Investigating the effect of emotional tone on learners’ reading engagement and peer acknowledgement in social annotation

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Social annotation fosters collaborative learning by encouraging knowledge sharing and a community of inquiry. However, research has primarily focused on the cognitive aspect of social annotation. This study aims to contribute an emotional perspective to the existing literature on social annotation. Specifically, we used the valence-aware dictionary for sentiment reasoning algorithm to measure students’ emotional tones in 1,954 comments posted during social annotation. We then utilised linear mixed-effect models to examine the effect of emotional tone on students’ reading engagement and peer acknowledgement, respectively. Our findings indicate that students who posted more positive sentiment comments were more likely to spend more time engaging in social annotation and receive peer acknowledgement. These findings offer insights into the significance of emotional tone in social annotation and the design of scaffolding strategies to foster positive emotional tone.

Implications for practice or policy:
- Undergraduates’ peer acknowledgement can be enhanced by positive emotional tone in social annotation.
- Undergraduates engage more in active reading when their written comment expressed more positive sentiment in social annotation.
- Instructional designers and researchers can use sentiment analysis as an analytic approach to evaluate learners’ written texts for promoting peer interaction and reading engagement.
- Instructors and educators should consider understanding and monitoring the emotional tones students convey in their social annotations.

Keywords: emotional tone, reading engagement, peer interaction, sentiment analysis, social annotation

Introduction

Social annotation (SA) is an interactive online educational technology that fosters collaborative efforts among users in the learning community, enabling them to engage in the process of knowledge creation and the development of shared understanding (Nkomo & Daniel, 2021). It allows individuals to collaboratively annotate and comment on various digital resources, such as texts, articles, documents or multimedia content, socially and interactively (Novak et al., 2012). Although SA is gaining more attention from school teachers, educators and learning scientists as a potential tool in facilitating learner engagement and knowledge sharing (e.g., Kalir, 2020; Novak et al., 2012; Zhu et al., 2020), research has predominantly focused on its cognitive support functions.

However, there is a growing interest in exploring the roles of emotions within collaborative learning contexts such as SA, given the reciprocal influence of cognitive and socio-emotional processes during collaborative learning (Isohätälä et al., 2018). In social learning contexts, an individual's emotions can be influenced by peers' emotional expressions (Dindar et al., 2022) and emotional tone (Isohätälä et al., 2020). Emotional tone refers to the vocal expression or dialogue of emotion that conveys a student's affective states (Chang et al., 2023; Ishii et al., 2003), existing in the form of voice or narrative text. Emotional tone is associated with students' knowledge-sharing behaviours, engagement and interaction (Dang-Xuan et al., 2013; Näykki et al., 2014; Rapisarda, 2002), suggesting its crucial role in shaping the overall learning experience in cognitive and social activities in collaborative learning. Research has shown that emotionally toned online comments have a significant impact on the quality and intensity of readers' subjective emotions (Syrjämäki et al., 2022). However, the specific role of emotional tone in shaping engagement and interaction within online collaborative learning environments, such as SA, remains under-explored.

Despite the recognised importance of emotions (Pekrun & Linnenbrink-Garcia, 2012) in self-regulated learning and collaborative learning contexts (Avry et al., 2020; Reis et al., 2018), there remains a dearth of studies examining learners' emotions within SA platforms. This study aims to address this gap by investigating the emotional tone conveyed through students' SAs and its potential influence on their collaborative learning experiences. By delving into the emotional dimensions of collaborative learning, this research aims to provide valuable insights into the intricate interplay between emotions and the learning processes. Such insights have the potential to inform the development of more effective collaborative learning strategies and contribute to the design of training programmes that help educators and facilitators recognise and respond to emotional cues in students' SAs. By gaining a deeper understanding of the emotional dynamics of SA, educators can design interventions and pedagogical strategies that leverage positive emotions to enhance student engagement, motivation and learning outcomes. For example, incorporating features that promote positive peer interactions, provide timely feedback and cultivate a supportive learning community within annotation platforms can contribute to a more enriching and effective learning experience for students.

Theoretical backgrounds

Emotional tone in computer-supported collaborative learning

Emotional tone plays a crucial role in shaping students' overall learning experience in computer-supported collaborative learning. It encompasses the way emotions are conveyed through vocal expression or written narratives, reflecting a student's or instructor's emotional states (Chang et al., 2023; Ishii et al., 2003). In online collaborative learning, emotional tones are expressed through social-emotional interaction in the form of narrative texts (Isohätälä et al., 2020). Emotional tone can significantly impact an individual's cognitive processes, consequently influencing both the individual's and the team's performance (D'Mello & Graesser, 2012; Imai, 2010). For example, Dehbozorgi and Mohandoss (2021) found a significant positive correlation between students' positive emotional tone and their performance in collaborative learning. Lawson and Mayer (2022) found that the instructors' positive emotional tone positively influences students' learning outcomes. Zhao and Mayer (2023) further examined and confirmed the positive effects of human and virtual instructors' positive emotional tone on students' knowledge transfer. By reviewing empirical studies in recent decades on social-emotional interaction in collaborative learning, Huang and Lajoie (2023) concluded that positive emotional interactions, whether self-regulated or facilitated by peers, are associated with increased learner satisfaction and improved collaboration quality.

In addition to the cognitive effects, emotional tone also affects knowledge-sharing behaviours, interactions and engagement in collaborative learning. First, emotional tone significantly impacts online communication by influencing individuals' knowledge-sharing behaviours. As highlighted by Dang-Xuan et al. (2013), emotional tone affects not only the quantity of information sharing but also its speed. Discussion posts that convey positive emotions receive more and quicker responses from peers. Secondly, an individual's emotional tone can trigger group members' emotions, thereby influencing socio-emotional interactions. By analysing students' notes posted on the Knowledge Forum, Yang et al. (2022) found that students' emotional tones tended to maintain consistency or be followed by similar emotions (e.g., frustration to boredom). The consistency of emotional tone among group or community members contributes to regulating group behaviours in collaborative learning (Avry et al., 2020). Thus, students' emotional tone can influence team cohesiveness and performance in online collaborative learning situations (Huang and Lajoie, 2023; Rapisarda, 2002).

Furthermore, a negative emotional tone can trigger socio-emotional interactions within a learning environment, which can impede valuable socio-emotional processes and students' engagement in the learning process. These negative interactions encompass various actions, such as overriding, which involves disrespecting or weakening the perspectives of other peers, and isolating, which refers to the act of excluding or alienating others within the group. Additionally, demeaning actions involve belittling or undermining someone's self-worth, and neglecting entails ignoring or disregarding the needs and contributions of others, both of which could discourage team members' involvement as an effective team. Furthermore, discouraged team members may result in social loafing, which is the tendency that some members reduce their effort in group tasks and rely on the contributions of others instead of fully engaging in a task (Donaldson, 2005). Such behaviours could potentially evoke more negative emotions and result in disengagement (Linnenbrink-Garcia et al., 2011; Näykki et al., 2014; Rogat & Linnenbrink-Garcia, 2011).

Emotional tone and peer interaction in SA

SA has been widely used in educational settings to improve literacy skills, support argumentation and inquiry, help process domain-specific knowledge and connect online learning spaces (Zhu et al., 2020). Many studies have also reported the success of using SA tools to facilitate collaborative learning and prompt peer interactions. For instance, Mendenhall and Johnson (2010) designed an SA model learning system called SAM-LS that aims to improve students' critical thinking skills. Using surveys and interviews to understand students' perceptions of SA, Mendenhall and Johnson reported that SAs provided an appropriate environment for peer critique activities. Kalir (2020) presented a qualitative case study of how educators voluntarily contributed to an open networked project, Marginal Syllabus, which uses SA to encourage discussion about equity topics. They conducted and analysed interviews and found that SA enabled group-level collaboration and shared meaning-making. However, Gao (2013) found that SA activities can sometimes be distracting to learners who are reading online texts.

On the other hand, in certain contexts, SAs may not have a significant influence or even have a negative impact on students' learning outcomes (e.g., C.-M. Chen et al., 2020; Gao, 2013; Kalir et al., 2020; Thoms & Poole, 2017). A study was conducted on the effectiveness of Hy-Lighter, an SA collaborative annotation system, in relation to students' academic emotions and motivations (Razon et al., 2012). Razon et al. found no statistically significant differences between the experimental group (using Hy-Lighter) and a control group (using hard-copy reading materials) in terms of emotions (excited, optimistic, happy, worried, distressed, uncertain, pessimistic). In another study, Lu et al. (2013) developed a decision-tree-based prediction model to forecast users' reading anxiety levels based on students' annotation behaviours (e.g., highlight, translation, comment and summary) and annotation interactions (e.g., feedback frequency, response frequency, peer acknowledgement). Lu et al (2013) found that instructors' assistive strategies only reduced predicted reading anxiety among male students. In some studies, unpleasant experiences were reported with SA tools. For example, both undergraduate and younger students expressed that a high volume of annotations can be distracting while navigating a gamification learning system (C.-M. Chen et al., 2020) or reading online texts (Gao, 2013). Additionally, one study found that poor-quality annotations can lead to a misunderstanding of topics among peers and create pressure and anxiety when learners attempt to make annotations that differ from those of their peers (Thoms & Poole, 2017).

Other studies have found that emotions play a significant role in shaping social interactions. For example, Van Kleef (2009) developed a model of emotions about social information and reported that individuals' emotional expressions have an impact on the behaviour of their observers, as they trigger inferential processes and/or evoke affective reactions within them. Therefore, emotions serve as important factors that can be used to regulate social activities and influence the social activities of others. In the context of SA, the emotional tone expressed in written texts can serve as an emotional indicator for social interactions. In particular, students' positive emotional tone may create a welcoming and encouraging atmosphere that motivates students to contribute actively. In summary, the findings from the above-mentioned studies shed light on the role of emotions in peer interactions within SA contexts. However, they also suggest the need for further investigation of this topic to provide a more nuanced understanding of the complex dynamics between emotions, SAs and learning.

The current study

Research has highlighted the significant impact of students' emotional tone on their academic performance, engagement and the quality of social interactions in computer-supported collaborative learning contexts. This study sought to further explore the role of emotional tone in shaping learner engagement and peer interactions within the specific context of SA. In our investigation, we assessed social interaction and learner engagement through two key indicators: peer acknowledgement and active reading time (referred to as reading engagement). We derived these metrics from the log files of SA activities. More specifically, we employed SA as a collaborative learning tool within the framework of an undergraduate educational psychology course. Students were tasked with assigned readings and encouraged to actively engage with the material by highlighting and commenting on key content. Furthermore, students interacted with their peers by responding to their posts and expressing agreement through upvotes.

This study focused on examining how emotional tone influences reading engagement and peer acknowledgement in a digital SA environment. More specifically, we utilised sentiment analysis and linear mixed-effect models, respectively, to investigate the following research questions (RQs):

- RQ1. What emotional tones are manifested in students' SAs, as revealed through sentiment analysis?
- RQ2. What relationships exist between learners' emotional tone, reading engagement, and peer acknowledgement in the context of SA?

Materials and methods

Participants, learning platform and data type

The study received approval from the Research Ethics Board office at the university where it was conducted. A total of 91 undergraduate students (53 female, 38 male students) from a large North American university participated in a SA platform called Perusall (https://www.perusall.com/) in a complementary course called Integrating Educational Technology in Classrooms. This course is part of the university's undergraduate programme offered by the education faculty. The data collection was conducted during the COVID-19 pandemic, which imposed substantial limitations on traditional data collection methods. As a result, the participants were recruited from a convenience sample of students enrolled in this course. Convenience sampling allowed us to gather data from readily available participants who were already enrolled in the courses and participated in the SA activities. This approach ensured the continuity of our research under the challenging circumstances while still providing valuable insights into student interactions and learning experiences. The data used in this study, collected during Fall 2021, was approved by the course instructor for using learners' de-identified information from extracted logfiles on the Perusall platform. The course readings included 29 articles on educational technology topics across the 13-week semester. These readings were selected by the course instructor to support practising and future teachers in integrating technology into their teaching practices in a project-based learning environment.

Perusall is a digital platform that facilitates collaborative reading and knowledge construction among students (see Figure 1). The platform, which is reasonably simple to use, encourages learners' engagement and interaction in online asynchronous reading and has become increasingly offered in higher education during the COVID-19 pandemic (Bharath & Brownson, 2021). It revolutionises solitary reading tasks into collaborative social and educational endeavors by harnessing social learning techniques (Adams & Wilson, 2020). Furthermore, it encourages students to adopt an active role in their learning process by allowing them to interact with the course content, engage in discussions with their peers and collectively build knowledge. Notably, Perusall offers various features to support these interactions, including the affordances to highlight content of interest and post comments. Importantly, these comments are shared publicly with the entire class, fostering a collaborative and transparent learning environment. Furthermore, Perusall incorporates mechanisms for peer interaction, enabling students to respond to each other's comments and express agreement or support by clicking the upvote button. In this study, students were required to initiate an annotation with comments or respond to three to five annotations for each assigned reading. Although peer acknowledgement was recommended, it did not directly impact their final score.

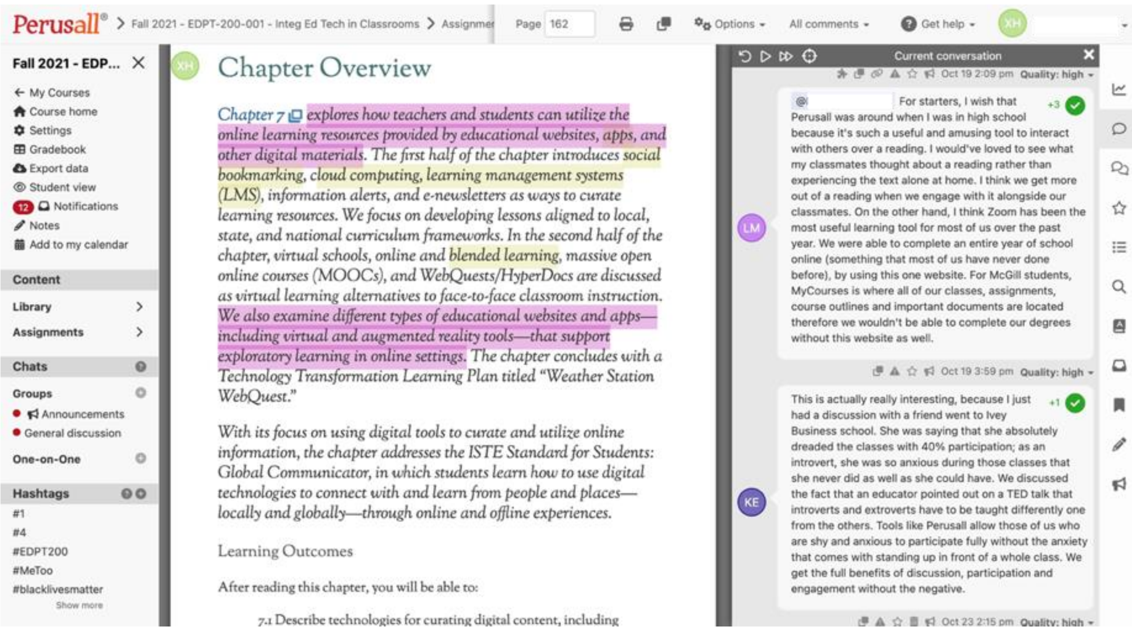

Figure 1. The interface of the SA platform

The data analysed for this study were retrieved from the log files generated by the Perusall platform. These data sources included students' active reading time and the number of upvotes received per reading. Active reading time was defined as the duration during which students interacted with the course materials, measured by when both the mouse and keyboard remained active within a certain location for a continuous period of 2 minutes (more details at the Perusall Support web page: https://support.perusall.com/hc/en-us). In contrast, if there was no mouse or keyboard activity for more than 2 minutes, it was recorded as total viewing time, indicating passive engagement with the content. The utilisation of active reading time as an indicator of reading engagement aligns with the study's focus on students' active involvement with course materials (e.g., creating comments, scrolling through the reading, taking notes). Studies using the same engagement indicator have found longitudinal behavioural patterns in SAs (F. Chen et al., 2024; Lin et al., 2024). Additionally, the total number of upvotes received on annotations was used to measure peer acknowledgements within the same reading (Li et al., 2024).

Upvotes on annotations serve as a form of peer validation, indicating that other students found the comment valuable or insightful. This recognition from peers acknowledges the contribution of the student who made the annotation. The total number of upvotes received can also be seen as an indicator of the level of engagement and interaction with the content by peers. Higher upvote counts suggest that the annotation resonated with multiple students, indicating active participation and acknowledgement within the community. Furthermore, using upvotes as a measure of peer acknowledgement is inclusive and accessible to all students. It allows every student the opportunity to acknowledge their peers' contributions without the need for complex or subjective assessment criteria. Last but not least, Perusall's design incorporates the upvote feature specifically for acknowledging and promoting peer interaction. Utilising this built-in functionality aligns with the platform's intended use and provides a standardised measure of peer acknowledgement across all users.

To summarise, each integrated SA by an individual for one reading is associated with an active reading time, as well as a quantified peer acknowledgement score indicated by the total number of upvotes received in that reading. The data types enable the examination of the influence of emotional tone on both individual reading engagement and peer interactions, providing a comprehensive understanding of the dynamics at play within the Perusall platform.

Data analysis

Sentiment analysis. In this study, we applied sentiment analysis, a powerful approach for extracting emotional tones, to extract students' emotional tones from their written annotations. Sentiment analysis, also known as opinion mining, is a classification technique widely used for the perceptual analysis of unstructured textual contents (Zou et al., 2015). It is widely used in research studies examining learner behaviours in online social learning (e.g., Nkomo & Daniel, 2021; Rueger et al., 2023). Specifically, it applies a natural language processing technique to determine the emotional tone (i.e., positive, negative or neutral) of digital text. By converting text into numerical data, applying natural language processing enables the utilisation of machine learning algorithms to make predictions and inferences (Tunca et al., 2023).

One highly effective approach in sentiment analysis is the valence-aware dictionary for sentiment reasoning (VADER), which is accessible through the Natural Language Toolkit library. VADER is a lexicon and rule-based tool for sentiment analysis of textual data. It considers both the polarity (positive or negative) and intensity (strength) of sentiment and can be directly applied to unlabelled text data (Hutto & Gilbert, 2014). Unlike other sentiment analysis methods, VADER utilises a pre-trained model that incorporates a sentiment lexicon, comprising a list of words or phrases with assigned sentiment scores. Specifically, each word in the lexicon is associated with a sentiment intensity score, indicating the degree of positivity or negativity it conveys. The lexicon also contains booster words that modify the sentiment intensity of nearby words, as well as a set of special rules for handling punctuations, capitalisation and other linguistic features. We chose VADER over other sentiment analysis tools due to its unique features, including its ability to accurately capture linguistic sentiment polarity and intensity, its compatibility with unlabeled text data and its accessibility through widely used libraries such as Natural Language Toolkit. Additionally, VADER's effectiveness in handling nuanced language expressions aligns with the complexity of students' written annotations in our study.

To apply the VADER algorithm, we used Orange3 data mining software (Demšar et al., 2013), to extract sentiment information from learners' comments. The process of natural language processing is illustrated in Figure 2, wherein sentiment analysis was conducted by setting appropriate metrics to pre-process the text (i.e., transformation, tokenisation, normalisation, filtering, N-grams range and parts of speech tagger) and then connecting it with the VADER Sentiment Analysis widget. Within this widget, the text data was processed, and sentiment scores were assigned to each instance based on the underlying lexicon and rule-based approach. These sentiment scores provided insights into the positivity, negativity and neutrality of the analysed text, while also yielding an overall compound sentiment score. The compound score serves as an aggregated measure, encapsulating the sentiment polarity of the text, ranging from -1 (indicating extreme negativity) to +1 (representing extreme positivity).

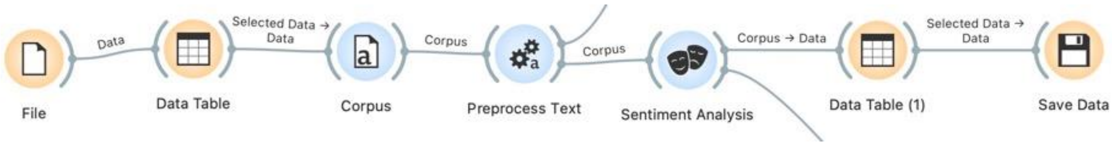

Figure 2. Text mining processing flow

Linear-mixed effect analysis. Linear mixed-effects analysis, also known as mixed-effects modelling or hierarchical linear modelling, is a robust statistical methodology employed in various fields (West et al., 2022), including the social sciences (Oshchepkov & Shirokanova, 2022) and education (e.g., Murayama et al., 2014). Linear mixed-effects analysis is particularly well-suited for analysing data with hierarchical structures, where observations are nested within groups. In our case, our grouping variable is the individual (represented by "ID"), with each student contributing multiple observations. This technique combines fixed effects (related to independent variables of interest) and random effects (related to group-level variability) within a single model, providing a more accurate representation of complex data. It is widely used to account for within-group correlations and individual differences while exploring the impact of factors on dependent variables.

Our data set consisted of behavioural metrics from undergraduate education students, each of whom contributed multiple SA entries. Specifically, at Level 1 of our hierarchical structures, we focused on dependent variables such as learner engagement and peer acknowledgement. At Level 2, we identified individual students by their unique IDs, each associated with multiple SA entries.

Traditional linear regression models may not adequately capture the intricate interactions between individual students' SA entries and those made by their classmates in the same course within this hierarchical structure. To address these complexities effectively, we turn to linear mixed-effects analysis. This methodology seamlessly integrates both fixed and random effects into the model, allowing us to account for within-group correlations and individual differences.

In this study, we applied two linear mixed-effects analyses to explore the relationships between emotional tones, learner engagement and peer acknowledgements, respectively. In our models, we incorporated random intercepts for the level two variable, representing individual students (ID). This inclusion of random intercepts is pivotal as it accounts for inherent group effects within our data. It acknowledges that each student may possess unique characteristics or experiences that influence their reading engagement and peer acknowledgement. By introducing random intercepts for the grouping variable, we effectively control for this group-level variation, allowing us to isolate and examine the impact of learners' extracted compound sentiment on our dependent variables.

Results

RQ1. What emotional tones are manifested in students' SAs, as revealed through sentiment analysis?

To answer the first research question, we first conducted a preliminary test to clean the data. After removing outliers with z scores greater than 3 or smaller than -3 in active reading time and peer acknowledgement, 1,954 valid SAs from a total of 29 readings throughout the semester remained for sentiment analysis. We extracted students' linguistic features from SAs and calculated their compound sentiment score to interpret their overall emotional tone per reading. As discussed earlier, the compound sentiment scores measure how positive or negative the tone of a student's comment is in SA. More specifically, we followed four steps in calculating the compound sentiment score (C). Firstly, the input text was tokenised into words or phrases. Second, sentiment intensity scores were assigned to each word based on a sentiment lexicon. Special rules and adjustments were applied to these scores, considering the context of the words. Third, the valence scores of all the words were summed up to obtain a raw sentiment score (S). Finally, the raw sentiment score was normalised to a range of -1 to +1, representing the overall sentiment polarity of the text. The following formula shows how a compound score is calculated:

$$C = S/\sqrt{S^2 + \alpha}$$

The result shows that the students expressed more positive sentiments on average, as indicated by the mean compound sentiment score of .86 (*SD* = .34).

RQ2. What relationships exist between learners' emotional tone, reading engagement and peer acknowledgement in the context of SA?

In addressing the second research question, the descriptive table (Table 1) illustrates the values of compound sentiment score, reading engagement and peer acknowledgement indicated by the number of received upvotes per reading.

Table 1
Descriptive statistics of compound sentiment, reading engagement and peer acknowledgement

	Compound sentiment	Reading engagement (minutes)	Peer acknowledgement (number gained)
Reading mean	.86	34.85	4.98
SD	.34	23.32	5.96
Minimum	-.99	5.00	0
Maximun	1.00	121.00	45

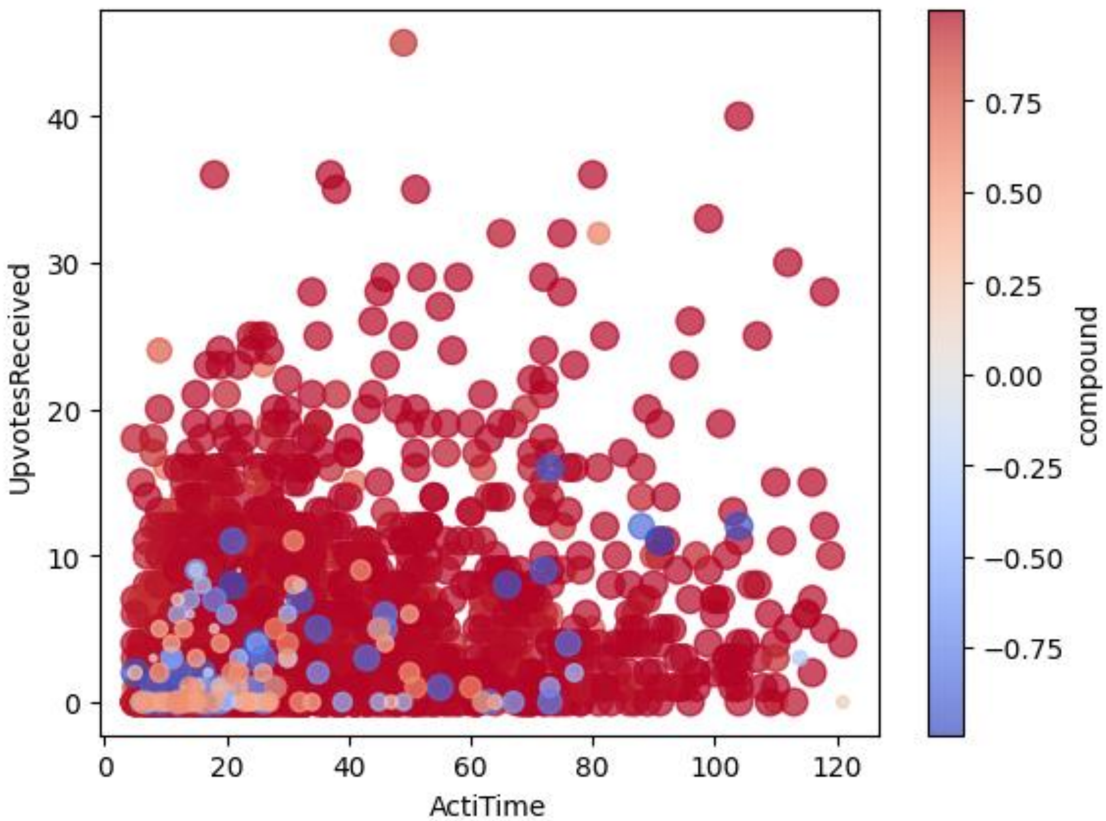

Figure 3. The relationships between compound score, reading engagement and peer acknowledgements

Additionally, as shown in Figure 3, we visualised the relationships between compound sentiment scores, reading engagement (ActiTime in the figure) and peer acknowledgements (number of received upvotes). The colour and size of the dots represent the compound sentiment score. Redder and larger dots refer to higher compound scores and vice versa. The position of the dots reflects the reading engagement and peer acknowledgement. From the plot, we can find that all posts with more than 20 upvotes had positive compound sentiment scores. Conversely, posts featuring negative compound sentiment scores tended to attract fewer upvotes. This phenomenon underscores a correlation between positive sentiment and increased peer acknowledgement. Furthermore, posts with negative compound sentiment scores were inclined to have shorter reading time; most of them were less than 60 minutes. In contrast, posts with positive compound sentiment scores display a more balanced distribution of reading times, diverging from the concentrated brevity observed in the negative score category.

Furthermore, we conducted two linear mixed-effects analyses to examine the effects of learners' extracted compound sentiment on their reading engagement and peer acknowledgement across multiple observations. Each analysis incorporated a mixed effects model to account for the group effect on individual students (N = 87, 4 students were excluded for missing records on the platform) by including random intercepts for the individuals' ID. Additionally, random intercepts for the grouping variable (*ID*) were included in the analysis to further address the group effect. The random effects analysis revealed significant variability between different students in terms of their baseline levels of the dependent variables. For reading engagement, the estimated variance for the random intercepts associated with the grouping variable was 154.4, with a corresponding standard deviation of 12.43; for peer acknowledgement, the estimated variance for the random intercepts associated with the grouping variable was 13.86, with a corresponding standard deviation of 3.72.

The result in Table 2 revealed a statistically significant effect of compound sentiment on reading engagement (p < . 05), with a t value of 4.43. For every one-unit increase in compound sentiment, there was an average increase of 6.39 units in active engagement time, while controlling for the group effect on individuals. The analysis also showed a significant effect of compound sentiment on peer acknowledgement (t = 5.38, p < .05). A one-unit increase in compound sentiment corresponded to an average increase of 1.70 units in received peer upvotes, while holding the group effect constant.

Table 2
Linear-mixed effect results of compound sentiment on reading engagement and peer acknowledgement while controlling individual differences

Variable	Fixed effect			Random effect		Model fit		
	Est.	SE	*t*	Variance	SD	#Obs.	REML	Cohen's *d*
Reading engagement	6.39	1.44	4.43	154.4	12.43	1954	17628.8	.25
Peer acknowledgement	1.70	.32	5.38	13.86	3.72	1954	11743.3	.68

Note. Est. refers to the estimated coefficient of the predictor variable compound sentiment, #Obs. refers to the number of observations and REML refers to the restricted maximum likelihood criterion.

In summary, the linear mixed-effects analysis revealed significant effects of compound sentiment on both reading engagement and peer acknowledgement, while controlling for the group effect on students. Specifically, students who posted comments with a more positive sentiment (i.e., higher compound score) were also more likely to spend more time engaging in SA and receive peer acknowledgement. These findings suggest that compound sentiment plays a meaningful role in influencing learner engagement and social interaction, providing insights into the impact of sentiment styles on students' digital SA.

Discussion

Our study responds to the growing need for more research on SA in educational contexts, as highlighted by Zhu et al. (2020). We examined the psychological impact of emotional tone on reading engagement and peer interaction within learning contexts, with a special focus on peer acknowledgement. To investigate this phenomenon, we employed sentiment analysis to quantify and unveil text-based emotional tone in educational contexts. Furthermore, we found that students who conveyed a positive emotional tone exhibited longer engagement time in SA and received more peer acknowledgement.

Sentiment analysis functions as a tool in extracting emotional tones in SA

Our study adds to the literature that applied sentiment analysis in extracting emotional tones by demonstrating that VADER can efficiently discern emotional tones within the context of SA. In our study, we utilised the VADER algorithm to measure students' emotional tones in a SA platform. Although VADER was first developed for social media contexts, it is more efficient and sensitive to affective expression than other lexicon-based sentiment analysis tools such as Senti WordNet (Bonta et al., 2019; Newman & Joyner, 2018) and, therefore, could be generalised to other contexts. Our study is one of the first to apply VADER in the context of SA to detect and differentiate students' emotional tones. Our findings reveal a wide range of emotional tones in students' annotations, spanning from extremely negative (-0.99) to extremely positive (+1). This diversity underscores the rich tapestry of emotions present within the learning process and highlights the importance of recognising and interpreting emotional cues. Emotions are known to play a pivotal role in learning experiences, either facilitating or impeding the learning process (Pekrun et al., 2002). Identifying and understanding these emotional tones is fundamental to monitoring students' learning progress and providing timely support, a critical aspect of educational practice (Artino & Jones, 2012).

This new approach opens up avenues for future research. One potential direction is integrating sentiment analysis tools like VADER into SA platforms as scaffolds for effective collaborative learning. By leveraging emotional tone analysis, educators and learners alike can gain deeper insights into the emotional dynamics of collaborative learning, fostering more engaging and supportive interactions. Furthermore, future research could extend the same approach to explore the relationship between emotional tone and collaboration in other educational domains, such as science, technology, engineering and mathematics education. This broader application could provide valuable insights into how emotions influence various learning contexts and inform strategies to optimise collaborative learning experiences.

Positive emotional tone is positively aligned with reading engagement

In addition, our analysis revealed a notable correlation between positive sentiment comments and increased engagement time in SA activities. This finding is consistent with research by Pekrun and Linnenbrink-Garcia (2012), which highlighted the significant impact of emotions on students' cognitive, motivational, behavioural, cognitive-behavioural and social-behavioural engagement during learning processes.

Specifically, positive sentiment comments may indicate an active and enthusiastic involvement with the reading assignments, leading to prolonged engagement in SA activities.

However, it is essential to acknowledge the complexity of emotional influences on engagement. Although our study predominantly focused on the positive correlation between positive emotional tone and engagement, it's worth noting that contradictory evidence exists. Some studies have suggested that emotions can have varying effects on engagement, depending on contextual factors and individual differences (e.g., Allcoat & von Mühlenen, 2018; Kanaparan et al., 2019). Therefore, a more nuanced examination of the interplay between different emotional tones and engagement levels is warranted.

Moreover, our findings suggest that positive sentiment comments not only contribute to individual engagement but also foster interaction among peers. This aligns with the research of Avry et al. (2020), which demonstrated that emotional sharing played a role in regulating collaborative actions between individuals. When students perceive that their contributions are met with appreciation and agreement in SA, they might be more inclined to participate further in the conversation, resulting in prolonged engagement time in the collaborative reading process.

Positive emotional tone benefits peer acknowledgement

Our findings also indicated that students who posted more positive sentiment comments were more likely to receive peer acknowledgement, as evidenced by a higher number of upvotes from peers. This finding can be attributed to the psychological dynamics occurring within SA settings (Garcia et al., 2016). SA platforms foster a collective learning environment where emotions spread among learners, influencing collaborative outcomes.

When students contribute comments with a positive tone, they inject discussions with a sense of encouragement, affirmation and inclusiveness, resonating favourably with their peers. This constructive interaction not only cultivates a sense of appreciation for contributions and but also promotes peer acknowledgement through upvoting. This aligns with insights from teamwork studies, indicating that emotions could be contagious in SA contexts, where individuals both affect and are affected by the emotional states of others (Van Kleef, 2009). Additionally, positive emotional expressions in comments often signal a deeper comprehension of the material and thoughtful engagement, further enhancing their attractiveness to fellow peers. Recent research employing latent profile analysis on SAs supports this idea, revealing that groups characterised by higher affective presence, including positive emotional tones, also exhibit higher cognitive presence. This manifests in clearer definitions of discussed content and more profound critical thinking among participants (Huang et al., 2024).

Our findings suggest a dual impact of positive emotional tone in SA: enhancing peer acknowledgement through supportive interactions and signalling higher levels of cognitive engagement and understanding of the content. Future studies should further explore the impact of emotional tones in diverse contexts and directions.

These findings hold significant implications for educational technology developers concerning the promotion of engagement and the enhancement of peer acknowledgement in student-student SA.
One actionable strategy is the implementation of adaptive prompts designed to stimulate positive comments among students. For instance, the system could prompt peers to respond with encouragement when a learner's comment reflects a sense of achievement or enthusiasm, reinforcing the positive emotional tone within the peer group. Similarly, if a learner's contribution exhibits a tone of confusion or uncertainty, peers can be prompted to provide clarification or additional resources to address their queries.

Furthermore, educators and technology developers should carefully assess how students perceive and respond to system feedback during active peer interactions. By focusing on enhancing peer interactions within the student-student SA process, educators and technology developers can create a supportive and engaging learning environment that aligns with the principles of collaborative learning.

Pedagogical implications

The findings of our study have several important pedagogical implications. Integrating sentiment analysis tools into SA platforms can provide educators with real-time insights into students' emotional states, allowing for timely interventions and support. Suppose an educator notices through sentiment analysis that a student consistently uses negative emotional tones in their annotations. This insight allows the educator to promptly reach out to the student to understand and address any issues they might be facing, such as difficulties with the course material or personal challenges. By intervening early, the educator can provide support that might prevent the student from falling behind or becoming disengaged. This can help foster a more emotionally supportive learning environment, which is crucial for student engagement and learning outcomes.

Additionally, encouraging positive emotional tones in student interactions can enhance peer acknowledgement and collaboration, further enriching the learning experience. When students see that their positive comments receive more upvotes or recognition from peers, they may be more inclined to continue contributing in a positive manner. For instance, a student who writes an insightful and encouraging annotation on a complex reading may receive multiple upvotes and appreciative replies from peers in the learning community. This acknowledgement can boost the student's confidence and encourage more active participation, while also promoting a collaborative learning environment where students support each other's learning.

Educators can also use these insights to tailor their teaching strategies to better meet the emotional and educational needs of their students. For example, an educator can use sentiment analysis data to identify common emotional responses to specific topics or assignments. If a particular reading consistently elicits frustration or confusion, the educator might decide to provide additional resources or modify their teaching approach for that material. Conversely, if a topic generates curiosity, excitement and positive engagement, the educator might incorporate similar materials or activities into future lessons to sustain that high level of engagement.

In summary, fostering a positive emotional tone within SA tools and leveraging sentiment analysis in real-time to adjust pedagogical approaches are essential strategies for promoting engagement and enhancing peer acknowledgement in online learning environments.

Limitations and future directions

Although our study has provided valuable insights into the impact of emotional tone on reading engagement and peer acknowledgement in SAs, it is essential to acknowledge its limitations and consider potential avenues for future research. Firstly, our research focused on a specific higher educational context, which may limit the generalisability of our findings to other learning environments and age groups. Future studies should explore the transferability of these findings across diverse educational settings to ensure broader applicability. Secondly, although sentiment analysis proved effective in assessing emotional tone within annotations, it is essential to acknowledge the inherent limitation of sentiment analysis tools in capturing nuanced emotional expressions accurately. Future research may benefit from incorporating complementary methods, such as qualitative analysis, to provide richer insights into the nature of emotional expressions within annotations. Additionally, the use of convenience sampling method in our study may have introduced selection bias, as the participants who chose to engage with SA tools may differ systematically from those who did not participate. Moreover, there is a potential for overestimating effects, as the sample may include individuals who are more motivated or engaged than average students. Future studies should consider employing more rigorous sampling methods to mitigate potential biases and ensure the representativeness of the participant sample.

In terms of future directions, researchers could delve into the potential interplay between emotional tone and other contextual factors, such as the type of content being annotated or the size of the annotation community. Exploring the emotional dynamics in varying contexts can provide a more comprehensive understanding of their influence on collaborative learning. Additionally, incorporating machine learning techniques to identify and categorise emotions within annotations can enhance the precision and depth of emotional analysis. Moreover, there is an opportunity to investigate the role of educators in facilitating and moderating emotional interactions within SA platforms, as their guidance and interventions can significantly impact the emotional climate of these learning environments. Finally, developing adaptive and personalised feedback mechanisms based on emotional tone could be a promising avenue to promote positive emotions and engagement in SA, ultimately optimising the learning experience. In summary, while our study has shed light on the significance of emotional tone in SAs, there is ample room for further research to expand our understanding of this complex phenomenon and its implications for educational practice.

Conclusion

In conclusion, our study underscores the significant impact of positive sentiment conveyed through emotional tones on reading engagement and peer acknowledgement within SAs. It highlights the constructive role that emotions, particularly positive ones, can play in enhancing students’ engagement and interaction. By harnessing the emotional content embedded within annotations, educators and researchers alike can gain deeper insights into the intricate emotional dynamics inherent in the learning process. This understanding paves the way for more informed and effective design strategies for SA platforms, ultimately supporting and enriching student learning experiences. In essence, our findings underscore the potential for emotional awareness to be integrated into educational technology, contributing to the creation of more engaging and supportive learning environments.

Author contributions

Author 1: Conceptualisation, Investigation, Data Curation, Writing – original draft, Writing – review and editing. **Authors 2–4:** Investigation, Formal analysis, Writing – review and editing. **Authors 5–7:** Investigation, Writing – review and editing. **Author 8:** Data curation, Writing – review and editing.

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