Proceedings of the 4th International Conference on Applied Physics and Mathematical Modeling
DOI: 10.54254/2753-8818/2026.35714

Natural Language Processing of Learner Emotion Transfer in Social Media Educational Discourse

Yu Shi

Sydney School of Education and Social Work, The University of Sydney, Sydney, Australia
lingwadesu@gmail.com

Abstract. Social media platforms have become important spaces where learners participate in online educational discussion, express learning experiences, and form peer interaction. Comments and replies contain rich emotional information related to confusion, frustration, encouragement, and recognition. Focusing on learner emotion transfer in educational social media discourse, this study applies natural language processing to public educational video comments, Reddit learning community posts, and open course discussion texts. It builds an experimental process that includes data collection, manual annotation, RoBERTa-based emotion recognition, and reply-chain transfer modeling. The results show that RoBERTa-base achieves strong performance in emotion classification, with an Accuracy of 0.846 and a Macro-F1 of 0.804. It performs better than VADER and TF-IDF plus SVM baselines. The emotion transfer results further indicate that frustration tends to persist in reply chains, but it can also shift into encouragement. Confusion is more likely to trigger supportive responses, while joy can promote positive interaction diffusion. These findings show that emotion in educational social media discourse is not isolated expression. It is continuously transmitted and regulated through interaction structures. The results provide computational evidence for affective support, comment moderation, and learner interaction guidance on online education platforms.

Keywords: natural language processing, learner emotion, social media, educational discourse, emotion transfer

1. Introduction

Social media platforms are reshaping the production of educational discourse, as learners interact around instructional videos, learning experiences, and knowledge explanations through comments and replies. These interactions are no longer limited to content feedback; they also carry confusion, anxiety, encouragement, resistance, and recognition. Educational communication studies have examined platform participation, learning satisfaction, and online interaction quality, while NLP studies have shown that large-scale texts can be used for emotion recognition and discourse analysis. However, the ways in which learner emotions continue, transform, or intensify along reply chains still require closer explanation within educational contexts and communication structures [1]. Learning analytics research on educational discourse modeling indicates that textual semantics, interaction order, and learning behavior are closely connected, so comment frequency alone cannot

DOI: 10.54254/2753-8818/2026.35714

represent learners' affective engagement [2]. Focusing on learner emotion transfer in social media educational discourse, the research covers public educational comment collection, manual emotion annotation, RoBERTa-based emotion classification, topic identification, and reply-network modeling. It further examines transfer probability, retention rate, and negative amplification between parent comments and replies, providing computational evidence for affective learning support and educational platform moderation.

2. Literature review

2.1. Educational social media discourse

Educational social media discourse has a clear cross-contextual nature. It maintains the educational functions of classroom questioning, knowledge explanation, and learning feedback, while also being shaped by platform recommendation, visibility ranking, and public comment atmosphere. Learning analytics on YouTube educational videos shows that learner comments often contain content evaluation, affective stance, and topic clustering at the same time, which means that social media discourse cannot be reduced to simple satisfaction feedback [3]. In open forums, learner expressions are commonly found in short sentences, informal assessment, and consistent responses. Emotional signals are combined with knowledge comprehension signals, hence making it hard to analyze shifts in meaning along interaction sequences using traditional manual analysis procedures. The NLP modeling of educational discourse draws attention to the interconnection between linguistic elements and learning processes, thus creating a methodological framework where comment texts, response mechanisms, and learner emotions can be viewed in one analytical perspective [4]. The educational social media discourse should therefore be examined through the lens of semantics, position in interactions, and platform visibility.

2.2. Learner emotion recognition

The technical route of emotion recognition on the basis of learners' texts went through lexical rules to semantic modeling in the context, since there is no guarantee that emotions will be conveyed via explicit emotional words. Methods of sentiment analysis applied to social media, like VADER, can be helpful for fast polarity detection and recognition of positive, negative, and neutral trends. However, they do not suffice when it comes to recognizing confusion, frustration, sarcasm, and implicit help-seeking [5]. With its bidirectional Transformer architecture, BERT takes into account the context relations, thus providing an opportunity for the model to evaluate the role of the same word in terms of emotions according to various meanings in the educational context [6]. RoBERTa makes pre-training approach and the choice of corpus even better, resulting in more stable classification basis based on a relatively small manually annotated set of data [7]. Emotion labels should embrace both generic emotional categories and learning-related ones. Thus, categories joy, anger, sadness, fear, confusion, encouragement, frustration, and neutral can stand for both types of affective states.

2.3. Emotion transfer mechanism

Emotion transfer concerns whether a learner's later reply becomes emotionally similar, emotionally opposite, or more intense after exposure to another learner's affective expression. Large-scale social network experiments have shown that individuals can be influenced by others' emotional content in platform environments, and emotional expression has the potential for diffusion at the group level [8]. In educational social media discourse, such transfer is not mechanical repetition. It is associated with learning topic, task difficulty, reply timing, interaction hierarchy, and user role. For example, learning frustration may continue through narratives of similar difficulty, but it may also be transformed by experience sharing and encouraging replies. Fine-grained emotion datasets such as GoEmotions show that multi-category emotion annotation can better represent complex affective differences in social media texts, offering a transferable reference for distinguishing encouragement, confusion, and frustration [9]. By calculating emotion retention rate, transfer probability, and negative amplification coefficient through directed relations between parent comments and replies, individual affective expression can be observed within interaction chains, moving emotion recognition from static classification toward dynamic discourse explanation.

3. Experimental methods

3.1. Data collection

Data collection focuses on public educational discourse on social media. The sources include comments on YouTube educational videos, posts from Reddit learning communities, and texts from open course discussion sections. The collection period is from January 2022 to December 2025. The collected fields include comment text, posting time, platform source, parent comment ID, reply level, number of likes, number of replies, and topic keywords. About 36,000 raw samples are obtained. After language detection, advertisement filtering, duplicate removal, and exclusion of comments outside educational contexts, 30,000 valid texts are retained. In the preprocessing stage, Python, spaCy, and NLTK are used for URL cleaning, emoji normalization, noise filtering, and text length screening. User IDs are processed through hashing. The cleaned data are indexed by platform, topic, comment level, and interaction intensity. This provides a unified data structure for later manual annotation and emotion transfer modeling.

3.2. Emotion annotation

The emotion annotation process takes place on the basis of a stratified sample of 3,000 texts chosen out of the 30,000 valid texts, following certain sampling standards including the source of the platform, the comment level, the popularity of interaction, and topic categories. In order to make sure that all of the common educational discourse contexts such as help-seeking, course evaluation, peer encouragement, knowledge confusion, and learning frustration will be covered, this stratified sampling will provide representative data. The labeling process includes joy, anger, sadness, fear, confusion, encouragement, frustration, and neutral emotions. The emotion intensity is also annotated using three-level standard ranging from 1 to 3. The three annotators trained in the field of educational linguistics annotate the texts independently following an annotation guide. Annotation agreement is tested using Cohen's kappa, with the target value set above 0.75. Disputed samples are reviewed, and the final label is determined by majority agreement. The final annotated dataset is divided into training, validation, and test sets at a ratio of 7:1:2.

3.3. Model construction

The model construction uses RoBERTa base as the main classifier. The input is cleaned educational social media text, and the output includes eight emotion labels and their confidence scores [10].

DOI: 10.54254/2753-8818/2026.35714

During training, the cross entropy loss function is used to measure the difference between the predicted distribution and the manually annotated distribution, as shown in Formula 1.

$$L=-\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C}y_{ic}\log\left(\hat{y}_{ic}\right) \tag{1}$$

In the formula, y_{ic} denotes the true label of the ith text in category c, $\hat{y}_{ic}$ denotes the predicted probability of the model, N denotes the number of samples, and C denotes the number of emotion categories.

Emotion transfer analysis constructs a transition matrix based on the directed relation between parent comments and replies. Each node is a text unit, and each edge represents a reply relation [11]. For parent comment emotion e_a and reply emotion e_b, the transfer probability is calculated by conditional frequency, as shown in Formula 2.

$$P\left(e_b|e_a\right)=\frac{n(e_a\to e_b)}{\sum_{k=1}^{C}n(e_a\to e_k)} \tag{2}$$

In the formula, $n(e_a\to e_b)$ denotes the number of replies transferred from emotion e_a to emotion e_b, and $\sum_{k=1}^{C}n\left(e_a\to e_k\right)$ denotes the total number of replies whose parent comment emotion is e_a.

4. Results

4.1. Classification performance

As shown in Table 1, RoBERTa base achieves an Accuracy of 0.846, a Macro F1 of 0.804, and a Weighted F1 of 0.842 on the test set. These scores are higher than those of VADER and TF IDF plus SVM. This indicates that contextual pretrained models are more suitable for processing complex emotional expressions in short educational social media texts. VADER has a certain ability to identify explicit emotions such as joy and anger. It performs weakly in distinguishing confusion from frustration, because learning confusion and learning frustration are often expressed indirectly through phrases such as I cannot understand it, I still cannot do it, and the explanation is too fast. TF IDF plus SVM can capture keyword features, but it is less sensitive to reply context, tone shifts, and implicit help seeking. RoBERTa base reaches an F1 score of 0.872 for encouragement, which shows that encouraging replies have relatively stable linguistic features. Its F1 score for confusion is 0.773, suggesting that confusion related discourse still needs further judgment through reply chain context.

Table 1. Comparison of emotion classification performance

Model	Accuracy	Macro F1	Weighted F1	Best Category F1	Weakest Category F1
VADER	0.681	0.624	0.657	joy 0.741	confusion 0.512
TF IDF plus SVM	0.758	0.711	0.746	encouragement 0.803	frustration 0.638
RoBERTa base	0.846	0.804	0.842	encouragement 0.872	confusion 0.773

4.2. Transfer pattern

As shown in Figure 1, emotion transfer in reply chains presents a clear direction. The transfer proportion from frustration to encouragement is 26.4%. This indicates that when learners express frustration, they often receive peer explanations, comfort, and experience based support. The

DOI: 10.54254/2753-8818/2026.35714

transfer proportions from frustration to sadness and anger are 18.7% and 14.2%, respectively. This shows that some difficult learning topics may continue to strengthen negative emotions. The transfer proportion from confusion to encouragement is 31.8%, which is higher than the 22.5% from confusion to frustration. This indicates that help seeking confusion is more likely to trigger supportive replies. The transfer proportion from joy to encouragement is 34.6%, which shows that positive learning experiences can generate more positive interaction. The highest retention rate among negative emotions is found in frustration, reaching 0.417. This indicates that learning frustration is more likely to persist in reply chains than general negative emotions.

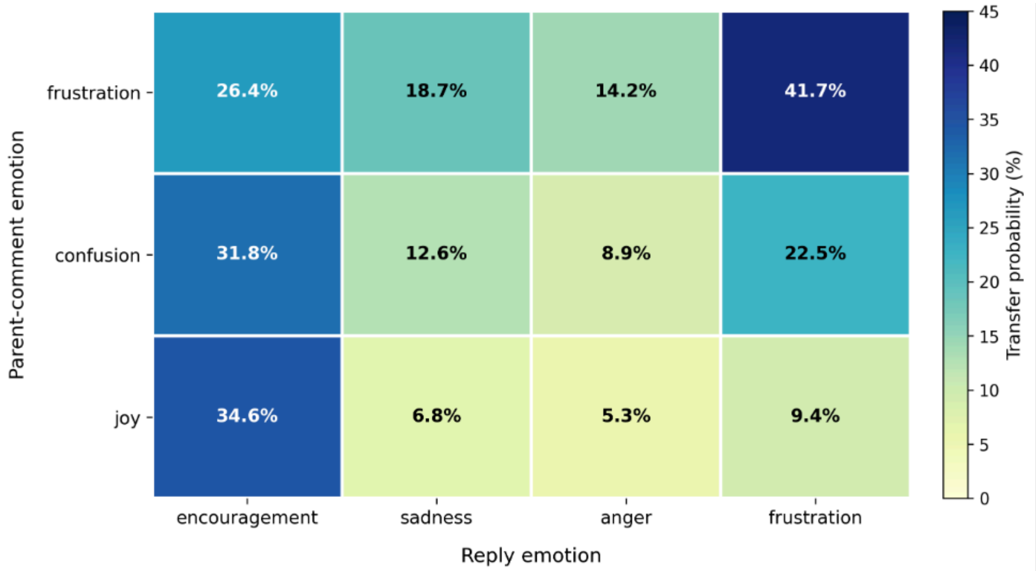

Figure 1. Sankey statistics of emotion transfer paths

5. Discussion

The classification results show that RoBERTa-base identifies encouragement and joy with relatively stable performance, which indicates that positive supportive expressions have clearer linguistic patterns. Misclassification still occurs between confusion and frustration. This suggests that learning confusion and learning frustration often share similar semantic features in short texts. In the transfer results, frustration can continue as negative emotion, but it can also be buffered by encouragement. This shows that peer responses play a clear regulatory role in educational social media interaction. The amplification of negative emotion around highly interactive nodes also suggests that platform visibility may strengthen collective resonance around learning pressure.

6. Conclusion

The research framework is created for studying the problem of transferring emotions of learners within social media educational discourses. The framework includes data collection from public resources, manual emotion annotation, emotion classification using RoBERTa, and network analysis of replies. Based on the experiment, it was proven that pre-trained language models are appropriate to be applied for the emotion identification task in short educational texts. In addition, the transfer paths between frustration, confusion, encouragement, and joy have been revealed. This information may be useful for online education platforms in order to detect affective risks, improve the process of responding to comments, and provide support with emotions of learners.

References

[1] Shaik, T., et al. (2023). Sentiment analysis and opinion mining on educational data: A survey. *Natural Language Processing Journal, 2*(1), 100003.
[2] Chalkias, I., et al. (2023). Learning analytics on YouTube educational videos: Exploring sentiment analysis methods and topic clustering. *Electronics, 12*(18), 3949.
[3] Alawadh, H. M., et al. (2023). English language learning via YouTube: An NLP-based analysis of users' comments. *Computers, 12*(2), 24.
[4] Grimalt-Álvaro, C., & Usart, M. (2024). Sentiment analysis for formative assessment in higher education: A systematic literature review. *Journal of Computing in Higher Education, 36*(3), 647–682.
[5] Sunar, A. S., & Khalid, M. S. (2023). Natural language processing of student's feedback to instructors: A systematic review. *IEEE Transactions on Learning Technologies, 17*, 741–753.
[6] Abdi, A., et al. (2023). Students feedback analysis model using deep learning-based method and linguistic knowledge for intelligent educational systems. *Soft Computing, 27*(19), 14073–14094.
[7] Koufakou, A. (2024). Deep learning for opinion mining and topic classification of course reviews. *Education and Information Technologies, 29*(3), 2973–2997.
[8] Baqach, A., & Battou, A. (2024). A new sentiment analysis model to classify students' reviews on MOOCs. *Education and Information Technologies, 29*(13), 16813–16840.
[9] Dake, D. K., & Gyimah, E. (2023). Using sentiment analysis to evaluate qualitative students' responses. *Education and Information Technologies, 28*(4), 4629–4647.
[10] Falcon, S., & Leon, J. (2023). How do teachers engaging messages affect students? A sentiment analysis. *Educational Technology Research and Development, 71*(4), 1503–1523.
[11] Yan, C., et al. (2023). Sentiment analysis and topic mining using a novel deep attention-based parallel dual-channel model for online course reviews. *Cognitive Computation, 15*(1), 304–322.