychiatry, clinical psychology, and neurology. Depressive conditions are one of the most common mental disorders. Semi-automatic and / or automatic health monitoring systems can be critical and important in improving depression detection and following observation. There are multimodal depression monitoring systems that use mood analysis and affective computation techniques [15].

In the relationship between the emotions of customers and decision-making about service maintenance was studied. Decision support systems need to be created for service recovery by adopting approaches to efficient computation, artificial neural networks and decision trees. Three experiments were conducted to evaluate the feasibility and effectiveness of a service restoration decision support system [16]. Experimental results showed that the decision support system for service recovery can have a high performance of customer recognition. Meanwhile, customer emotions can be the key to enabling the companies to make the right service decisions during the service recovery process.

V. AFFECTIVE COMPUTING TOOLS

Emotions strongly influence a human's decision making. This fact is considered by affective computation to adapt the decision support to the emotional states of individuals. However accurate emotion recognizing in narrative documents is challenging due to the complexity and ambiguity of the language. Increase of productivity can be achieved by using deep learning. But the specificity of this task requires the setting of recurrent neural networks [17]. Moreover, the authors suggest a sent2affect adapted learning form for affective computation. It is pre-trained for the task of sentiments analyzing, and the output layer is further tuned for the task of recognizing emotions. The result is assessed in a holistic environment using six basic sets of emotions.

The processing of emotionally colored information from voice messages is also important [18]. Vocal media have become a highly popular communication method in modern society. Sending such messages, not only semantic information is transmitted. Voice messages also contain a lot of emotional information as well. The authors apply data mining to recognize emotions and assess their dynamic changes in three-dimensional PAD (Position-Arousal-Dominance) space. Numerical experiments are carried out on data from the social networking site WeChat.

On the basis of the theory of affective psychology, the factors and transformations that the affective state of a person makes are analyzed [19]. After receiving results, a multi-layered affective model of decision-making was proposed for establishing a connection between character, mood and movement. The model represented changes in moods and emotional spaces. The experiment showed that the characteristics of human emotions are consistent with the theory under consideration, thereby providing a basis for modeling a system of human-computer interaction.

So many works are devoted to the relationship between the analysis of emotions and opinions of Internet users. Some researchers present a quantitative analysis of how a person's emotional state can be formalized using browser history and how a person's emotional state affects their friends on a social network. Using a statistical analysis of the dynamics of human emotions, the authors found several interesting patterns [20]. They used it to study the distribution of emotional states in people and collective moods. The assumption about the possibility of quantitative analysis of human emotions has been confirmed by studies in mobile social networks and in virtual network environments.

In affective computing, there is a big question about formalizing emotions. There is a multimodal approach for detecting affective states of people who are influenced by visual narratives [21]. Four methods are used to detect emotions - visual facial behavior, heart rate measurements, thermal imaging, and verbal descriptions - and then show how to predict the changes in affects people experience when exposed to audiovisual stimuli (positive or negative).

There is the problem of modeling an autonomous agent that makes decisions, in part dependent on affective factors, through interactions with people and other agents. Social robots at home and in the workplace are no longer considered lifeless and insensitive. Agents need to include affective elements. The solution uses attachment as the main element in the decision-making process when communicating between robotic agents that provide more human responses [22]. Experiments on the interaction of the proposed model with various types of users have been carried out, which have shown greater adaptability to decision-making in comparison with insensitive agents and simpler emotional models.

An interesting attempt is to combine approaches related to cloud computing and efficient computing. This combination is presented in the form of a software as a service solution,

which is hosted in a public cloud environment [23]. A framework was proposed for the Affective Computing as a Service (ACaaS) solution, that uniquely considered that it uses previously created public cloud computing services. Then framework will transform into a working implementation that consist of PHP front-end and Python back-end. The system can process text, graphics and voice input files and extract emotional information from them. Then results are presented and evaluated. It demonstrates that in most cases multimodal inputs will facilitate the use of affective computing as a service solution which will provide necessary information for affective computing purposes.

The development of effective decisions is impossible without considering the emotions of the subjects of the decision-making process. There are problems of considering the emotions of the opinions of experts in a group agreement. Traditional methods of Multiple Attribute Group Decision Making (MAGDM) focus on computing sub-attribute weights and expert preferences. But they do not discuss the affective interactions of decision makers and their impact on decision preferences and group consistency. There is an offer of a multilayered affective computational model based on the group trend index and attachment-preference stimulation mechanism [24]. It can help simulate the MAGDM process and explore the decision-making preferences of the group expertsA multi-agent affective interactive method MAGDM (MAAI-MAGDM) is proposed, which determines a new group convergence index and an alternative entropy of group decision making. Numerical experiments confirmed that the proposed MAAI-MAGDM method considered the affective characteristics of each expert, reduced dependence on aggregation and weight analysis operators, eased the workload of group experts, and effectively reduced the complexity of the decision-making process.

Affective elements influence decision making by individuals and groups. Research is being conducted on how emotions and mood affect the degree of competition and collaboration in groups. There is a parametric model for regulating group decision making [25]. It introduces a negotiation scheme to facilitate group formation based on affective elements. A virtual platform was created for the proposed model and numerical experiments were carried out.

Analysis revealed a wide range of applications of the emotionally colored information and affective computing in different areas. Some authors have focused on the affective computation tools and another have tried to deeply formalize certain shades of emotions. There are authors who have applied emotionally charged information in different subject areas. In our work, we want to consider the use of emotionally colored information in the service sector at different stages of the life cycle of the service provision process.

VI. EMOTIONALLY COLORED INFORMATION ACCOUNTING IN DECISION SUPPORT SYSTEMS

The problem of improving the efficiency of management and decision-making in intelligent decision support systems can be solved by developing models, methods, and algorithms for processing emotionally colored information by using affective computing technologies.

In service sector emotions and affects of customers are critically important, because the assessment of the quality of service provision directly depends on the level of customer satisfaction, and the efficiency of the providing service process depends on the individual characteristics and preferences of customers. The authors are interested in the application of the affective computing tools in the service sector: the health and beauty industry, the tourism sector, the financial sector, and online education. (figure 3). In this article, we will discuss in more detail an example of an enterprise in the health and beauty industry.

Customer preferences and satisfaction are poorly formalized emotionally colored information. Consideration of such information is necessary at every stage of the life cycle of an intelligent decision support system.

The structural schema of management for an enterprise in the health and beauty industry was developed importantly by using emotionally colored information in decision-making (figure 4) [26]. To improve the efficiency of decision-making, it is necessary to integrate an emotion accounting unit into this scheme. Emotions should be accounted at the planning stage of the service delivery process in the form of individual customer preferences and at the stage of assessing satisfaction of provided service.

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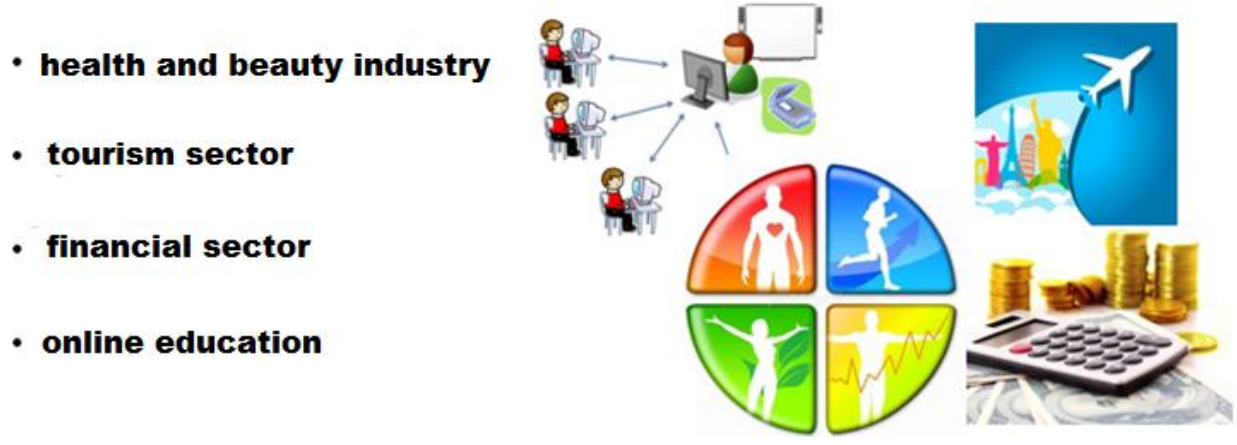

Fig. 3. Discussed subjects' areas

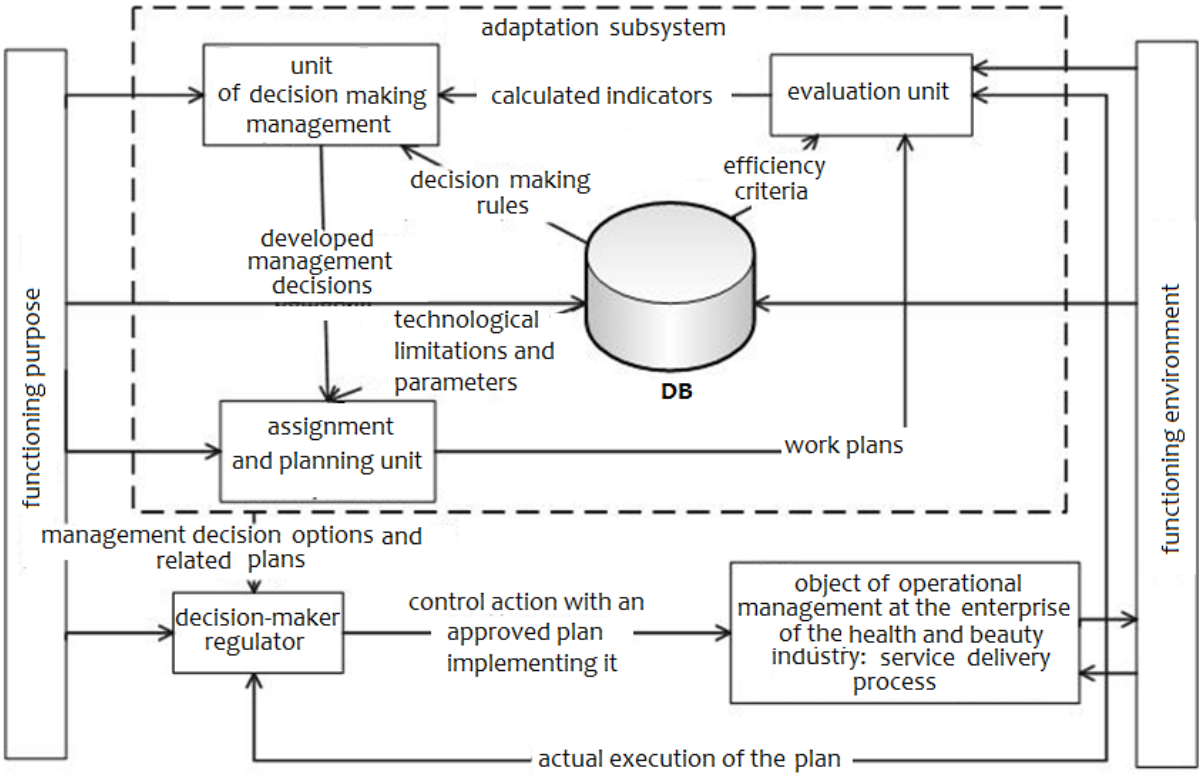

Fig. 4. Structural diagram of enterprise management in the beauty and health industry

At each stage of the decision support system development life cycle are methods and approaches of both affective computing and artificial intelligence technologies, such as: fuzzy logic, machine learning, text mining, game theory's methods, multi-agent approach, principles of building neural networks, ontological approach, etc.

Further research will be aimed at developing methods, models and algorithms for processing emotionally colored information for IDSS in various subject applications.

VII. Conclusion

In this article the actual task of detecting, formalizing, and accounting for emotionally colored information in intelligent decision support systems was studied. An overview of existing approaches to the application of Affective Computing to solve the problem of processing and interpreting emotionally colored information was made. The task is to take into account emotions in decision support systems in different areas of the service sector. An example of taking into account emotionally colored information in managing the process of providing services at an enterprise in the health and beauty industry is given.

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