Reading Together: A Case Study of a Collaborative Reading System in Classroom Teaching

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ABSTRACT

Social annotation is an effective tool to cultivate learners' literacy skills. Besides the learners themselves, their peers and teachers are also involved in the annotating process. To facilitate effective interactions among the different types of subjects, we redesigned the social annotation activity into a four-step learning mode and developed a collaborative reading system to support this learning mode. In this system, learners can not only annotate on specific content but also interact with their peers to exchange ideas. Specifically, before the class, learners annotate individually. In the meantime, they can see their peers' annotations and make replies. During the class, each group collaboratively reflects on the individuals' before-class annotations and completes an assigned group learning task on the system. At last, the teacher gives a summarization for the whole class. Through conducting three studies in different settings and data analysis, we found that individual annotation can positively influence the learners' understanding of learning materials and the following collaborative learning process. During the before-class annotation activity, making learners able to see peers' annotations encourages the learners to think deeply and constructively. Moreover, the detailed learning feedback on the group's annotation performance is helpful for individual and collaborative learning. Now that most of the feedbacks are crafted manually or by traditional machine learning algorithms, state-of-the-art natural language processing technology like pre-trained language model has been used to automatically detect learners' cognitive engagement and will be used to automatically generate feedback in the future. Finally, we put forward two recommendations for further design of social annotation tools: (1) Using annotation filtering mechanisms to hide low-quality comments; (2) Providing automatic learning feedback and interventions to encourage learners to interact with their teammates.

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CHI EA '23, April 23–28, 2023, Hamburg, Germany

ACM ISBN 978-1-4503-9422-2/23/04.
https://doi.org/10.1145/3544549.3573840

CCS CONCEPTS

• **Human-centered computing** → Human computer interaction (HCI); Interactive systems and tools.

KEYWORDS

Social annotation, Collaborative learning, Classroom teaching, Pre-trained language model

ACM Reference Format:
Shuwen Wang, Lishan Zhang, Sixv Zhang, Bocheng Lin, Lili Liu, and Min Xv. 2023. Reading Together: A Case Study of a Collaborative Reading System in Classroom Teaching. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems (CHI EA '23), April 23–28, 2023, Hamburg, Germany.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3544549.3573840

1 INTRODUCTION

Literacy skill is fundamental and essential for 21st-century readers. It is an expanding set of knowledge, skills, and strategies that individuals build on throughout life in various contexts through interaction with peers and the wider community [1]. As a form of collaborative learning, collaborative reading is an effective learning paradigm for cultivating such skills. Moreover, the social annotation has been an effective way to engage learners in collaborative reading [2], in which learners can collaboratively contribute their reading annotations in digital texts and share them synchronously or asynchronously [3, 4]. Several social annotation tools can support learners in reading collaboratively, making annotations, and exchanging ideas, such as Hypothesis [5], Perusall [6], and WASP [7]. Moreover, many studies have suggested that social annotation could enhance learners' reading comprehension and metacognitive skills [8, 9].

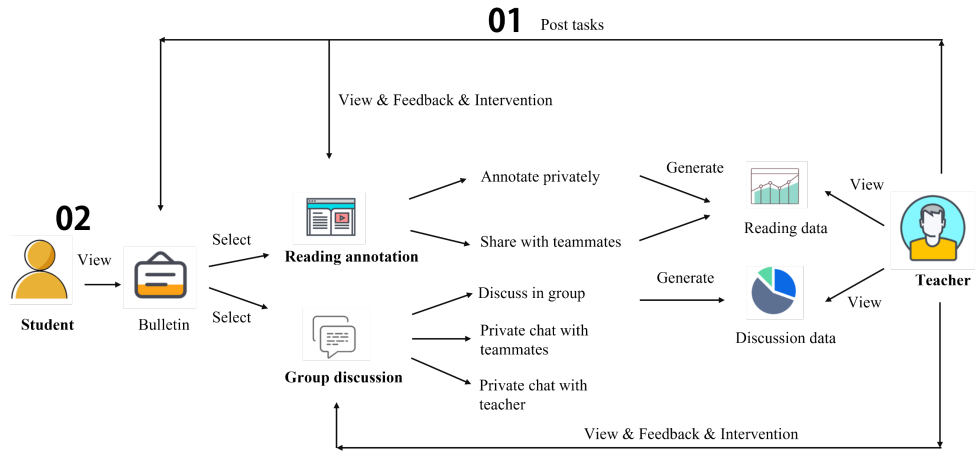

Figure 1: System functions

Nevertheless, studies have seldom considered the influence of individual annotations on collaborative learning, even though some studies stated that individual preparation would play an important role in collaborative learning [10]. Therefore, this study developed a collaborative reading system with annotation and group discussion and redesigned the social annotation activity into a four-step learning mode for collaborative reading (individual preparation, group reflection, intra-construction, and summarization, short for IRIS) to better support learners to interact with their peers and the teacher in the system. Then, we put forward our main research question: how does the collaborative reading system with annotation and group discussion influence learners' learning performance in reading courses? Specifically, we aimed to know the role of feedback on social annotation and peers' annotations in learners' learning performance. We conducted three quasi-experiments in real contexts, and collected annotations and questionnaires to answer this question. Furthermore, most of previous feedbacks were mainly crafted manually [11] or by traditional machine learning algorithms [3, 12]. Because pre-trained language models, such as bidirectional encoder representation from the transformers (BERT), have performed well in many text classification tasks [13], we utilized BERT to automatically detect learners' cognitive engagement for exploring more intelligent intervention methods in this study. And we aimed to examine if BERT will perform better in classifying reading annotations than traditional machine learning models.

The contribution of our work is twofold. On the one hand, the results could provide insights into designing social annotation tools for the HCI community. On the other hand, this study sheds some light on the experiment design in the field of HCI in practice, which means that design-based research can be applied to examine system functions' effectiveness in a real context progressively. At last, two design recommendations for social annotation tools are provided: (1) Using annotation filtering mechanisms to hide low-quality comments; (2) Providing automatic learning feedback and interventions to encourage learners to interact with their teammates.

2 DESIGN OF THE COLLABORATIVE READING SYSTEM WITH ANNOTATION AND GROUP DISCUSSION

In the design phase, we investigated the essential functions of several social annotation systems, such as highlighting, annotating, and replying to others. Moreover, we co-designed with an expert teacher to learn about her teaching needs. Then, we used Vue.js framework to develop the front end and Spring Boot + Mybatis framework to develop the back end of this system. Furthermore, we followed the principles of human-computer interaction, including people-oriented, identifiable and operational, and easy to communicate [14]. The overall system functions are shown in Figure 1. Next, we will introduce two main functions: collaborative annotation and group discussion. Although the system is in Chinese and the case study was only conducted with Chinese students, the design pattern and our lesson learned should not be restricted to this language. For the readers' ease of understanding, the Chinese interface has been annotated with English explanations (see Figure 2, Figure 3, Figure 4, and Figure 5).

2.1 Reading Annotation

Teacher can upload reading materials and posts learning tasks on the system. Then, learners can check the bulletin and select specific learning tasks. After entering the reading interface, they can read the materials and make annotations asynchronously or synchronously. There are two optional buttons in the reading interface, "private" and "visible to my group" (Figure 2), meaning that learners can self-determine to make annotations private or public.

When learners choose the "Private" button, they can only see their annotations. When learners choose the "Visible to my group" button, both the students themselves and their group members can see the highlights and the annotations, which means that learners can comment on their peers' annotations to exchange ideas. Moreover, if learners think their group members' comments are helpful for their knowledge enhancement, they can click the star button to express their praise.

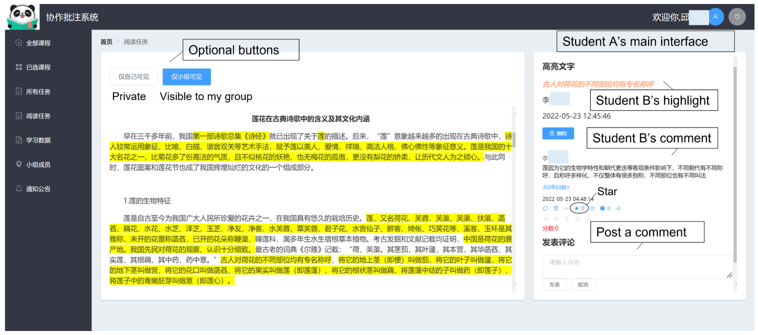

Figure 2: The interface of reading annotation

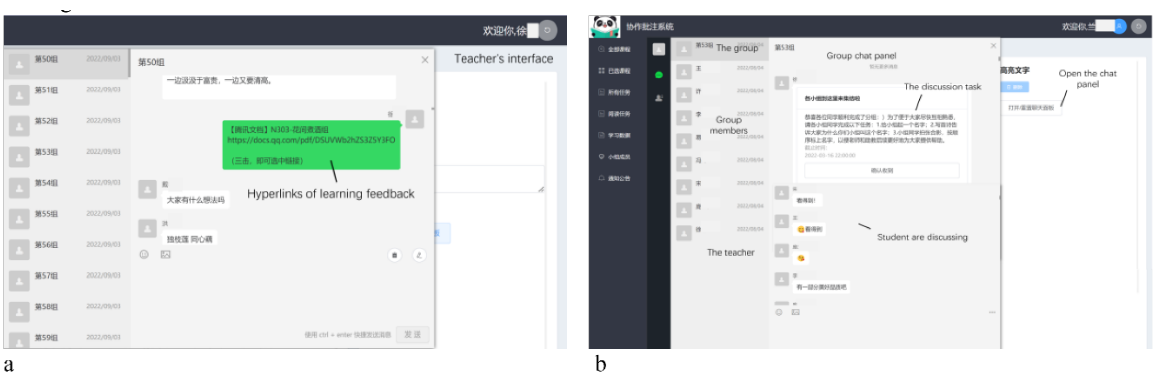

Figure 3: The interface of group discussion

2.2 Group Discussion

As shown in Figure 3, in the group discussion panel, teacher can share the link of learning feedback (Figure 3. a); then, learners can click on the link to see the learning feedback on the group's performance. In addition, the teacher can launch discussion tasks and set the deadline for the task (Figure 3. b). Learners can not only discuss with their teammates in a group but also chat privately with any member of the group and the teacher. During the discussion phase, the teacher can enter any group's discussion space and give real time interventions. After the group establishes common agreement on the assigned collaborative task, they can submit their final responses. If learners have questions, they can also send messages to the teacher.

3 CASE STUDY

3.1 Procedure

We conducted three quasi-experiments in different learning contexts in a university of China to answer our main research question based on the paradigm of design-based research (Puntambekar, 2018). In Study 1, the participants were 73 undergraduate learners enrolled in the Poetry Appreciation course in the fall of 2021; 18 were male, 55 were female. The learners were from different subjects, including history, artificial intelligence, and physics, with ages between 18 to 21. As we aimed to know the impact of individual annotation on collaborative learning, we did not design any interventions, and the learning activities were the same for all learners. In Study 2, participants consisted of 84 undergraduate learners who enrolled in the course in March in the spring of 2022. The learners were from different subjects, including history, artificial intelligence, mathematics, and chemistry, with ages between 18 to 21. In this study, to explore whether the learning feedback on the group's performance of individual preparation would positively influence the learning process, we randomly selected one class as the experimental class (N=45; 12 were male, 33 were female) with detailed learning feedback and the other class as the control class (N=39; 12 were male, 27 were female) with brief learning feedback (Figure 4). Specifically, there were three main differences in the learning feedback between the two classes: (1) learners in the experimental class were instructed on how to use this learning feedback, while learners in the control class did not know these instructions (Guiding words); (2) Learners in the experimental class could see the common highlights and comments from all group members, while learners in the control class could only see the word cloud map (Part 2); (3) Learners in the experimental class could see who contributed what ideas to the mind map of the generative summarizations, while learners in the control class could only see the summary (Part 3).

In Study 3, the learners were the same as those in Study 2, but this study was conducted from late May to early June 2022 and lasted two weeks. To investigate whether peers' annotations positively affected subsequent learning, we changed the front end of our

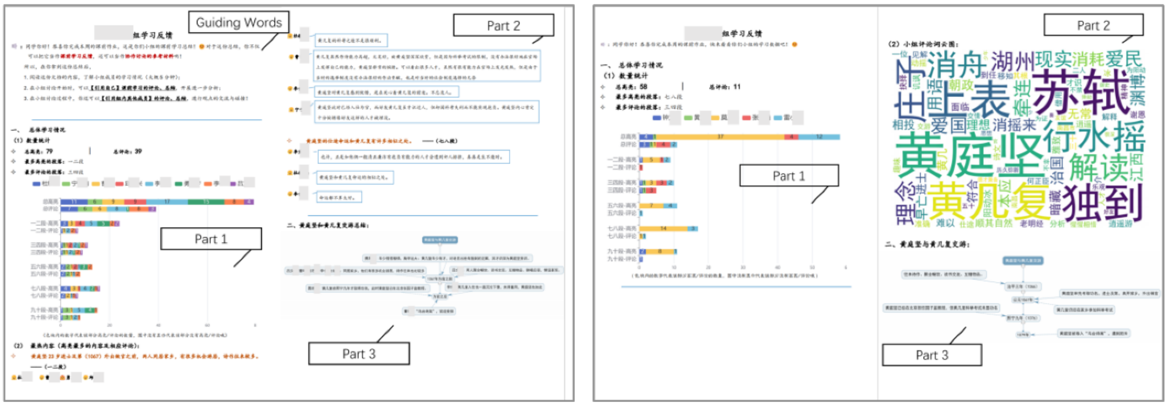

Figure 4: Learning feedback of the experimental class (left) and the control class (right)

Figure 5: Learning interface of the experimental class (left), of the control class (right)

system and retained only one button. Learners in the experimental class could see their peers' annotations, whereas learners in the control class could not see their peers' annotations (Figure 5). The detailed process is as follows.

3.1.1 Before the experiment. Learners formed groups (6-8 individuals per group) by their own, and all learners learned how to use the collaborative annotation system before these three quasi-experiments.

3.1.2 The activities flow (IRIS learning mode). 1. Individual preparation. Before the collaboration, learners need to prepare to construct knowledge individually. Specifically, they can log in to the system, highlight and comment on the learning materials. Besides, they can see and comment on their peers' annotations in real time. In general, learners have 2-3 days to complete the reading assignment.

2. Group reflection. Learning feedback can be an effective tool for reflection [15]. Therefore, we provide learning feedback on the group's performance of individual annotation to scaffold group reflection. Generally, based on the database of the collaborative reading system, we can easily obtain the data of learners' highlights, comments, and interactions with their teammates. In our design, the learning feedback contains guiding words, overall learning performance, group members' common highlights, and comments. After generating the learning feedback, we post it in the group discussion panel, requiring each learner to click on the link and read the learning feedback carefully.

3.Intra-construction. The teacher posts task-oriented collaborative discussion tasks. Each group discusses and builds collective knowledge.

4. Summarization. Finally, all groups submit their learning artifacts to the collaborative annotation platform. According to the evaluation criteria provided by the teacher, each group conducts an intra- and inter-group evaluation. At last, the teacher gives a summarization.

3.1.3 After the class. After the class, learners completed questionnaires to self-report their perceptions of the learning process.

3.2 Measuring Tools

3.2.1 Questionnaires and surveys. In Study 1, learners completed a 5-point Likert scale (1: totally disagree, 5: totally agree). All the three questions were about learners' perceived usefulness of social annotation, including "*I think the individual annotation activity before the class helped me better understand the learning content.*", "*I found the individual annotation before class significantly influenced collaborative discussion in class, because the pre-class study helped me grasp the basic knowledge.*", and "*During the collaborative learning in class, our group can discuss based on what we had learned on the annotation platform before the class.*". Cronbach's $\alpha = 0.719$.

Table 1: Questionnaire of Study 3

Category	Questions
Perceived usefulness	(1) "*During the social annotation process, I found the perspectives of my peers in the group very helpful for my understanding.*"; (2) "*During the social annotation process, I think my peers' ideas helped me better complete the generative reading tasks.*"; (3) "*I think the usefulness scores for Part 1 of the feedback are (1 point - 5 points, higher scores mean more useful).*".
Intention to use	(4) "*I would like to continue to use the annotation platform for social annotation in my subsequent studies.*".
Perceived learning	(5) "*I think social annotation improved my understanding of floral imagery.*". (6) "*During the social annotation process, I think the views of my group members contributed to my understanding of floral imagery.*".
Open-ended questions	(7) "*What do you like most about social annotation?*". (8) "*What do you like most about the learning feedback for the pre-course social annotation?*". (9) "*What do you think could be improved about the learning process and the learning feedback for the pre-course social annotation?*".

Table 2: The coding scheme of cognitive engagement during online annotation reading.

Category	Description	Code
Highlighting only	Highlighting only, or the comment is not related to the highlight	A1
Copying learning materials	Highlighting and directly or selectively copying learning material	A2
Knowledge construction	Extrapolating, generalizing, or summarizing based on the highlight	C1
Knowledge integration	Integrating other information in the materials or other materials and comparing or connecting	C2

In Study 2, the questionnaire about perceived usefulness was adapted from the technology acceptance model [16], including five questions: (1) "*I think the learning feedback can help me better understand the perspectives of other members in the group.*"; (2) "*I think the learning feedback can help me discuss better with my peers.*"; (3) "*I think the usefulness scores for Part 1 of the feedback are? (1 point 5 points, higher scores mean more useful)*"; (4) "*I think the usefulness scores for Part 2 of the feedback are? (1 point - 5 points)*"; (5) "*I think the usefulness scores for Part 3 of the feedback are? (1 point - 5 points)*". Cronbach's $\alpha = 0.793$.

In Study 3, the items about perceived usefulness and intention to use were adapted from the technology acceptance model [16], including four questions. Besides, we also measured learners" perceived learning. Cronbach's $\alpha = 0.861$. Moreover, we asked three open response questions. The detailed information is in Table 1.

3.2.2 Coding scheme. To explore learners' cognitive engagement during social annotation, we developed a coding scheme to classify learners' annotations (Table 2) based on the ICAP framework [17], which connected learners' external behaviors to implicit cognitive engagement and delineated different levels of engagement patterns: passive learning, active learning, constructive learning, and interactive learning. The coding scheme is shown in Table 2. A1 and A2 correspond to active learning, which is shallow learning. C1 and C2 correspond to constructive learning, which is deep learning. Two authors of the manuscript randomly selected 691 (20.12%) annotations to code together (Kappa = 0.80) with a good inter-rater agreement [18]. The remaining annotations were coded separately by the two coders.

3.2.3 RoBERTa-WWM-EXT model. To explore the possibility of inventing intelligent interventions in the future, we aimed at automatically detecting learners' cognitive engagement in this study. BERT uses the Masked Language Model (MLM) method to train semantic understanding of words and the Next Sentence Prediction (NSP) to train inter-sentence understanding to build pre-trained language model for downstream tasks. It is a state-of-art natural language processing model in many text classification tasks [19]. Promisingly, RoBERTa improves on BERT and can be better generalized to downstream tasks. Hence, we adopted RoBERTa-WWM-EXT (https://github.com/ymcui/Chinese-BERT-wwm., a Chinese pre-training model with full word masking released by the Joint Laboratory of HIT and iFLYTEK (HFL), to perform our cognitive engagement detection, which is essentially a text classification task.

4 RESULTS

4.1 Perceived usefulness of social annotation

In Study 1, for question 1, 30.99% of learners chose "strongly agree", and 59.15% chose "Agree". For Question 2, 28.17% of learners chose "strongly agree", and 54.93% chose "agree". 54.93% of learners chose "agree". In question 3, 32.39% of learners chose "strongly agree", and 52.11% chose "agree". 52.11% of learners chose "agree". The mean values of all the three questions were well above the median value of 3, indicating that most learners felt that the individual annotation helped them better understand the learning material and further positively influenced the collaborative process in the class.

4.2 Perceived usefulness of learning feedback

In Study 2, compared to the control class, learners in the experimental class thought the learning feedback could help them better

Table 3: Distribution of the types of cognitive engagement between the two classes.

	A1(Highlighting only)	A2(Copying learning materials)	C1(Knowledge construction)	C2(Knowledge integration)
Exp. Class	1089 (69.85%)	106 (6.80%)	204 (13.09%)	160 (10.26%)
Con. Class	1377 (73.13%)	180 (9.56%)	204 (10.83%)	122 (6.48%)

understand the perspectives of other members in the group (t (57) = -1.787, p = 0.079) and help them discuss better with their teammates (t (57) = -1.822, p = 0.074). Moreover, for question 4, compared to learners in the control class, the experimental class scored higher on the usefulness of Part 2 of the learning feedback (t (57) = -1.977, p = 0.053). Although the answers to all the three questions are merely marginally significant, it still makes sense that the detailed learning feedback is more beneficial for the collaborative learning process. But according to the open-ended question of Study 3, there is still something to improve. Some learners thought Part 1 of learning feedback was not so helpful and said, "*The statistical chart format does not seem to work.*". Moreover, several learners hoped to see more different ideas about their teammates. Therefore, we will keep exploring the more effective design of learning feedback.

4.3 Learners' cognitive engagement and perception of their peers' annotations

In Study 3, we utilized the chi-square test to investigate the differences in the distribution of cognitive engagement between the two classes. The results showed a significant difference in the distribution of cognitive engagement between the experimental and control classes ($x^2 = 27.649, df = 3, p < 0.001$). As shown in Table 3, the learners both in the experimental and control classes most focused on "A1" and "C1". However, learners in the experimental class paid more attention to "C2" while learners in the control class were more engaged in "A2". It may be because learners in the experimental class could see more diverse opinions during social annotation, which could help to awake their tacit knowledge and make more comments by integrating other information in the materials, comparing, or connecting with different viewpoints. Therefore, being able to see peers' annotations during social annotation can inspire high levels of cognitive engagement.

Results showed that compared to the control class, learners in the experimental class thought that the perspectives of their peers in the group were more helpful for their understanding during the social annotation process (t (69) = -2.002, p = 0.049). They would like to continue to use the annotation platform for social annotation in subsequent studies (t (69) = -1.993, p = 0.051). The open-end questions also evidence this. Some learners said, "*Reading before class helps me understand what I will learn in this lesson and also helps me understand the opinions of my teammates.*", and "*It helps me understand my thoughts and others' perspectives in real-time.*".

Furthermore, learners in the experimental class (being able to see their peers' annotations) engaged more deeply during the social annotation, and they said their peers' opinions could help them understand the learning materials deeply. Moreover, they would like to continue to use the collaborative reading system in subsequent studies. However, they still put forward some drawbacks and improvements for the system. Firstly, some learners thought other teammates' annotations were overwhelmed, which made them troublesome. For example, one learner said: "*When reading and annotating, I cannot hide other teammates' comments. Therefore, if I annotate late, there will be a screen full of comments, and then I get overwhelmed and feel like I am just repeating someone else's work.*". Secondly, several learners considered some annotations were homogeneous and meaningless. Furthermore, one learner mentioned that the fixed article column size affected reading on large screens.

Table 4: Accuracy of classification of reading annotation types.

Algorithms	Accuracy
Decision Tree	49.51%
Naive Bayes	57.76%
Logistic Regression	53.12%
Random Forest	58.08%
KNN	58.94%
RoBERTa-WWM-EXT	63.36%

4.4 Cognitive engagement detection based on a pre-trained language model

Based on the manual coding in Study 3, 20% of the data were used as the test set, and the remaining 80% of the data were input into the model for 10-fold cross-validation. We took the average as the final performance of the model. Specifically, because A1 did not involve any comment, three categories of cognitive engagement were adopted for the classifications of annotation data, i.e., 'A2', 'C1', and 'C2'. In addition, based on the word vectors generated by RoBERTa, we utilized five traditional machine learning algorithms, 'Decision Tree', 'Naive Bayes', 'Logistic Regression', 'Random Forest', and 'KNN', for comparison. The results are shown in Table 4. The accuracy of RoBERTa-WWM-EXT was 63.36%, which was the best compared to the other five algorithms.

5 DISCUSSION AND IMPLICATIONS

This case study highlights the benefits of enhancing reading performance in the context of reading courses using a collaborative reading system. Our findings showed: (1) the individual annotation can positively influence the learners' understanding of learning materials and the following collaborative learning process; (2) During the social annotation, peers' annotations could inspire learners' more deep learning, especially making the comments through integrating, comparing, or connecting with other information in the materials; (3) The detailed learning feedback on the group's annotation performance helps students learn about their teammates' perspectives so as to facilitate group knowledge co-construction. Furthermore, state-of-the-art natural language processing technology like pre-trained language model has been used to automatically detect learners' cognitive engagement and will be used to automatically generate feedback in the future. Based on the findings, we put forward two design recommendations for further study.

Design Recommendation 1: Use annotation filtering mechanisms to hide low-quality comments. Previous work [20] used a novel web-based collaborative reading annotation system with two quality annotation filtering mechanisms to enhance learners' reading performance. In this study, pretrained language model (i.e., RoBERTa-WWM-EXT) performed well in the text classification task. Hence, to reduce learners' cognitive load caused by the large number of low-quality comments, we can use state-of-art natural language processing models to automatically classify learners' annotations, and then, hide the low-quality comments in the reading interface, making other group members not see these comments.

Design Recommendation 2: Provide automatic learning feedback and interventions to encourage learners to interact with their teammates. According to the ICAP framework, interactive learning achieves the most significant level of learning, greater than constructive learning, greater than active learning, and greater than passive learning [17]. Therefore, to help learners gain more learning, we could possibly provide machine generated learning feedback and interventions to facilitate more interactive learning. For example, we can develop an engagement detector utilizing the natural language processing algorithm. When the detector detects that a learner is at low cognitive engagement, a prompt message will appear on the reading interface to encourage the learner to reply to his/her peers' comments or express his/her own ideas. After learners complete a reading task, we can use intelligent algorithms to automatically generate learning feedback to help learners reflect on their prior learning processes.

This case study contributes to the body of the functions design of social annotation tools and the experimental design of examining the system functions. Our recommendations are built on the results of three quasi-experiments with 157 undergraduate students in China. We hope these recommendations will shed some light on the design of the social annotation tool for the HCI community. Nevertheless, our work still faces several limitations. First, our collaborative reading system was designed in Chinese and only used in one university of China. For a broader application, in the future, we may translate our system into different languages (for example, English) and support learners to choose their preferred language while they log in. In the meantime, we also need to consider the accessibility, smoothness, and stability of the system in different scenarios. A further limitation was that we did not analyze the learning behaviors utilizing multimodal data, which may reveal more information about how learners used the system to read and discuss collaboratively. Therefore, in the future, we will use more data from different modalities to investigate learning modes in the collaborative reading system and explore other effective scaffoldings to inspire more productive learning.

ACKNOWLEDGMENTS

This study was supported by the National Key Research and Development Program of China (No. 2020AAA0108800), the Teaching and Research Project of Hubei Province of China (No. 2020140) and the Self-determined Research Funds of CCNU from the Colleges' Basic Research (No. CCNUTEI2022-02).

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