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REVIEW ARTICLE

Sentiment analysis in education research: a review of journal publications

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ABSTRACT
Sentiment analysis (SA) is widespread across all fields and has become one of the most active topics in education research, and there is a growing body of papers published. So far, however, there has been little discussion about comprehensive literature reviews in SA in education. Therefore, this study aims to review the high-qualified scientific literature of SA in education and reveals the future research prospects of SA based on the reviewed papers. After systematically searching five online bibliographic databases, 41 relevant articles were located and included in the study. Results show that most studies focus on higher education, and more studies adopt smaller datasets. SA is actively employed in the learning domain of engineering and technology, and teachers/educators are the primary stakeholders considered of studies. Further, utilizing hybrid approaches for SA research is predominant, more studies have refined the granularity of sentiment categories in education. Finally, four major SA research topics, including designing SA methods/systems, investigating learners' satisfaction/attitude/concerned topics, evaluating teachers' teaching performance as well as examining the relationship among sentiment, behavior, performance, and achievement, were identified and discussed deeply. Accordingly, several implications and research issues for SA in education research are provided.

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Keywords
Sentiment analysis; online learning; education; emotions; literature review

1. Introduction

Emotions are defined as individual experiences and responses concerned with the situations in which they appear in human societies (Dupre et al., 2015). Emotions have a pivotal role in human cognition, as well as the human life of each person (Imani & Montazer, 2019). In a learning context, emotions affect students' motivation and the outcome of the learning process (Shen et al., 2009). Therefore, timely discovery and management of students "emotional information help understand students" potential needs to provide suggestions or content to students to adapt to the emotional state at that time (Ortigosa et al., 2014). Moreover, it is becoming a trend to employ an emotional perspective and to position emotions as the center of educational research (Yadegaridehkordi et al., 2019). At the same time, there has been an increasing interest in exploring emotion recognition, monitoring, expression, and intervention in the field of education (Arguel et al., 2017; Lajoie et al., 2019; Malekzadeh et al., 2015). In an online environment, especially massive open online courses (MOOCs), students need to establish an online presence (Colace et al., 2015). In this context, a promising method is sentiment analysis (SA): the process of identifying user's opinion from the text and classifying it into

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different sentiments or emotions to determine the user's attitude toward an object or entity (Liu, 2010; Rani & Kumar, 2017; Wang et al., 2013).

In recent years, a family of studies explores the methods of sentiment recognition in different educational situations, emphasizing the value and prospects of SA in education research (Colace et al., 2015; Liu et al., 2016; Oramas Bustillos et al., 2019; Yang et al., 2014). Moreover, text-based SA has unique advantages over the emotional detection of bodily and physiological sensors because it requires no specialized hardware, is cost-efficient, and it is more conducive to the application from the laboratory to the classroom teaching environment (D'Mello & Graesser, 2012). From the unique advantages and the growing research interest of SA in education, it is necessary to systematically review previous works to provide direction and reference for future research. Thus, two representative literature reviews were found as follows. Mite-Baidal et al. (2018) reported a systematic literature review to explore techniques used, digital education resources, and the main benefits of SA in education, and Dolianiti et al. (2019) reviewed the research status of SA in educational domain. However, there are some shortcomings in the two literature reviews. They: (1) did not guarantee the quality of reviewed articles, as the selected papers include conference papers (Xia & Zhong, 2018); (2) did not pay attention to the experimental processes and methods of SA in education, leading to a lack of understanding of application detail of SA in the educational domain; (3) did not consider the sentiment categories, research purpose, and key findings.

Hence, this study is a new attempt to compensate for these limitations, the purpose of our study is twofold: (1) to review of high-quality journal articles on SA in education systematically; (2) to explore the future research prospects of SA in education based on literature review. To manage the literature review and achieve the research goals, this study is guided by the following questions.

RQ1: What are the general characteristics of educational research of SA?

RQ2: What approaches employed, and the sentiment categories considered in the selected papers?

RQ3: What are the research objectives and key findings of these studies?

2. Method

2.1. Search strategy

For this study, we had searched five databases. Specifically, the digital databases used include Springer, ISI Web of Knowledge, IEEE Explore, Educational Resources Information Center (ERIC), and ScienceDirect. The leading search phrase was "sentiment analysis in education/learning". Besides, since the text is the measurement channel of SA (Rani & Kumar, 2017) and "emotions" and "sentiments" have often been used interchangeably (Munezero et al., 2014), this study conducted parallel searches by using the query string "text AND (sentiment OR emotion) AND (education OR learning)". All searches were limited to titles, abstracts, and keywords.

2.2. Study selection process

The last search was conducted on 6 April 2020. A total of 1014 articles were collected. Endnote is a bibliographic package that used to manage and sort articles (Kitchenham, 2004). We excluded 235 duplicate articles from the above database in Endnote. The remaining 779 articles were randomly assigned to two authors for independent review. In the selection process, the article's title, abstract, and keywords were analyzed using the inclusion and exclusion criteria shown in Table 1. For the divergent literature, two researchers conducted a meeting to discuss whether they met the inclusion or exclusion criteria. After screening at this stage, there are 74 articles left, the same method was used to read and screen the full text of these articles, and 41 papers were finally determined for data extraction. Most of them were retrieved from SSCI/SCI journals (21 SSCI/SCI journals, and 5 other peer-reviewed journals).

Table 1. Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
Published between January 2010 and April 2020.	Publications were except, such as lectures, workshops, book chapters, and posters.
Peer-reviewed journal article.	Duplicated studies.
Papers written in English.	The study must not be review, meta-analysis, or commentary article.
Applied to text-based SA techniques.	The publication does not suit the research questions.
Described SA in the educational domain.	

2.3. Data extraction and coding

In this study, we used Endnote and MS Excel spreadsheets to extract and code the required data from the review literature. According to research questions, the data extraction and coding were divided into seven columns (see Table 2). Inter-rater reliability was calculated as 0.93 with Cohen's kappa analysis. Finally, we conducted a meeting to negotiate an agreement about the inconsistent coding results, thus completing the coding procedure.

3. Results

3.1. What are the general characteristics of educational research about SA?

The number distribution of educational contexts in the 41 papers is shown in Figure 1. 63% (26/41) of studies selected the educational context for higher education, and 24% (10/41) of studies were MOOCs. However, the educational context of only one paper was K-12 (Arguedas et al., 2018), and four studies did not specifically mention the educational context, accounting for 10% of total studies.

Figure 2 presents the data size of 41 studies. Among them, studies with data sizes of 1001–10,000 and 10.001–100,000 each accounted for 34% (14/41). Studies with smaller datasets (less than 1000 samples) accounted for 7% (3/41), and the smallest data size was 119 (Leong et al., 2012). There were two studies with a larger dataset (greater than 100,000), and the maximal data size was 402,812 (Shen & Kuo, 2015). Eight studies did not specifically mention the data size, accounting for 20% of total studies.

The QS World University Rankings list (2020) is adopted to identify learning domains. Figure 3 provides the distribution of learning domains in 41 studies. Among them, the main domains of the study were "Engineering and Technology" (17%), followed by "Arts and Humanities" (7%), "Social Science and Management" (7%), "Natural Science" (5%) and "Life Science and Medicine" (2%). 10% of studies conducted in mixed learning domains. However, more than half of the studies (51%) did not specify any learning domain as they mainly focused on designing SA methods or systems.

Figure 4 depicts the frequency distribution of studies for each stakeholder. Please note that nine studies provide two stakeholders. Teachers or educators were the main target of most research (63%), followed by administrators or decision-makers (24%), students or learners (17%), developers or researchers (12%), and providers or facilitators (5%). We notice that when researchers were the stakeholders of studies, they were usually also the designers and developers of the system.

Table 2. The coding schemes.

Extracted data	Description
Educational contexts	Examples: K-12, higher education, MOOCs
Data size	Fill in according to the actual situation
Learning domains	The coding referred to the QS World University Rankings list (2020)
Stakeholders	The intended recipients of the analysis results
Approach employed	Examples: hybrid approach, machine learning approach, lexicon-based approach, and manual approach
Sentiment categories	Examples: positive, negative, boredom, anger, anxiety, etc.
Research objectives	The purpose as stated in the paper

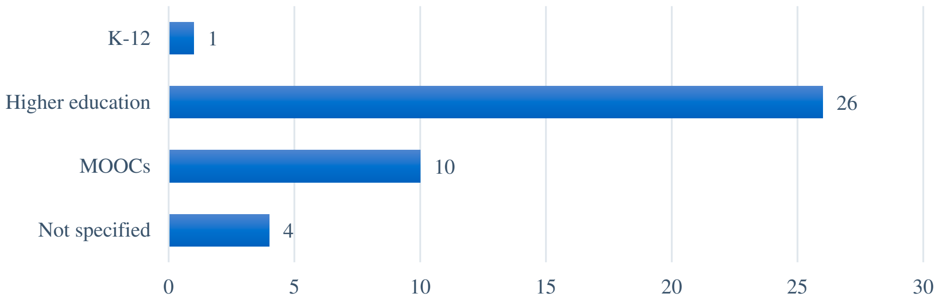

Figure 1. Distribution of educational context.

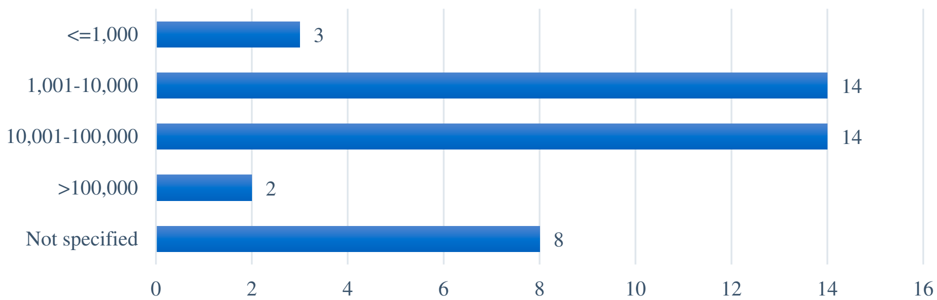

Figure 2. The data size of these studies.

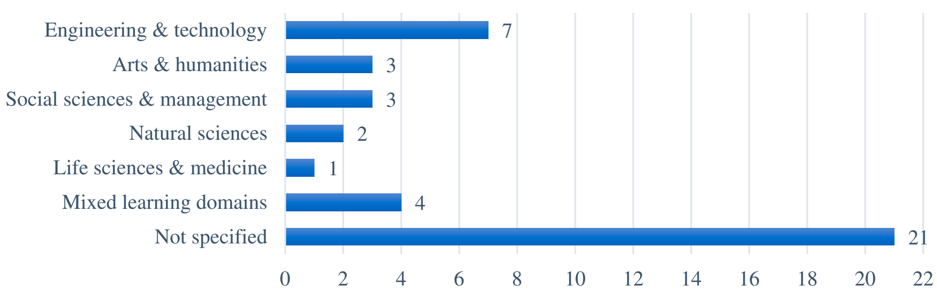

Figure 3. Learning domains of these studies.

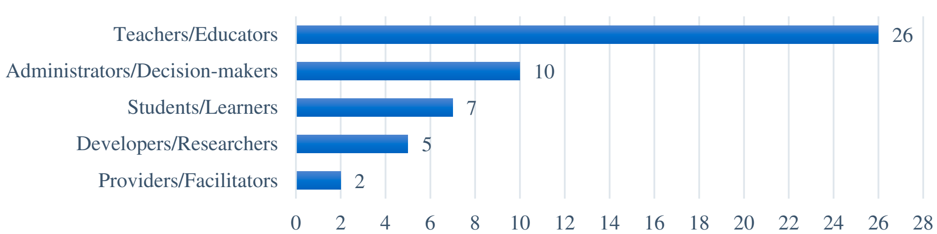

Figure 4. Stakeholders focus of these studies.

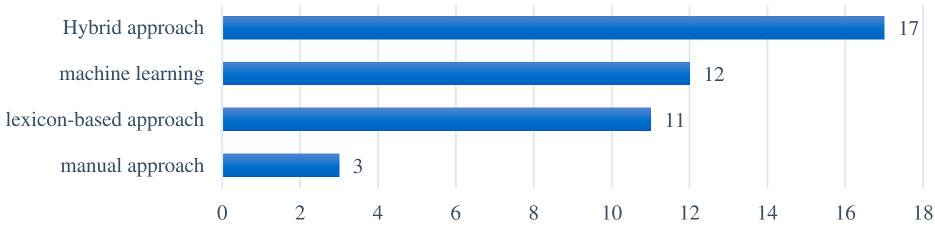

Figure 5. Approaches employed in these studies.

3.2. What approaches employed, and the sentiment categories considered in the selected papers?

Figure 5 shows the number of studies using each approach, please note that Ortigosa et al. (2014) provided application results of three approaches. Most studies (41%) utilized a hybrid approach that combines lexicon-based approach with machine learning approach, followed by a machine learning approach (29%), dictionary-based approach (27%), and manual approach (7%). We notice that sometimes, a manual approach is a good idea for SA in education research owing to the data scale, lexicon professionalism, accuracy, and other factors, which is also supported by Feldman and Ungar (2012).

Positive and negative were commonly utilized emotional states in SA (in 27 studies). However, the emotional granularity of this classification method is too large, which is not conducive to educators to carry out further learning intervention (Li, 2018). Surprisingly, there were 13 studies beyond positive and negative emotions and refined the granularity of SA in educational research. Moreover, we found that some studies paid more attention to negative emotions of students (such as confusion, bored, anxiety), and this result is also supported by Malekzadeh et al. (2015) and Yadegaridehkordi et al. (2019). Generally, if students can manage well the negative emotions in the learning process, their learning performance would be significantly improved (D'Mello & Calvo, 2013).

3.3. What are the research objectives and key findings of these studies?

3.3.1. Research objectives

The results in Figure 6 show that the most common research objective was designing SA methods/systems (39%), followed by investigating learners' satisfaction/attitude/concerned topics (34%), and 17% of studies examining the relationship among sentiment, behavior, performance, and achievement, with only 10% of studies evaluating teachers' teaching performance.

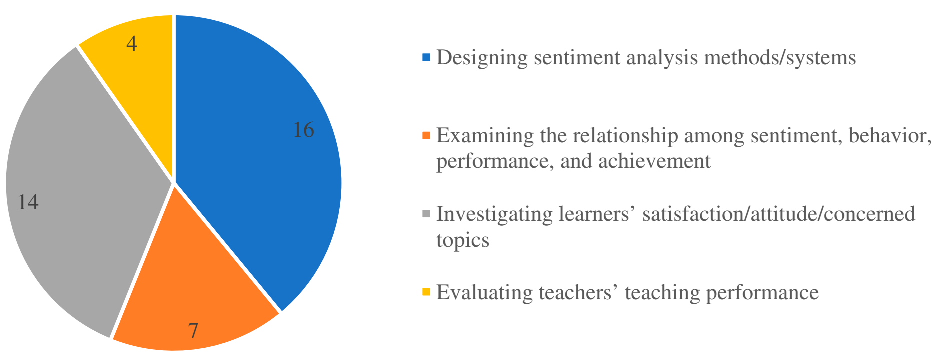

Figure 6. Research objectives of these studies.

3.3.2. Key findings

3.3.2.1. Application of SA methods or systems. These results correspond to studies with research objectives as designing SA methods or systems. A summary of the results of these studies was that:

- System enhancement: SA could be incorporated into various systems (such as management systems, online learning systems, evaluation systems), which had contributed to realize the real-time analysis of student feedback (Elia et al., 2019; Lin et al., 2019; Oramas Bustillos et al., 2019; Rani & Kumar, 2017; Tseng et al., 2018). In system development, SA helped interface design and enhanced immersion in the learning process (Lin et al., 2014), and had great potential for improving teaching effectiveness (Rani & Kumar, 2017). Moreover, SA could mine the potential information of course reviews to help administrators improve the platform construction (Liu et al., 2019a).
- Learning intervention: SA could be used to mine the satisfaction of students in the learning process to achieve learning early warning (Ortigosa et al., 2014). When students had negative emotions, the results of SA may help teachers and administrators to carry out timely teaching interventions (Liu et al., 2019a). Li (2018) utilized emotional intervention or learning process intervention for learners based on emotion intensity and duration. Tian et al. (2014) constructed a database of emotion regulation strategies and employed case-based reasoning to intervene in learning. The results indicated that this method had a positive role in emotion regulation in interactive text-based applications.
- Visual feedback: The visual presentation can improve the readability of SA results (Pong-inwong & Songpan, 2019). On the one hand, visual feedback could help students perceive their emotions (Arguedas et al., 2018) and enhanced ability to adjust their emotions (Yu et al., 2018). on the other hand, it also intuitively presented student satisfaction to teachers, which provided suggestions and guidance for improving the curriculum (Cunningham-Nelson et al., 2019). Currently, there are three main types of visual feedback: virtual agents, word clouds, and dashboards. Accurately, virtual agents could express and feedback different emotional states to enhances the attractiveness of the learning system (Lin et al., 2014) and had a significant positive impact on students' learning performance (Arguedas et al., 2018). Some studies found that word cloud or graphical methods (Ortigosa et al., 2014) to present the results of SA was convenient for teachers to analyze students' learning interest (Rani & Kumar, 2017), satisfaction (Santos et al., 2018), and related topics (Troisi et al., 2018). Besides, dashboards were often utilized to display SA results (Elia et al., 2019; Yu et al., 2018).
- Identified challenges when applying SA methods and systems: (1) Classification performance. many studies ignored the importance of data preprocessing in SA, which leads to the poor performance of SA (Jena, 2019). (2) System promotion. In the actual educational scene, there was a large amount of unlabeled data since the labeled data was very limited (Yang et al., 2014). Additionally, the SA module should not be extremely complicated, and the requirements for system equipment should not be too high, otherwise it is not conducive to system promotion (Li, 2018). (3) Analysis result. The results obtained through the SA method may deviate from the real situation, which still needed to be verified by logical reasoning (Liu et al., 2019a) or psychological motivation survey (Liu et al., 2019b).

3.3.2.2. Understand learning behavior and performance

These results correspond to the studies with research objectives as examining the relationship between sentiment, behavior, performance, and achievement, including:

- The interplay of behavior and sentiment: different interactive behaviors of learners may trigger different learning emotions in online discussions, and learners exhibited more abundant emotions and more in-depth interactive behaviors in group-oriented learning tasks (Huang et al., 2019). In the MOOC forum, learners tended to be more active after teachers' actions (Moreno-Marcos et al., 2019). Exposure of positive deactivating emotions had the most significant positive impact on the survival of learners. In contrast, the positive activations emotions expressed or exposed by students did not affect the survival of students (Xing et al., 2019). Surprisingly, complex terminology affected user understanding in MOOC privacy documents (Prinsloo et al., 2019).

- The sentiment was related to academic performance: student enthusiasm was positively related to academic achievement (Liu et al., 2018). However, there was no significant difference among high-, middle- and low-achieving students on negative sentiments (Liu et al., 2018). Furthermore, the study found that Emotional awareness and feedback had a positive effect on students' learning performance (Arguedas et al., 2018), and the utilization of SA could improve the accuracy of early academic failure (Yu et al., 2018).
- Importance of temporal characteristics of sentiments: Considering the temporal characteristics of sentiments may help to identify and intervene students at risk (Liu et al., 2019b), and could improve the classification performance of the classifier (Tseng et al., 2018). Therefore, it is recommended to combine temporal features to conduct a dynamic analysis of sentiment (Leong et al., 2012). At the beginning and end of a semester, the possibility of sentiment expression was higher (Liu et al., 2019b). The learner's sentiments changed as experience continues to increase Over time, and sentiment expression gradually utilized more neutral Language (Hixson, 2020). The study found that in the online learning process, learning sentiments presented a periodic feature (Huang et al., 2019). Ortigosa et al. (2014) recommend narrowing the temporal window to detect changes of sentiment.

3.3.2.3. Improve the process of teaching and learning

These results correspond to the studies with research objectives as investigating learners' satisfaction/attitude/concerned topics or evaluating teachers' teaching performance. These findings were summarized as follows:

- Satisfaction with a course: The use of SA techniques could change the overall impression of course evaluation (Cunningham-Nelson et al., 2019; Nimala & Jebakumar, 2019) to facilitate course improvement (Leong et al., 2012) and further the quality of the decision-making process (Elia et al., 2019). A study found that in the MOOC course, course instructor, content, assessment, and schedule had a significant predictive effect on student satisfaction. In contrast, Course major, duration, perceived workload, and perceived difficulty had no impact on it (Hew et al., 2020). Besides, learners paid more attention to the theme of course content with positive emotions, as well as course logistics and video production with negative emotions (Liu et al., 2019a). However, A study pointed out that students' confusion and negative emotions come from the content aspect (Liu et al., 2019b). 80% of students had a positive attitude towards learning experience with MOOC course (Shapiro et al., 2017), and the public had mixed opinions on MOOC, with slightly more negative opinions than positive opinions (Shen & Kuo, 2015).
- Experience in the platform: SA was helpful to understand the attitude of using the software for the first time or novice (Hixson, 2020), and could also explore students' learning experience on the platform. For example, students positively evaluated the learning experience in the online BIM learning platform (Suwal & Singh, 2018).
- Attitude towards institution: Santos et al. (2018) presented that higher education institutions may become more attractive online if they financially support expenses of living, provide courses in English, and promote an international environment. A study found that the main factors affecting selection of university were training offers, followed by physical structure, work opportunities, reputation, affordability, communication, organizational, and environmental sustainability (Troisi et al., 2018).

- Evaluation of teacher performance: the utilization of SA could evaluate teachers' teaching performance (Nimala & Jebakumar, 2019; Pong-inwong & Songpan, 2019) to select excellent teachers (Tseng et al., 2018). Sindhu et al. (2019) claimed to evaluate teaching performance from six dimensions: teaching pedagogy, knowledge, assessment, experience, behavior, and general. Lin et al. (2019) suggested evaluating teaching performance from the perspective of multi-model fusion comprehensively.

4. Discussion and conclusion

4.1. Incorporation of SA into education research

As shown in Figure 7, we conducted a statistical analysis of 41 review papers published in 2010–2020 and found that only one paper was published before 2014. Since then, the number of SA papers published in journals has increased dramatically, reaching a peak of 15 in 2019. The trend line (see the red line in Figure 7) reflects the potential of SA in future research, which shows that SA is increasingly vital in education research.

Generally, young children are more expressive than adults in the emotional aspect (Baker et al., 2010). However, there was less study of SA in the K-12 context of the 41 papers. A possible explanation for this might be that there is mainly face-to-face classroom teaching in the K-12 context. It is inconvenient to collect text data related to sentiments, which makes it hard to utilize text-based SA methods directly. Another possible explanation for this is how younger students' emotions affect their cognitive performance has been given little attention. Therefore, we call on the future works to strengthen the SA of younger students.

As indicated in Figure 2, most of the studies (41%) datasets employed are less than 10,000. In the process of sentiment modeling and automatic analysis, the smaller dataset affects the reliability and relevance of the results (Kagklis et al., 2015). According to the adopted approaches, we recommend that large-scale datasets are utilized for training models in automatic sentiment mining as much as possible to obtain more stable analysis results, which is supported by Nimala and Jebakumar (2019), and Yu et al. (2018). Besides, we have not found public datasets on SA in education, which may hinder the research of SA techniques or methods in education.

SA has been widely employed in different learning domains. Since learning sentiments vary according to the type of knowledge (Li, 2018), take a MOOC learning for example, a learner may take more interest in learning "Engineering and Technology" but hold a negative attitude towards "Life Science and Medicine", we can infer that it is urgent to explore cross-domain SA methods or systems. Regrettably, the research about this is very little. Therefore, future research can design

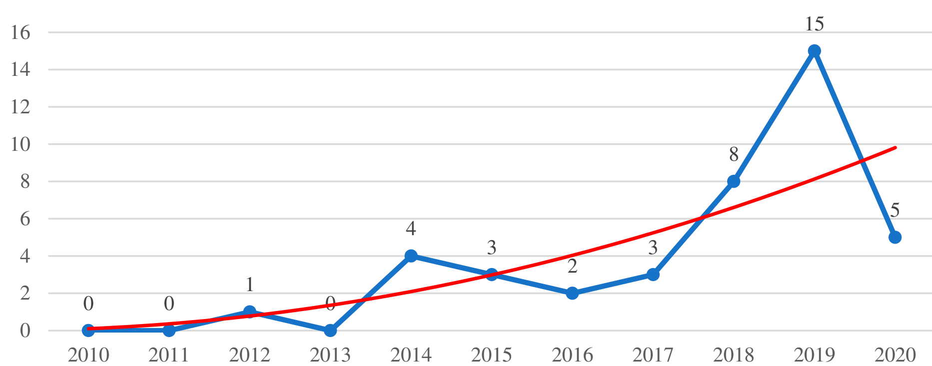

Figure 7. Publication time of these studies.

and develop SA methods or systems that are suitable for cross-domain, which will accelerate the application of SA in various learning domains.

Among the 41 papers, the main stakeholders considered were teachers or educators, followed by administrators or decision-makers. Specifically, SA is mainly applied to improve the teaching or learning process, as well as provide valuable information for education management. Students receive results of SA through visual tools (such as virtual agents, word clouds, and dashboards) to improve learners themselves capabilities of emotional management. Therefore, in the future, the results of SA ought to be presented as visually as possible for stakeholders.

4.2. Effective approaches in SA in education research

Most studies (70%) applied the machine learning approach and the hybrid approach. Despite these two approaches that can perform automatic SA on large-scale data, they cannot discover the internal reasons behind the sentiment aspect. Considering the above limitations, we recommend future work can be combined with qualitative (such as questionnaire, interview) methods to verify the results and explore the psychological motivation behind learning sentiment.

With the development of new and more powerful technologies, especially neural networks, the deep learning techniques represented by Convolutional Neural Networks (CNN) and Recurrent Neural Network (RNN) are being widely utilized in SA research, and their analysis results are superior to traditional machine learning (Barrón Estrada et al., 2020; Onan, 2020; Oramas Bustillos et al., 2019; Sangeetha & Prabha, 2020). It should be noted that the performance of sentiment classification is also related to dataset quality, feature selection, and other factors.

We found that 32% of the studies refined the sentiment categories in education research, which may be an essential trend in sentiment classification in education research. However, there require different techniques to recognize and regulate the refined sentiment categories. It can thus be suggested that more studies are needed to explore and solve this problem in the future. Another exciting direction for future research is to find intervention strategies that promote and trigger the conversion of negative emotions into positive emotions based on temporal characteristics, which may improve student learning to a large extent.

4.3. Implications for SA in education research

Since the education application of SA has developed rapidly since 2014 (see Figure 7), it is not surprising that people still a lack of awareness about the method or system for SA. Therefore, some studies were devoted to designing SA methods or systems (Jena, 2019; Lin et al., 2019; Liu et al., 2016). At the same time, it is crucial to explore the relationship between sentiment, motivation, and cognition with a reliable SA method in the academic context (Burić et al., 2016). However, none of the 41 studies explored the relationship between sentiment, motivation, and cognition, so this may be an important direction for future research. Yadegaridehkordi et al. (2019) claimed that it is expected that almost all learning applications and platforms will have embedded capabilities to detect and monitor learner emotions in the future. In view of this development, researchers in the education sector should accelerate the modularization of the SA process to integrate and embed platforms, or environments related to education.

The using of SA can enhance relevant systems in the field of education and visually present the results to facilitate teachers or educators to carry out learning intervention. From this perspective, it is recommended to incorporate sentiments into the learner model to improve the sentiment awareness and adjustment ability of the learning system, thereby further enhancing the student's learning experience.

Behavior and performance are highly correlated with learners' sentiments, and temporal features are crucial in understanding dynamic learning sentiments. However, little is known about whether there are specific patterns among sentiments, behaviors, and performances. Furthermore, the impact of demographic characteristics (such as gender, age group, and academic background) on learners' emotions, behaviors, and performance remains unclear, which deserves more attention from researchers.

SA plays a critical role in improving teaching, management, and evaluation through investigating learners' satisfaction with courses, platforms, institutions, and teachers. However, how to solve the problems exposed in teaching, management, and evaluation according to the satisfaction of learners is what practitioners in the education field need to pay attention to since it is crucial for regulating the emotions of learners.

In summary, the findings in this study provide a new understanding of SA in education research. It is hoped that the findings can be used as the basis for educational researchers to find new research directions in this field. This study can also be better to help policymakers and practitioners on how to apply SA in education field. However, there are some limitations of this study. In terms of search strategy, despite similar and interchanged terms were used for search, there are still some related papers that do not match our search terms. In addition, we only reviewed journal publications from 2010 to 2020, so it cannot stand for the trends of all studies. Therefore, it is recommended to conduct large-scale review in the future to gain a broader view of SA studies.

Disclosure statement

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