Mircea Radu Georgescu
Alexandru Ioan Cuza University of Iasi
Accounting, Economic Informatics and Statistics, The Faculty of Economics and Business Administration, Romania
E-mail: mirceag@uaic.ro

Ioana Andreea Bogoslov
Lucian Blaga Univeristy of Sibiu
Department of Finance and Accounting, Faculty of Economic Sciences, Romania
E-mail: andreea.bogoslov@ulbsibiu.ro

IMPORTANCE AND OPPORTUNITIES OF SENTIMENT ANALYSIS IN DEVELOPING E-LEARNING SYSTEMS THROUGH SOCIAL MEDIA

Preliminary communication
UDK: 37.018.43:004
JEL classification: O35, I20
Accepted for publishing: October 31, 2019

Abstract

The means of communication and interaction have benefited from incredible changes over the past decade, Social Media increasingly replacing traditional environments. Considering the collaborative nature of the learning sector and consequently the importance of communication and interaction within it, we intuitively realize that Social Media represents the future of educational systems, the research in this field pointing towards the integration of e-Learning with Social Media. However, in order to deliver efficient educational systems, it is not enough to identify the technological means that are conducive to their development, but is also important to shape these means depending on the needs of the target group. When we discuss about Social Media and learning, it is noticed that individuals are the direct beneficiaries and the main force of these environments. Therefore, it is important to understand their behavior, their needs and wants. Analyzing students' attitudes, identifying their positive or negative reactions, or even the refined emotions they have towards learning, can be an extremely difficult task due to their diversity in countless ways. In this regard, an increasingly used tool whose accuracy cannot be challenged is the Sentiment Analysis. The inherent nature of Social Media tools offers multiple areas of application of Sentiment Analysis. Therefore, this paper will discuss the importance of Sentiment Analysis towards e-Learning development through Social Media, considering current evidence. Secondly, the paper aims to identify the opportunities offered by Social Media with regards to Sentiment Analysis implementation and how feedback on educational data can be collected via such online environments to help improve educational processes in an e-Learning context.

Keywords: Sentiment Analysis, e-Learning, Social Media

1. INTRODUCTION

Driving forces in developing and streamlining teaching and learning processes, computers, the Internet and new information technologies have become a crucial part of education. Collectively known as the e-Learning Systems for more than 20 years, these ICT tools have redefined teaching and learning strategies, methods and concepts, meeting the need of today's society to support and enhance lifelong learning.

The e-Learning phenomenon represents the bridge ensuring the transition from the traditional means of teaching and learning to modern means that satisfy the needs of contemporary learners. Those learners are, in fact, individuals whose developmental environment was from the beginning guided by technology and social environments. In this context, their requirement to benefit from familiar educational backgrounds supported by social technology tools is obvious.

The need to integrate Social Media instruments into educational processes is also underlined by the latest modern learning paradigm, well-known as the theory of connectivity or connectivism, whose creators are considered George Siemens and Stephen Downes. This theory has been developed based on the idea that people process information by forming connections (Siemens, Connectivism: A Learning Theory for the Digital Age, 2005; Downes, 2007).

The new learning trend suggests that the learning process is uninterrupted, individuals continuing to learn beyond formal education by obtaining information from multiple and predominantly external ways, such as social networks, websites, blogs and other tools provided by technology. At the same time, learning (defined as actionable knowledge) may exist outside of us (within an organization or database), being focused on connecting specialized information sets and connections that allow us to gather additional information that are more important than the current state of knowledge. (Siemens, Connectivism: A learning theory for the digital age, 2005)

In view of the above mentioned aspects and considering the fact that we are witnessing a continuous expansion of the Social Media tools, whose accessibility is almost unlimited, the need to integrate e-Learning systems with Social Media becomes compulsory. However, creating such an educational environment, which is considered familiar to modern learners, is not enough when it comes to making education more efficient.

Subjectivity represents one of the main characteristics of individuals. The subjective nature of people, closely linked to their feelings, emotions and opinions, affects any action, including their learning experience. The ability to interact with individuals knowing this substrate of their character, namely subjectivity, can have many advantages in terms of efficient use of e-Learning systems.

In this respect, one of the new areas of interest for researchers is the *Sentiment Analysis*, also called *Opinion Mining*. The underlying purpose of such analysis is to identify the emotional, positive, negative or, in rare cases, neutral, which a text/reaction of the user can have.

It is clear that the direct beneficiaries of any teaching and learning process are the learners and the satisfaction of their needs is crucial to improving educational processes. They, like any other individual, express their views in complex ways, directly or less obviously. Understanding the aspects of the subjectivity of their actions thus becomes a difficult task.

Social Media tools can, however, shape learning environments that facilitate the analysis of learners' feelings in a context of learning and teaching through e-Learning systems. Therefore, the preliminary goal of this article is to identify the importance of analyzing feelings when developing e-Learning instruments through Social Media, taking into account current evidence. Moreover, the paper aims to identify the opportunities offered by Social Media for the implementation of Sentiment Analysis and how collecting feedback on educational data through such online environments can help the improvements of educational processes in a context of e-Learning.

2. DATA AND METHODS

In order to meet the stated objectives of this paper, the research is primarily based on external sources, analyzing existing research in the field. Therefore, the literature review process is considered as the main data collection tool with respect to the present paper. However, the literature review, as a means of collecting pertinent and significant information to the topic of interest, implies a mixed approach, collecting and analyzing both qualitative and quantitative studies provided by authors in this field. Moreover, the observations, findings and proposals of the authors, aim to bring value to solving the research scope.

Although studies that involve linguistics and natural language processing (NLP) have been previously developed, little research on people's opinions and feelings has been done before 2000. Since then, the field of research has become very active, firstly due to the wide scope of Sentiment Analysis application in almost any field, and on the other hand due to the proliferation of applications and technological tools that facilitate this type of process. Thereby, the concept of Sentiment Analysis has benefited from several approaches, the perspectives being different, especially in terms of how this type of study is carried out.

In general terms, the Sentiment Analysis represents a field of study whose main purpose is to analyze the opinions, feelings, assessments, attitudes and emotions of individuals in relation to various entities such as products, services, organizations, persons, issues, events, their subjects and attributes. (Liu, 2012)

On the other hand, highlighting the dependence of this type of information technology analysis, Kechaou et al. (Kechaou, Ben Ammar, & Alimi, 2011) have defined Sentiment Analysis, also known as the classification of sentiment or opinion mining, as a computational technique that attempts to understand and explain opinion and sentiment by analyzing large amounts of data in order to help decisions making.

According to Vohra and Teraiya (Vohra & Teraiya, 2013), there are two main approaches to Sentiment Analysis: the analysis based on machine-learning and the lexicon-based analysis. The lexicon approach, also called the symbolic approach (Boiy & Moens, 2009), uses artisanal rules and lexicons, while the automated learning or machine-learning approach uses supervised or poorly supervised learning to build a model from a corpus of large scale, with supervised models here being the most popular.

Practically, in the case of a machine-learning analysis, the classification technique is used in order to categorize text-based content. In contrast, the lexicon-based method is founded on a sentiment dictionary that contains words expressing opinions, which are then compared to the collected data in order to determine their polarity. In this case, words describing opinions are attributed to sentiment scores that describe how positive, negative, and objective they are.

Extending the previous view on how the Sentiment Analysis could be conducted, Rahmath and Ahmad (Rahmath & Ahmad, 2014) considered three main approaches: Sentiment Analysis based on supervised machine-learning technology; Sentiment Analysis based on the lexicon technique; Sentiment Analysis developed by combining the two approaches above. Hence, they stated the existence of a hybrid method of analysis, resulting from the combination of two clearly distinct methods. Actually, the third method could be used to improve performance in the classification of sentiment.

In 2016, Devika et al. (Devika, Sunitha, & Amal, 2016) conducted a comparative analysis of three main approaches to Sentiment Analysis: the machine-based approach, rule-based analysis, and lexicon-based analysis. In the authors' view, based on the analysis of the existing literature, the strategy based on machine-learning works by creating a "training" algorithm with a set of data before applying it to the real data set. The rule-based approach has been described as the method that works by defining different rules for obtaining opinions created by tokenizing each sentence in each document and then testing each token or word for its presence. At the same time, lexicon-based techniques have been described as starting from the hypothesis that the collective polarity of a sheet or document represents the sum of polarities of individual expressions or words.

With a broad approach based on existing evidence, Wang and Zhai (Wang & Zhai, 2017) identified, in turn, two main ways of achieving this type of analysis: rule-based analysis and statistical model-based analysis. In case of rule-based analysis, human expertise is used to create rules (referring to the lexicon of feelings) to determine the feelings behind a text. When a Sentiment Analysis based on statistical models is involved, these models are estimated on the basis of labeled data or on the basis of previously generated human data to learn "soft" sentiment prediction (learning-based methods).

As it can be easily observed, regardless of the exposed vision and the considerations of the researchers in the field, the starting point in any Sentiment Analysis is represented by the automated approach or the lexicon-based approach. Of course, these main approaches can also be divided into different sub-methods depending on the specificity of the field in which the Sentiment Analysis is undertaken. At the same time, the technological tools used for the purpose of developing a Sentiment Analysis are increasingly more complex, the evolution in this field being a steady development process.

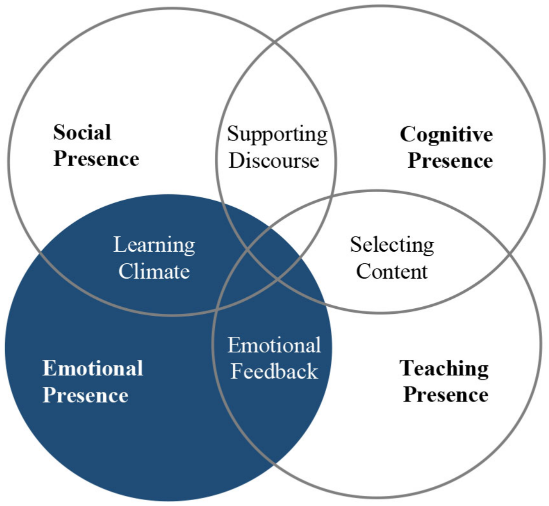
3. RESULTS AND DISCUSSION

Although it is expected that the next generation of e-Learning systems will provide learners with a familiar environment, conducive to the efficiency of teaching and learning processes, other aspects that can influence this evolution should be considered. Carrying educational and formative activities in a predominantly online environment through Social Media tools offers many advantages, demonstrated and understood over time, but also limits face-to-face interaction, which affects the process of understanding students' learning characteristics and needs.

Moreover, the rapid evolution of Sentiment Analysis and the synchronization of this progress with the explosive popularity of Social Media tools and technologies have led to new research spheres involving both areas simultaneously. The importance of using social online environments as a starting point of the Sentiment Analysis has been increasingly understood by researchers in the field, the analysis of opinions currently representing the central focus of Social Media research.

3.1. The Importance of the Emotional Presence on Social E-Learning Systems

Among other issues that may influence the effectiveness of educational processes, affective and emotional factors seem to have effects on students' motivation and, in general, on the outcome of the learning process (Shen, Wang, & Shen, 2012). If initially a distinction was made between cognitive presence, social presence and teaching presence (Garrison, 2011), these being considered the key elements that determine the proper functioning of online learning systems, further research has increasingly highlighted the importance of emotional presence (Figure 1) in streamlining online learning processes (Stenbom, Cleveland-Innes, & Hrastinski, 2014).



Notes: The figure was reproduced by the authors

Source: From Rienties & Rivers (Rienties & Rivers, 2014) – Adapted from Stenbom et al. (Stenbom, Cleveland-Innes, & Hrastinski, 2014)

Figure 1 Community of Inquiry Framework for Online Learning

Thus, it can be asserted that, in learning contexts, the ability to detect and manage information about student emotions can, at one point, help us to understand their potential needs at that time (Clarizia, et al., 2018) which consequently determine the improvement of educational processes by providing personalized learning environments.

As mentioned above, online learning environments set clear barriers in understanding user sentiments, in this case those involved in the educational processes, as a result of the inability of users to physically interact. Thus, in an e-Learning context, the difficulty can be encountered when precisely considering the involvement of the emotional part of the subjects. This emotional side, which is hard to identify in an online environment, is expected to be found and exposed through the content distributed predominantly in the form of text, but also in other forms chosen by users as a means of online expression.

Aiming to overcome the limits of knowing and understanding the emotional side of the users, Sentiment Analysis becomes extremely important when developing and using e-Learning systems through Social Media. Communication represents the dominant factor behind the connection or isolation of the involved parties in the educational processes held in such distributed environments. The huge mass of information displayed by users through online Social Media offers almost endless opportunities when they are participating in educational processes and also requiring special attention.

Emphasizing the importance of choosing the Sentiment Analysis as a User Generated Content research (UGC), Yu et al. (Yu, Duan, & Cao, 2013) mentioned the following benefits of this type of study:

- Converts large, unstructured content into a form that allows specific predictions of certain results without institutional market mechanisms.
- Develops models to aggregate the views of the collective population and leads to obtaining information about group behavior that is useful in predicting future trends.
- Applies the collected information on how people react to specific objects, designing then various marketing and advertising campaigns.

While the previously identified advantages were linked to the impact of social and conventional media on firm equity value, they can be easily adapted and applied in the context of e-Learning through Social Media. In this case, the Sentiment Analysis exerts the primary importance on the efficiency of educational processes and, as strong points of its use, the above benefits take the following form:

- Converts large, unstructured content into a form that allows analysing students' learning characteristics, which facilitates the learner-centered learning.
- Develops models to aggregate the views of the collective population and lead to obtaining information about group behavior that is useful in predicting future trends.
- Applies the obtained information on how learners react in specific circumstances or stimuli, helping to further design the educational content and contexts.

Thus, Sentiment Analysis can play a dual role when e-Learning systems integrate Social Media tools. First of all, it can serve as means of identifying views, opinions and sentiments on educational content and contexts at a given point in time. At the same time, this type of analysis can be used to detect changes that may occur with respect to the emotional side of users.

Therefore, we can state that Sentiment Analysis represents useful mean of identifying the less obvious side of the users behavior, i.e. of learners. This can be considered a valuable resource when finding hidden insights about emotions and feelings that influence students' learning, attitudes and skills, and consequently educational processes.

3.2. Sentiment Analysis Opportunities on Social Media

With the emergence and explosive advancement of Social Media tools, considered part of Web development since its second generation, the possibilities to analyze masses of publicly exposed information in the form of text and beyond, have greatly multiplied. Online forums, blogs, social networks such as Facebook and Twitter, can all be considered Social Media tools. These social online environments have the ability to capture views of individuals around the world.

The main feature of Social Media tools is providing users with common interests the possibility to generate and post public content on the Internet, embracing various forms, predominantly text or media content. This content represents valuable data and information as it can be used to provide real-time perspectives on people's feelings or opinions.

Freedom of expression offered to users within Social Media platforms is one of the main advantages provided by such technologies for performing Sentiment Analysis. Generally, online social interactions provide a level of anonymity and confidentiality, quite unusual in real interactions. Thus, individuals feel less constrained in expressing opinion in social online environments, which results in more realistic views. As Kang (Kang 2000) mentioned, the cyberspace intensifies and facilitates interaction with strangers.

The communication and availability of real-time user feedback through Social Media technologies has revolutionized computational linguistics and Sentiment Analysis. Research areas have diversified over time, the Sentiment Analysis conducted through Social Media being a growing area that includes a variety of modeling and analysis techniques that can be applied to different areas. Therefore, in the following we will focus on the ways in which the Sentiment Analysis can be used within Social Media, highlighting the opportunities offered by these online environments, especially in the context of e-Learning.

Mainly, Sentiment Analysis within Social Media platforms is based on user feedback that can take the form of text, including comments, recommendations and reviews, or graphically based on emoticons made available by these Social Media applications or on media content:

- **The Text-Based Sentiment Analysis on Social Media**

In terms of text-based Sentiment Analysis starting from text posts from social environments, including simple comments, discussions, hashtags, and other character posts, we identify between both simple methods of retrieving and classifying the text and semantic methods.

Classification of text is the most common method of analyzing sentiment within Social Media, consisting in collecting text data and placing it in three main categories, depending on the expressed emotional load: positive, negative or neutral. Expressional texts are the most common form of stating opinions on Social Media platforms. Their existence varies from simple comments to conversations and reviews on specific entities. Basically, lists of positive, negative and neutral terms are made in such a way that they can be counted when used, for example, in a text comment that mentions a service or product name.

With regard to semantic Sentiment Analysis methods, it is considered that they can calculate lexical "distances" between the name of a product and each of the two opposite terms, such as "poor" and "excellent", to determine feelings about these (Thomas & Cook, 2006).

Considering the above-mentioned issues, our belief is that text-based analysis is not only the most commonly used method of identifying Social Media sentiment, but it is also the easiest to undertake. This ease of use is due to the annotation of text-based environments, in which the underlying tokens are often explicit character groups.

- **The Emoticon-Based Sentiment Analysis on Social Media**

Within Social Media environments, emoticons represent tools very often used by users, which are extremely diverse and capable of expressing a multitude of opinions and feelings. The popularity of these methods of expression cannot be denied, some of which being even included in the Oxford English Dictionary. In addition, with the new features offered by different social platforms like Facebook, reactions to specific posts can be directly expressed through emoticons.

Emoticons are firstly expressed in the form of faces that represent happy or sad feelings, although there is a wide range of non-facial variations. Therefore, they can be used as visual analytical systems in Sentiment Analysis, having the ability to reveal the hidden structure of individuals perception.

The polarity of these emoticons can be classified, similar to the text-based method, as positive, negative, and neutral. In this regard, Gonçalves et al. (Gonçalves, Araújo, Benevenuto, & Cha, 2013) classified the main emoticons used within social online environments as follows (Table 1):

Table 1 Emoticons and their variations

<table>
<tr><th>Emoticon</th><th>Polarity</th><th>Symbols</th></tr>
<tr><td>☺</td><td>Positive</td><td>:) :] :} :o) :o] :o} :-] :-) :-} =) =] =} =^] =^) =^} :B :-D :-B :^D :^B =B =^B =^D :’) :’] :’} =’) =’] =’} <3 ^.^ ^-^ ^_^ ^^ :* =* :-* ;) ;] ;} :-p :-P :-b :^p :^P :^b =P =p \o\ /o/ :P :p :b =b =^p =^P =^b \o/</td></tr>
<tr><td>☹</td><td>Negative</td><td>D: D= D-: D^: D^= :(:[:{ :o(:o[:^(:^[:^{ =^(=^{ >=(>=[>={ >=(>:-{ >:-[>:-(>=^[>:-(:-[:-(=(=[={ =^[>:-=(>=[>=^(:’(:’[:’{ =’{ =’(=’[=\ :\ =/ :/ =$ o.O O_o Oo :$:-{ >:-{ >=^{ :o{</td></tr>
<tr><td>😐</td><td>Neutral</td><td>:| =| :-| >.< >< >_< :o :0 =O :@ =@ :^o :^@ -.-.-’ -_- -_-’ :x =X :# =# :-x :-@ :-# :^x :^#</td></tr>
</table>

Source: Classification made by Gonçalves et al. (Gonçalves, Araújo, Benevenuto, & Cha, 2013)

Surely, the classification of these emoticons differs depending on the Social Media tool or platform being used. Relying on the instrument in which the data is collected, users may receive a different form of emoticon characters, researchers facing the difficulty of not having a generally valid grading of emoticons from the collected data.

However, emoticons are an easy way of appreciating content or expressing opinion with respect to certain content, being extremely used by Social Media users. Therefore, in an e-Learning context through Social Media, it is helpful to approach these forms of expressing in order to analyze learninrs or other participants' sentiments.

- **The Media-Based Sentiment Analysis on Social Media**

Identifying the sentiments behind the user-generated media content can be considered a real challenge while conducting a Sentiment Analysis. When we talk about media content, we refer to images, music, video, and more recently live streaming, but also to many other similar means.

In contrast to text-based analysis or emoticon-based analysis, where the tokens underlying them are easier to classify, in non-textual environments these base tokens are considerably less explicit. In terms of media content, for example images and video content, base tokens are actually pixel groups (compared to the character groups, which can form words in the text). In addition to the multiple dimensions that tokens can have, their variation is much higher even when they express exactly the same concept. Thus, the use of dictionaries and other traditional text-based tools becomes impossible. At the same time, the existence of the semantic gap between what computer vision can achieve and the level of understanding required for Sentiment Analysis determines the immense difficulty in extracting and understanding sentiments behind media content. (Maynard, Dupplaw, & Hare, 2013)

Surely, progress in this type of analysis can not be challenged, with visual content being among the most valuable assets on Social Media. Thus, this field of research has gradually evolved, being initially focused on visual Sentiment Analysis using pixel-level features (Siersdorfer, Minack, Deng, & and Hare, 2010) and later on deep visual features (You, Luo, Jin, & and Yang, Robust image Sentiment Analysis using progressively trained and domain transferred deep networks, 2015) and analyzing sentiment using multi-modalities, such as text and image content (You, Luo, Jin, & and Yang, Cross-modality consistent regression for joint visual-textual Sentiment Analysis of social multimedia, 2016; You, Jin, & Luo, 2017).

Although considered perhaps the most difficult method to carry out the Sentiment Analysis on Social Media environments and not only, media content analysis represents a real opportunity to understand the emotional side of the participants in educational processes. This is mainly due to the preference of new generations of learners to gain knowledge through music, photos and video files instead of text (Oblinger, Oblinger, & Lippincott, 2005).

4. BRINGING EFFICIENCY TO SOCIAL E-LEARNING SYSTEMS

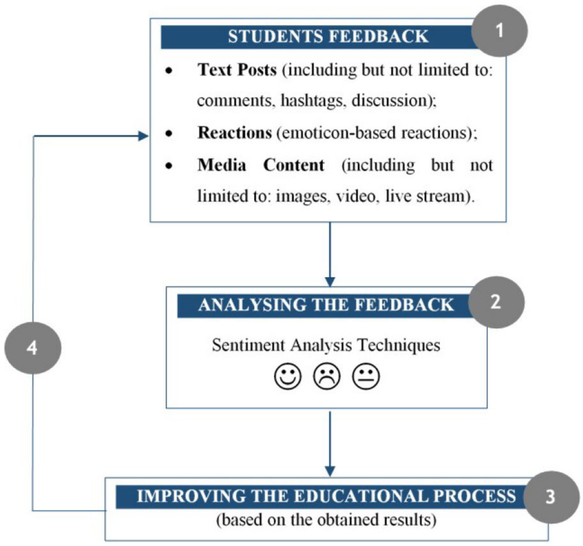
Following the previous analysis of what the Sentiment Analysis is, the importance and opportunities that it can have on the development and efficiency of e-Learning systems through Social Media, it becomes clear the need to implement this kind of study in the educational sphere. User feedback is particularly important, serving as a tool to provide personalized educational content and contexts that meet learners needs and requirements.

Social Media tools, facilitating collaborative communication and learning, provide quick feedback at a given time and during a teaching/learning situation. Understanding the feelings behind the user-exposed content determines the adoption of measures that will make the performance of educational processes more efficient.

Altrabsheh et al. (Altrabsheh, Gaber, & Cocea, 2013) proposed a pattern of application of Sentiment Analysis in education, aimed at text-based analysis in the form of tweets. Starting from the idea of the authors, our proposed framework attempts to expose an architecture that fully benefits from all the opportunities offered by Social Media in an e-Learning context. It tends to offer a broad vision in the form of a general scenery that can be adapted and used indifferently by the chosen Social Media platform.

Hence, the proposed architecture (Figure 2) assumes that the feedback is obtained from learners in the form of text posts (including but not limited to comments, hashtags, discussion), reactions (emoticon-based reactions) and media content (including but not limited to: images, video, live stream). Subsequently, the data obtained can be studied using the techniques offered by the Sentiment Analysis, Naive Bayes and Vector Support being mentioned by Altrabsheh et al. (Altrabsheh, Gaber, & Cocea, 2013) as extremely useful, individually or combined with respect to the educational reviews and data.

As a result of the Sentiment Analysis, using the common classification offered by it, the aspects that negatively affects the learning process results, the aspect that favour the educational processes or the neutral aspects can be highlighted. These aspects, in fact, mark the emotional side that guides the learning behavior of the subjects, namely the learners. Therefore, specific measures can be taken in order to hereditate or mitigate the deficiencies of the educational content, situations and processes, the learners finally benefiting from what they really need.



Source: Authors proposed architecture

Figure 2 Applying Sentiment Analisys on Social E-Learning Systems

Of course, combining the three types of Sentiment Analysis can be a tough task even in the context of e-Learning through online social environments. The proposed architecture is merely a simplistic or generalized approach to what the inclusion of Sentiment Analysis involves in improving educational processes. The three steps presented in this working framework can be analyzed in depth and there are many other aspects that can be examined, but this work can be considered a good starting point that opens new perspectives to the context of learning through the Social Media.

5. CONCLUSION

The research carried out in this paper leads to the following notable findings regarding the application of Sentiment Analysis in the context of online learning through Social Media tools:

- The emotional presence represents one of the key successful factors in improving the educational processes, the necessity of adopting this kind of study being evident even in the context of online learning supported by Social Media instruments;
- Online social environments offer valuable opportunities for analyzing user's sentiment, while also representing proper means of facilitating freedorm of expression and familiar interaction environments for the new generations of learners;
- Understanding the students' learning needs fosters the creation of personalized learning environments, supporting the contemporary student-centered approach of learning;
- Applying Sentiment Analysis in the context of online learning through Social Media tools can significantly diminish the barriers to understanding learners' needs and requirements for gaining knowledge;
- Understanding the emotional side of content distributed by learners provides clear opportunities for adopting measures aimed to foster the proper development of educational processes and their outcomes.

Furthermore, this paper raises the awareness on a general framework that can be experienced when the application of the Sentiment Analysis on the e-Learning systems through Social Media is desired. The suggested architecture can be adapted and used according to specific needs, but it also leaves open doors to new research areas in the field of applying Sentiment Analysis in the online educational contexts.

Certainly, this work, being predominantly focused on reviewing existing evidences in the analysed field, requires continuity in highlighting the importance and opportunities of Sentiment Analysis on the development of e-Learning systems through Social Media. Therefore, it is advisable to extend the research through the experimental application of Sentiment Analysis in the context of online social learning.

REFERENCES

Altrabsheh, N., Gaber, M., & Cocea, M. (2013). SA-E: Sentiment Analysis for Education. *Frontiers in Artificial Intelligence and Applications, 255*. doi:10.3233/978-1-61499-264-6-353

Boiy, E., & Moens, M.-F. (2009). A Machine Learning Approach to Sentiment Analysis in Multilingual Web Texts. *MF. Inf Retrieval, 12*(5), 526-558.

Clarizia, F., Colace, F., De Santo, M., Lombardi, M., Pascale, F., & Pietrosanto, A. (2018). E-learning and sentiment analysis: a case study., (pp. 111-118). doi:10.1145/3178158.3178181

Devika, M. D., Sunitha, C., & Amal, G. (2016). Sentiment Analysis:A Comparative Study On Different Approaches. *Procedia Computer Science*, 44-49.

Downes, S. (2007). An introduction to connective knowledge. *The International Conference on Media, Knowledge & Education - Exploring new Spaces, Relations and Dynamics in Digital Media Ecologies.* Retrieved from http://www.downes.ca/post/33034

Garrison, D. (2011). *E-Learning in the 21st century: A framework for research and practice* (2nd ed.). London: Routledge/Taylor and Francis.

Gonçalves, P., Araújo, M., Benevenuto, F., & Cha, M. (2013). Comparing and combining sentiment analysis methods. *COSN '13 Proceedings of the first ACM conference on Online social networks*, (pp. 27-38). Boston, Massachusetts.

Kechaou, Z., Ben Ammar, M., & Alimi, A. (2011). Improving e-learning with sentiment analysis of users' opinions. *Global Engineering Education Conference (EDUCON) - "Learning Environments and Ecosystems in Engineering Education"*, 1032-1038.

Liu, B. (2012). *Sentiment Analysis and Opinion Mining.* Morgan & Claypool Publishers.

Maynard, D., Dupplaw, D., & Hare, J. (2013). Multimodal Sentiment Analysis of Social Media. *CEUR Workshop Proceedings*, 44-55.

Oblinger, D., Oblinger, J. L., & Lippincott, J. K. (2005). *Educating the Net Generation.* New York:Brockport Bookshelf. Retrieved August 8, 2017, from http://digitalcommons.brockport.edu/cgi/viewcontent.cgi?article=1278&context=bookshelf

Rahmath, H., & Ahmad, T. (2014). Sentiment Analysis Techniques - A Comparative Study. *IJCEM International Journal of Computational Engineering & Management, 17*(4), 25-29.

Rienties, B., & Rivers, B. A. (2014). Measuring and Understanding Learner Emotions: Evidence and Prospects. *Learning Analytics Review*(1), 5. Retrieved from http://www.laceproject.eu/learning-analytics-review/measuring-and-understanding-learner-emotions/

Shen, L., Wang, M., & Shen, R. (2012). Affective e-learning: Using ''Emotional'' data to improve learning in pervasive learning environment. *Educational Technology & Society*, 176–189.

Siemens, G. (2005). Connectivism: A learning theory for the digital age. *International Journal of Instructional Technology & Distance Learning*, 3-10.

Siemens, G. (2005). Connectivism: A Learning Theory for the Digital Age. Retrieved from http://www.elearnspace.org/Articles/connectivism.htm

Siersdorfer, S., Minack, E., Deng, F., & and Hare, J. S. (2010). Analyzing and predicting sentiment of images on the social web. *ACM MM*, 715–718.

Stenbom, S., Cleveland-Innes, M., & Hrastinski, S. (2014). Online Coaching as a Relationship of Inquiry: Mathematics, online help, and emotional presence. *The Canadian Network for Innovation in Education Conference.*

Thomas, J. J., & Cook, K. A. (2006). A visual analytics agenda. *IEEE Computer Graphics*.

Vohra, S. M., & Teraiya, J. B. (2013). A COMPARATIVE STUDY OF SENTIMENT ANALYSIS TECHNIQUES. *JOURNAL OF INFORMATION, KNOWLEDGE AND RESEARCH IN COMPUTER ENGINEERING*, 313-317.

Wang, H., & Zhai, C. (2017). Generative Models for Sentiment Analysis and Opinion Mining. *A Practical Guide to Sentiment Analysis* (pp. 107-134). Springer International Publishing .

You, Q., Jin, H., & Luo, J. (2017). Visual Sentiment Analysis by Attending on Local Image Regions. *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence (AAAI-17)*, 231-237.

You, Q., Luo, J., Jin, H., & and Yang, J. (2015). Robust image sentiment analysis using progressively trained and domain transferred deep networks. *Proceedings of the Twenty Ninth AAAI Conference on Artificial Intelligence*, 381–388.

You, Q., Luo, J., Jin, H., & and Yang, J. (2016). Cross-modality consistent regression for joint visual-textual sentiment analysis of social multimedia. *Proceedings of the Ninth ACM International Conference on Web Search and Data Mining*, 13-22.

Yu, Y., Duan, W., & Cao, Q. (2013). The impact of social and conventional media on firm equity value: A sentiment analysis approach. *Decision Support Systems, 55*(4), 919-926.