An automated analysis of topic distributions and features approach to promoting group performance, collaborative knowledge building and socially shared regulation in online collaborative learning

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Online collaborative learning has been widely used in the field of education. However, unrelated or off-topic information is often included in online collaborative learning. Furthermore, the content of online discussion is often too shallow or narrow. To achieve productive collaborative learning, this study proposed and validated an automated analysis of topic distributions and features (AATDF) approach. In total, 189 college students in China participated in this study and were assigned to one of two experimental groups or a control group. Experimental Group 1 participated in online collaborative learning with the AATDF approach. Experimental Group 2 participated in online collaborative learning with the automated analysis of topic distributions (AATD) approach. The control group participated in traditional online collaborative learning without any specified approach. The results indicate that the AATDF approach can significantly promote group performance, collaborative knowledge building and socially shared regulation compared with the AATD and traditional online collaborative learning approaches. The results and implications are also discussed in depth. The main contribution of this study is that the AATDF approach can improve learning performance and bring online collaborative learning onto new ground.

Implications for practice:

- The AATDF approach is very useful and effective for promoting group performance, collaborative knowledge building and socially shared regulation.
- Teachers and practitioners can provide personalised interventions and optimise collaborative learning design based on the analysis results of topic distributions and features.
- Developers can adopt deep neural network models to develop intelligent online collaborative learning tools to help teachers and students.

Keywords: topic distributions, topic features, online collaborative learning, knowledge building, group performance

Introduction

As an effective pedagogy, online collaborative learning has been widely employed in the field of K-12 and higher education. Online collaborative learning involves learners who are geographically isolated learning together online to complete authentic tasks, solve problems and develop real-world abilities (Reeves et al., 2004). However, studies have found that learners experience challenges in online collaborative learning. For example, learners have difficulty focusing on discussions due to unrelated or off-topic information (Wu, 2022; Zheng et al., 2022). The problem of off-topic discussion leads to deviation from the discussion and superficial understanding of the subject matter (Wu, 2022). Furthermore, learners are often unaware of the entire group's process and progress during online collaborative learning (Yilmaz & Yilmaz, 2020).

With the rapid development of artificial intelligence, increasing attention has been given to integrating text mining technologies with artificial intelligence technologies to develop intelligent online collaborative learning environments to improve online discussion quality. For example, X. Peng et al. (2020) adopted topic tracking models to analyse student-generated posts in the discussion forums of small private online courses. C. M. Chen et al. (2021) developed a topic analysis feedback system to analyse topic features to promote online discussion quality. However, very few studies have automatically analysed both topic distributions and topic features in the online collaborative learning context. In this study, topic distributions are the topic classifications of a group and all groups combined as well as the cognition, metacognition, behaviour and emotion classifications entailed by the topics. Topic features are the latent text features detected through topic modelling techniques. This study proposes an automated analysis of topic distributions and features (AATDF) approach to improve group performance, collaborative knowledge building and socially shared regulation (SSR) in online collaborative learning. Group performance is determined by the quantity or quality of the products yielded by group members (Weldon & Weingart, 1993). Collaborative knowledge building is a social interaction process in which learners co-construct knowledge and form a cycle of personal and social knowledge building (Stahl, 2000). SSR is conceptualised as the process by which group members regulate their collective activities by setting learning goals and making plans, monitoring, reflecting and evaluating learning processes and outcomes (Hadwin et al., 2011). This study supposed that the proposed AATDF approach not only helps learners grasp online discussion topics and improve group performance but also promotes collaborative knowledge building and SSR compared to the automated analysis of topic distributions (AATD) and traditional online collaborative learning (TOCL) approaches. The research questions addressed are as follows:

(1) Can the AATDF approach improve group performance compared to the AATD approach and the TOCL approach?
(2) Can the AATDF approach improve collaborative knowledge building compared to the AATD approach and the TOCL approach?
(3) Can the AATDF approach promote SSR compared to the AATD approach and the TOCL approach?

Literature review

OCL

As a widely used OCL activity, online discussions can enable learners to share ideas and solve problems anywhere and anytime (C. M. Chen et al., 2021). Learners generate large amounts of discussion content during OCL. However, online discussion content is often disorganised, which leads to content being lost in the information space and students spending much time trying to find useful information (C. M. Chen et al., 2021). X. Peng et al. (2020) found that teachers and students have difficulties effectively tracking topics during OCL. Therefore, it is necessary to conduct topic analysis to provide real-time feedback in the OCL context. However, automated analysis of topic distributions and features remains lacking in the OCL field. To close the research gap, this study proposed an AATDF approach to promote group performance, collaborative knowledge building and SSR.

Topic distributions and feature detection

A topic is conceptualised as a set of activities that are strongly related by seminal real-world events (Allan, 2002). Topic detection is conceptualised as an automatic technique for finding topically related material in streams of data (Wayne, 1998). Regarding topic distributions, studies have adopted K-means methods (Xu et al., 2019), structural topic modelling (X. Chen et al., 2020) and topic probabilistic models (Z. Liu et al., 2018) to detect topic distributions for various purposes. Furthermore, studies have also revealed that deep neural network models (DNNs) such as bidirectional encoder representations from transformers (BERT) perform well for topic distributions using Chinese corpora (Hu et al., 2022). DNNs are the neural networks used in deep learning (Sze et al., 2017). As a kind of DNN, BERT aims to pre-train deep bidirectional representations from unlabelled texts, and it is empirically powerful since it can capture the semantic relationships among labels (Devlin et al., 2019). However, very few studies have adopted BERT to detect topic distributions in the OCL context.

With respect to topic features, studies have adopted various methods to detect topic features to identify hot topics or off-topic information. Furthermore, several studies have revealed that latent Dirichlet allocation (LDA) is an effective method for detecting topic features (C. M. Chen et al., 2021; X. Peng et al., 2020). LDA is a generative probabilistic model of a text corpus, in which each item of the text corpus is modelled as a finite mixture over a hidden set of topics and each topic is modelled as an infinite mixture over a hidden set of topic probabilities (Blei et al., 2003). As an efficient text mining algorithm, LDA can be adopted for both small and large data sets for topic feature detection, and it is superior to using only the co-occurrence of keywords to detect topics (Wong et al., 2021).

In summary, most studies have adopted traditional methods to detect topic distributions and topic features, but few have adopted DNNs to detect topic distributions and features. Moreover, studies have ignored the cognitions, metacognitions, behaviours and emotional characteristics associated with particular topics. To close the research gaps, this study integrated DNNs and LDA to automatically analyse topic distributions and features in an OCL context. The significance of the AATDF approach is threefold. First, the AATDF approach contributes to gaining a better understanding of discussion content and identifying irrelevant or unexpected discussions, which help reduce workloads and provide timely feedback. Second, the AATDF approach sheds light on the cognitions, metacognitions, behaviours and emotions related to various topics as well as how topics evolve over time, which contributes to obtaining a holistic view of the dynamic social interaction and fine-tuning collaborative learning design. Third, the AATDF approach can assist in formative assessment of whether learners have achieved the expected learning objectives.

Collaborative knowledge building

Collaborative knowledge building focuses on collaborative work and co-constructing knowledge of value to the community (P. J. Li et al., 2020). Studies have adopted various methods to facilitate collaborative knowledge building. However, studies have analysed collaborative knowledge building through manual coding after collaborative learning, which does not enable just-in-time feedback. Very few studies have adopted an AATDF approach to promoting collaborative knowledge building. Therefore, the innovative AATDF approach is called for to improve collaborative knowledge building.

SSR

SSR focuses on jointly forming the regulated learning space to achieve shared understanding and outcomes (Järvelä et al., 2019). As a group-level phenomenon, SSR occurs when learners collectively regulate and align common perceptions of collaborative learning (Isohätälä et al., 2017). However, learners often fail to develop SSR during collaborative learning (Zheng et al., 2021). Järvelä et al. (2016) proposed that developing smart tools for SSR contributes to success in collaborative learning. Nevertheless, there is a lack of studies on developing tools for the AATDF approach to promote SSR. Thus, the literature calls for the AATDF approach to be applied to facilitate SSR in the OCL context.

Methodology

An AATDF approach

This study proposes an AATDF approach to automatically analyse topic distributions and features in OCL. This approach consists of three phases. The first phase involves collecting online discussion transcripts, which are automatically recorded through an OCL platform. The second phase involves automatically analysing and demonstrating topic distributions and features of individuals, each group and all groups combined. This study adopted BERT to automatically analyse topic distributions since the accuracy of BERT (0.89) was higher than that of the long short-term memory (0.75), support vector machine (0.74), logistic regression (0.72) and naive Bayes (0.68). In this study, we adopted the Chinese BERT-base as the pre-trained model with 12 layers, a hidden size of 768, 12 self-attention heads and 110 M parameters based on Devlin et al. (2019). Figure 1 shows the detected topic distributions for one group in OCL. Figure 2 shows the topic distributions for all groups during OCL. Furthermore, this study adopted BERT to identify the characteristics of the cognitions, metacognitions, emotions and behaviours related to various topics, as it achieved the highest performance, according to Table 1. Figure 3 shows the topic-metacognition analysis results of one group. Then, topic features were detected through LDA, which has excellent properties and high performance ratings in topic detection (C. M. Chen et al., 2021). In this study, we selected the topic coherence score to evaluate the LDA performance since topic coherence can measure the semantic similarity degree among high scoring words (Stevens et al., 2012). We selected LDA and varied the topic number from 1 to 8 to fine-tune the model. This study selected the final model that yielded the highest topic coherence score. Figure 4 shows that the topic coherence score reaches the highest when the topic number equals 5. Furthermore, topic features were visualised using LDAvis, which is an open-source tool that can visualise topic features (Sievert & Shirley, 2014). Figure 5 shows the topic features diagram of one group, with the diagram on the left indicating the expected topics that can be stored in the database ahead of time and the diagram on the right representing the actual generated topics of a group. The third phase involves providing personalised group feedback and resources according to the predefined rules.

Table 1
The accuracy of models

Models	Accuracy			
	Topic-cognition	Topic-metacognition	Topic-emotion	Topic-behaviour
Naive Bayes	0.68	0.80	0.78	0.68
Support vector machine	0.74	0.83	0.83	0.76
Logistic regression	0.73	0.82	0.82	0.75
Long short-term memory	0.75	0.84	0.83	0.79
BERT	0.87	0.90	0.94	0.91

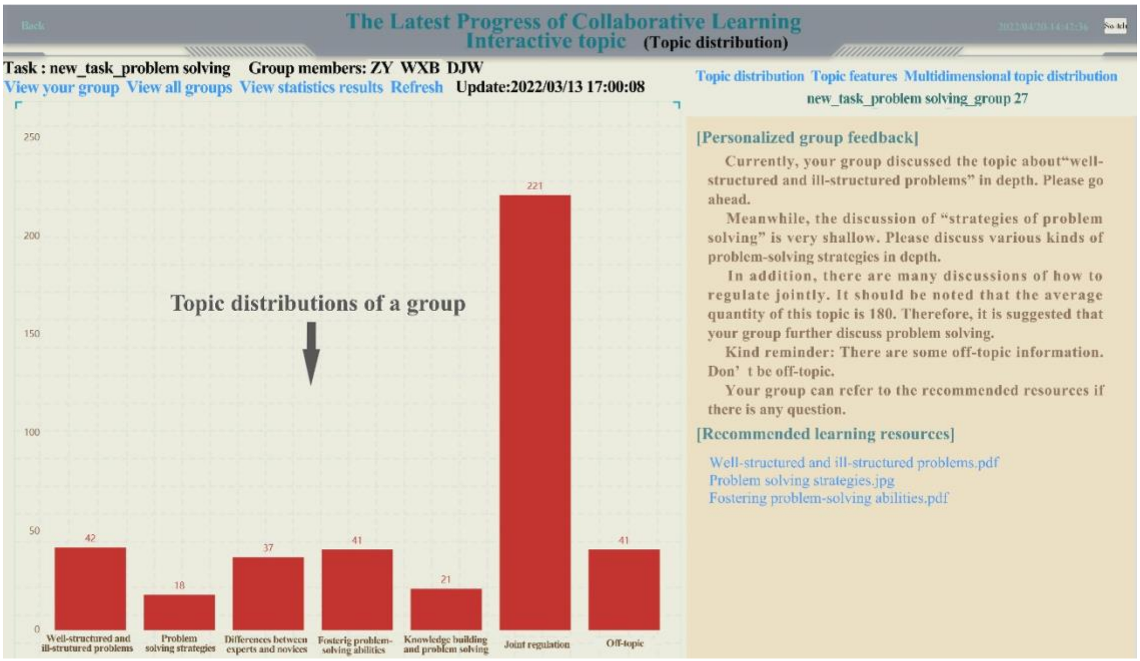


Figure 1. The topic distributions of a group

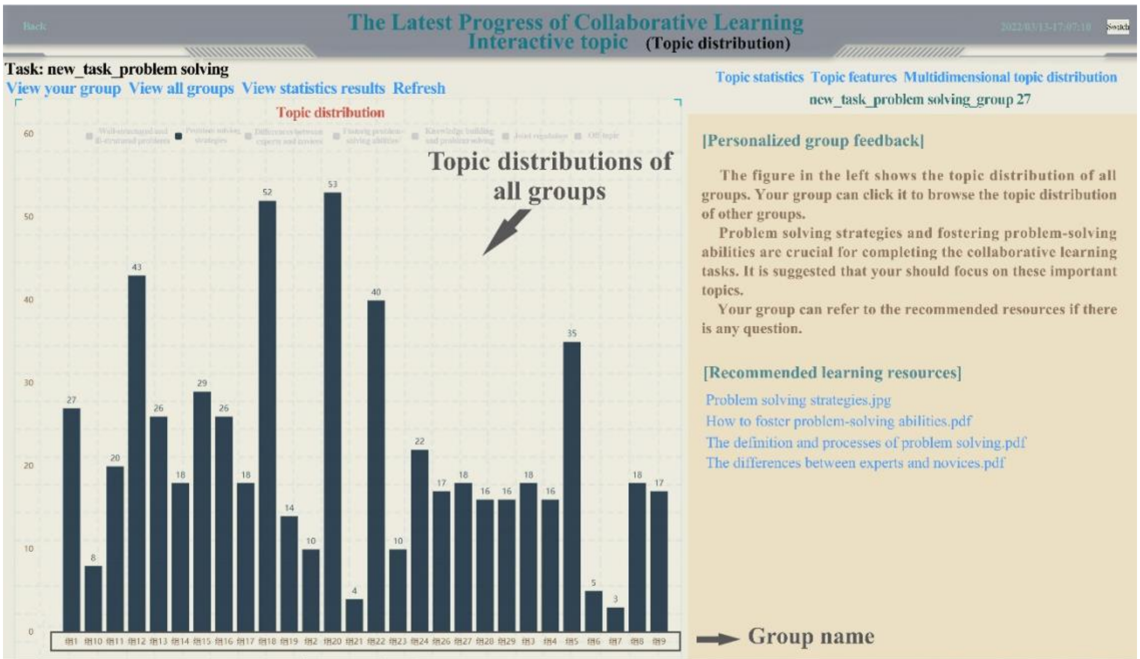


Figure 2. The topic distributions of all groups

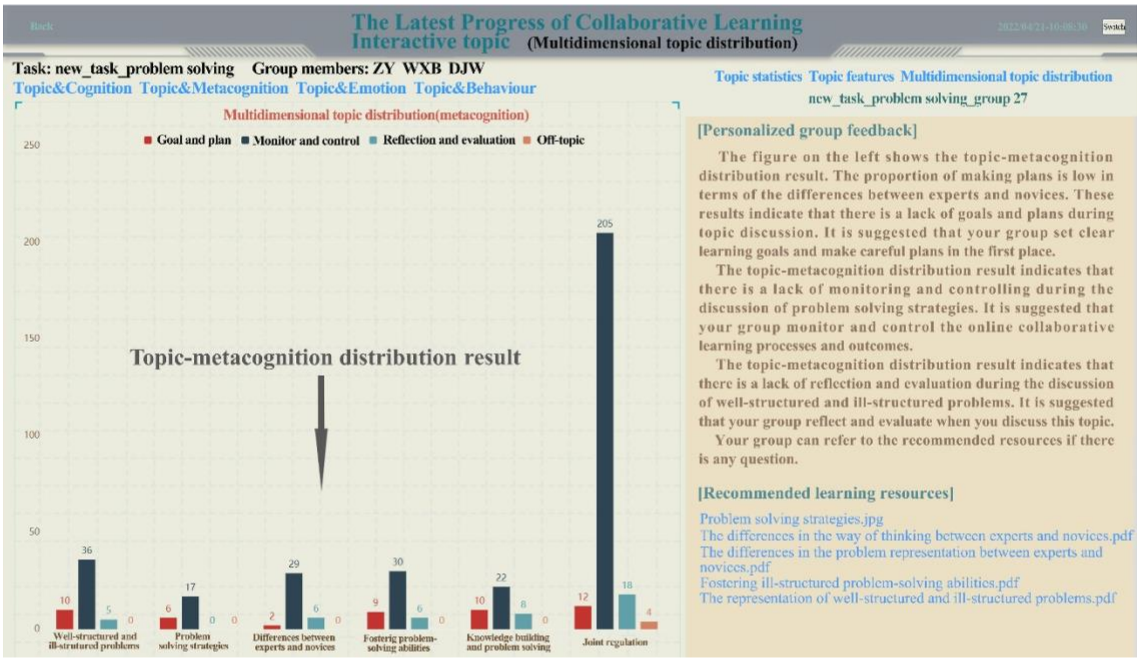


Figure 3. The topic-metacognition distributions

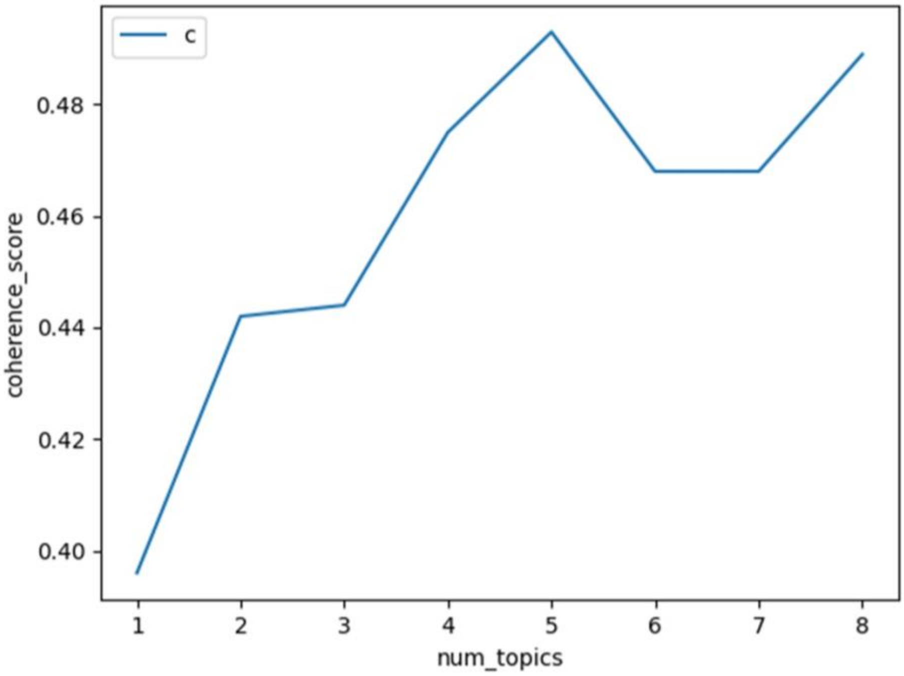


Figure 4. The results of topic coherence scores

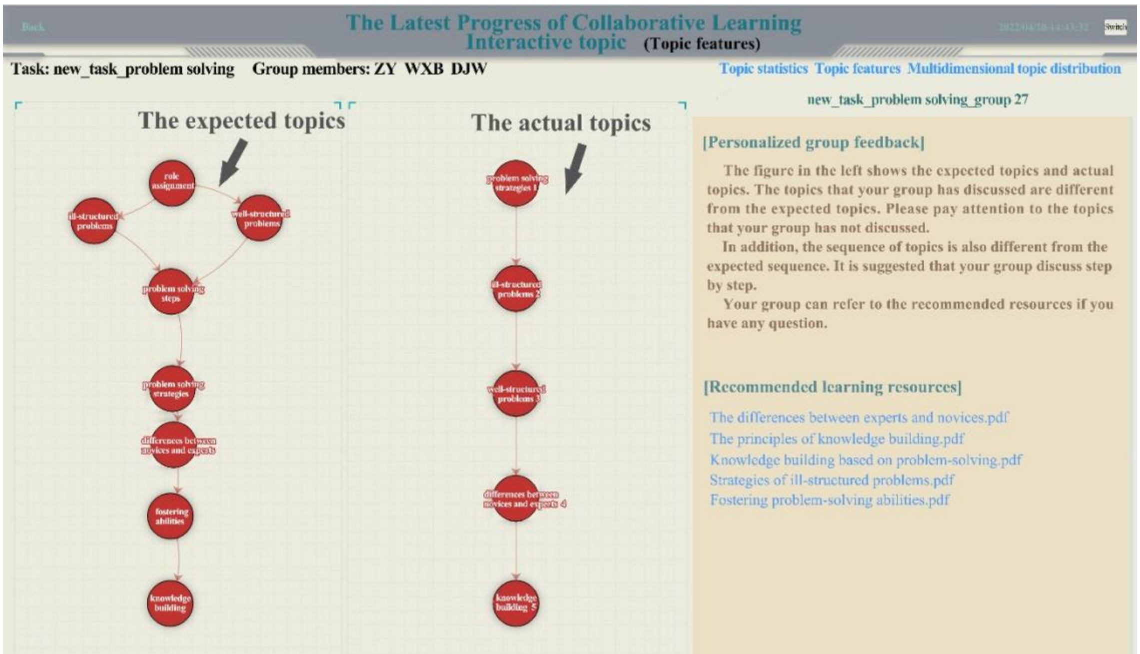


Figure 5. The detected topic features diagram

Participants

The participants were 189 college students who were enrolled through posters at a top-10 public university in China. There were 28 males and 161 females with an average age of 22 (SD = 2.25). They majored in psychology, education, literature, management, history, mathematics and foreign linguistics. The 21 experimental groups with 63 students composed the AATDF group and experienced OCL with the AATDF approach. Another 21 experimental groups with 63 students composed the AATD group and experienced OCL with the AATD approach. The 21 control groups with 63 students composed the TOCL group and experienced TOCL without any specified approach. Each group contained three students. There were no significant differences in gender (X^2 = 6.00, *p* = .112), major (X^2 = 28.00, *p* = .260), age (*F* = .535, *p* = .586) or prior knowledge (*F* = .008, *p* = .992) among the two conditions of the experimental groups or the control groups. This study was not conducted within a course context, and all participants joined this study in their spare time. Informed written consent was obtained from all participants, and they could withdraw from the experiment at any time.

Experimental procedure

This study conducted a quasi-experimental design to examine the impact of the AATDF approach on collaborative knowledge building, group performance and SSR. The entire study lasted for 5 months. The experimental procedure consisted of six phases, as shown in Figure 6. The first phase was to conduct a pretest for 20 minutes to examine the prior knowledge of the three groups. The pretest was developed by two experienced experts and consisted of 10 multiple-choice items, two short-answer questions and two essay questions, with 100 being a perfect score. The Cronbach's alpha value of the pretest was 0.83, indicating acceptable internal consistency (Cortina, 1993). The second phase was to explain the AATDF, AATD and TOCL approaches to the students in separate groups. The third phase was to conduct OCL in different time slots and complete the same collaborative learning task for the same duration. The topic of OCL tasks was problem-solving. More specifically, the task consisted of five subtasks: What are the characteristics of well-structured and ill-structured problems? How can well-structured and ill-structured problems be solved? What are the differences between experts and novices in problem-solving? How can problem-solving abilities be improved through instruction? How can knowledge be built based on problem-solving? To compare the differences among the three approaches, this study designed two experimental groups and one control group. Experimental Group 1 experienced OCL with the AATDF approach. Experimental Group 2 undertook OCL with the AATD approach. The control group experienced TOCL without any specified approach. By the end of the OCL, all participants collaboratively edited an online document regarding the solutions to collaborative learning tasks as a group product. In the fourth phase, the post-test was administered to all participants for 20 minutes. The post-test was also developed by two experienced experts and consisted of 10 multiple-choice items, two short-answer questions and two essay questions, with 100 being a perfect score. The Cronbach's alpha value of the post-test was 0.80, indicating acceptable internal consistency (Cortina, 1993). In the fifth phase, the participants were interviewed face-to-face for 30 minutes to obtain their learning perceptions. Taking the AATDF approach as an example, the interview guide consisted of six main interview questions: Do you think whether the AATDF approach contributes to revising and refining group products, and why? Can the AATDF approach promote reflecting and evaluating group products, and why? Do you think the AATDF approach contributes to acquiring new knowledge and skills, and why? Can the AATDF approach promote the coconstruction of knowledge, and why? Can the AATDF approach facilitate SSR, and why? Do you think the AATDF approach contributes to improving efficiency and confidence, and why? Finally, a delayed post-test was administered to all participants 3 days later. The items of the delayed post-test were the same as those of the original post-test. The Cronbach's alpha value of the delayed post-test was 0.80, indicating acceptable internal consistency (Cortina, 1993).

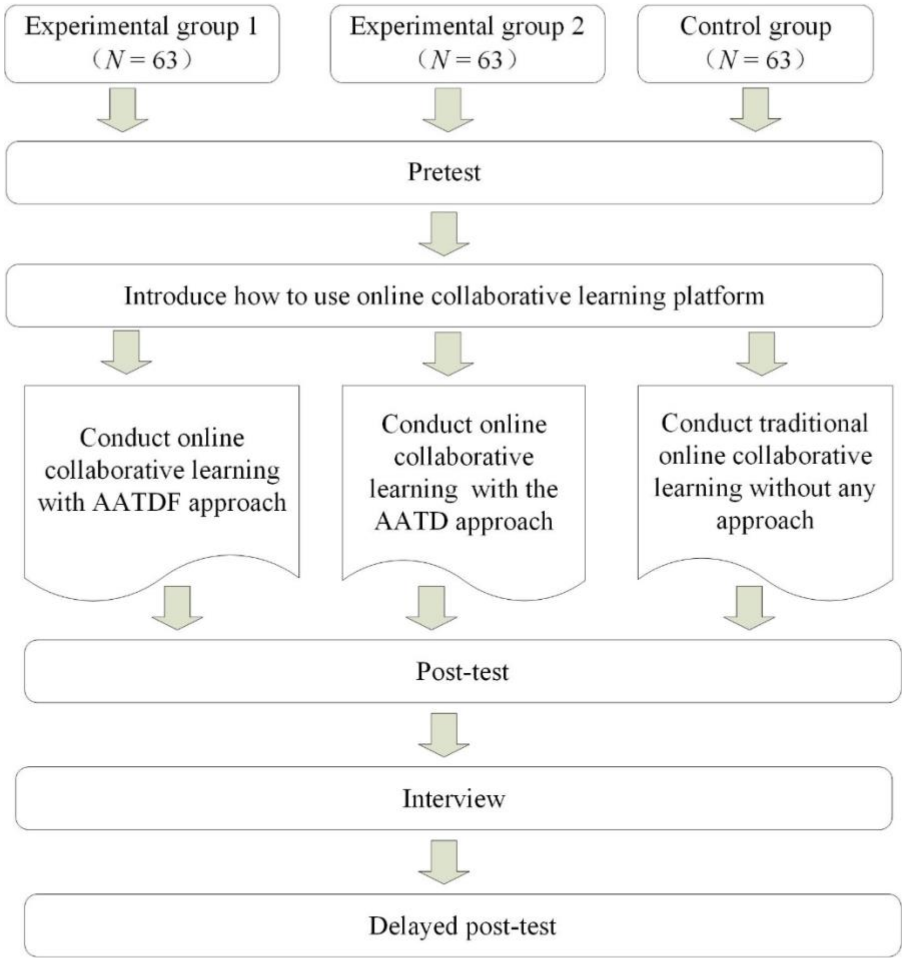


Figure 6. The experimental procedure

Data collection and analysis method

The data sets collected in this study consisted of 189 pretests, 189 post-tests, 189 delayed post-tests, the online discussion transcripts of 63 groups, 63 group products and the interview records of 63 groups. The independent variables were the learning approaches (AATDF, AATD and TOCL), and the dependent variables consisted of group performance, collaborative knowledge-building level and SSR. The covariate was the pretest score of prior knowledge. The data analysis methods consisted of the content analysis method, the computer-assisted knowledge graph analysis method and the lag sequential analysis method.

First, the 189 pretests, 189 post-tests and 189 delayed post-tests were independently rated by two raters; the kappa values were 0.83, 0.80, and 0.80 respectively, which indicated good reliability. Second, the online discussion transcripts of 63 groups were analysed using the computer-assisted knowledge graph analysis method to calculate the collaborative knowledge-building level. The method was proposed by Zheng et al. (2015) and has been validated by Zheng et al. (2021) and Zheng et al. (2022). This method consists of three steps, namely drawing the target knowledge graph, coding online discussion transcripts and calculating the collaborative knowledge-building level automatically through a specifically developed tool. The collaborative knowledge-building level is equal to the sum of the values of activity quantity in each knowledge node in a knowledge graph. The activity quantity represents the information entropy of online discussion transcripts, which can be calculated using a validated formula (Zheng et al., 2015). The two research assistants independently coded the online discussion transcripts for 63 groups; the kappa value was 0.82, indicating high acceptable internal consistency (Cortina, 1993).

Third, the group products of the 63 groups were independently rated by the two research assistants based on the assessment criteria shown in Table 2, which has been validated by Zheng et al. (2022). The inter-rater reliability calculated by the kappa value was 0.83, indicating high internal consistency (Cortina, 1993). The group performance was equal to the scores of the group products.

Fourth, the online discussion transcripts of the 63 groups were analysed to identify SSR behaviours based on the coding scheme shown in Table 3, which has been validated by Zheng et al. (2021). GSEQ version 5.1 software was adopted to conduct behavioural sequence analysis (Quera et al., 2007). Two research assistants independently analysed all online discussion transcripts for the 63 groups; the inter-rater reliability was 0.91, indicating high internal consistency (Cortina, 1993).

Finally, the interview transcripts were analysed based on thematic analysis methods (Braun & Clarke, 2006) to classify them into three themes: improving group performance, improving collaborative knowledge-building andpromoting SSR. The two research assistants analysed all the interview transcripts, and any discrepancies were resolved via face-to-face discussion. The inter-rater reliability of the interview was 0.9, indicating good reliability.

Table 2
Assessment criteria for group products

Dimension & rating	16–20	11–15	6–10	1–5
Correctness (20)	Correct solutions, explanations and examples.	Correct solutions and explanations but incorrect examples.	Correct solutions but incorrect explanations and examples.	Wrong solutions, explanations and examples.
Rationality (20)	The solutions and evidence were logical and appropriate.	The solutions and evidence were partly logical and appropriate.	Only solutions were logical and appropriate.	Neither the solutions nor the evidence were logical and appropriate.
Feasibility (20)	The solutions to all problems were feasible.	The solutions to all problems were partly feasible.	The solutions to all problems were not feasible.	The solutions to all problems were lacking.
Originality (20)	The solutions were original.	The solutions were partly original.	The solutions lacked originality.	The solutions were from others or the Internet.
Completeness (20)	The solutions were complete and well-organised.	The solutions were partly complete.	The solutions were incomplete and disorderly.	The solutions were sloppy and incomplete, and there were many errors.

Table 3
The coding scheme for SSR behaviours

Dimensions	Examples
Orienting goals (OG)	"We need to establish the task demands and orient goals first."
Making plans (MP)	"We can make a detailed plan to complete collaborative learning tasks efficiently."
Enacting strategies (ES)	"We can adopt a heuristic strategy to solve this problem. Let's try it."
Monitoring and controlling (MC)	"Time flies. We should move on the third task now."
Evaluating and reflecting (ER)	"Let's evaluate and reflect on our solutions first and then revise it further to make it perfect."
Adapting metacognition (AM)	"There are some problems with our solutions. We should change strategies immediately."

Results

Analysis of group performance

Group performance was examined through post-test, delayed post-test and group products. To analyse the difference in post-test results among the two experimental groups and one control group, one-way analysis of covariance (ANCOVA) was employed in the present study. Before ANCOVA, the Kolmogorov–Smirnov test was performed to examine the normality distribution for all data sets. The results indicated that all data sets were normally distributed ($p > .05$). In addition, the homogeneity of variance for the post-test was examined through Levene's test and was not violated ($F = 1.912$, $p = .151$). The homogeneity of regression slopes was confirmed, indicating that ANCOVA can be performed to examine the impact of the proposed approach ($F = .648$, $p = .524$). Table 4 shows the ANCOVA results of the post-tests for the three groups. The findings revealed that there were significant differences in post-test scores among the three groups ($F = 32.45$, $p < .001$). Furthermore, post hoc analysis was performed through the least significant difference (LSD) test to examine the specific differences among the three approaches. The results indicated that the post-test scores of the AATDF groups were significantly higher than those of the AATD and TOCL groups.

Furthermore, the impact of the proposed approach on delayed post-tests was also examined. All data sets were normally distributed ($p > .05$). The homogeneity of variance for the delayed post-test was examined through Levene's test and was not violated ($F = .759$, $p = .470$). The homogeneity of regression slopes was confirmed, indicating that ANCOVA can be performed to examine the impacts of the proposed approach ($F = .209$, $p = .812$). Table 5 shows the ANCOVA results of the delayed post-tests for the three groups. The findings revealed that there were significant differences in the delayed post-test scores among the three groups ($F = 14.59$, $p < .001$). Furthermore, post hoc analysis was performed through the LSD test to examine the specific differences among the three approaches. The results indicated that the AATDF groups' delayed post-test scores were significantly higher than those of the AATD and TOCL groups.

In addition, the difference in group products among the two experimental groups and one control group was examined through ANCOVA. Before ANCOVA, the Kolmogorov–Smirnov test was performed to examine the normality distribution for all data sets. The results indicated that all data sets were normally distributed ($p > .05$). Additionally, homogeneity of variance was examined through Levene's test and was not violated ($F = 1.022$, $p = .366$). The homogeneity of regression slopes was confirmed, indicating that ANCOVA can be performed to examine the impacts of the proposed approach ($F = .451$, $p = .639$). Table 6 shows the ANCOVA results of the group products for the three groups. The findings revealed that there were significant differences in group products across the three groups ($F = 24.08$, $p < .001$). Furthermore, post hoc analysis was performed through the LSD test to examine the specific differences of the three approaches. The AATDF group product score was significantly higher than those of the AATD and TOCL groups. Therefore, the students who learned with the AATDF approach had higher group performance than the students who learned with either the AATD or TOCL approach.

To obtain a better understanding of learners' perceptions of using the AATDF approach, the interview records were analysed; Table 7 shows the interview analysis results, including the themes, subthemes and frequencies of the AATDF and AATD groups. Although both the AATDF and AATD approaches could promote reflecting on and evaluating group products, the AATDF approach better promoted revising and refining group products (86%) than the AATD approach (81%). For example, one interviewee said, "Our group often browses the analysis results about topic features and revises our group products. It is truly helpful for us to refine group products". Therefore, the students who learned with the AATDF approach had better group performance than the students who learned with the AATD approach.

Table 4
ANCOVA results of post-test

Groups	N	Mean	SD	Adjusted mean	SE	df	F	Post hoc
(1) AATDF group	63	76.93	11.07	76.91	1.25	2	32.45***	(1) > (2)
(2) AATD group	63	69.88	10.32	69.89	1.26			(1) > (3)
(3) TOCL group	63	62.55	9.09	62.58	1.26			(2) > (3)

***$p < .001$

Table 5
ANCOVA results of delayed post-test

Groups	N	Mean	SD	Adjusted mean	SE	df	F	Post hoc
(1) AATDF group	63	74.92	12.94	75.00	1.59	2	14.59***	(1) > (2)
(2) AATD group	63	68.61	13.67	68.66	1.59			(1) > (3)
(3) TOCL group	63	62.92	11.37	62.81	1.60			(2) > (3)

***$p < .001$

Table 6
ANCOVA results of group products

Groups	N	Mean	SD	Adjusted mean	SE	df	F	Post hoc
(1) AATDF group	63	82.76	6.50	82.74	1.97	2	24.08***	(1) > (2)
(2) AATD group	63	75.00	9.44	74.99	1.98			(1) > (3)
(3) TOCL group	63	63.43	10.68	63.44	1.97			(2) > (3)

***$p < .001$

Table 7
The interview results

Themes	Subthemes	AATDF groups	AATD groups
Improve group performance	Revising and refining group products based on the analysis results.	86%	81%
	Reflecting on and evaluating group products based on the analysis results.	90%	90%
Improve collaborative knowledge building	Acquiring new knowledge and skills according to the analysis results.	86%	81%
	Co-constructing knowledge together.	100%	90%
Promote SSR	Jointly regulating such as adapting goals, plans, or strategies according to the analysis results.	95%	71%
	Contributing to improving efficiency and confidence.	95%	71%

Analysis of collaborative knowledge building

To analyse the difference in collaborative knowledge building among the two experimental groups and one control group, ANCOVA was employed in the present study. Before ANCOVA, the Kolmogorov–Smirnov test was performed to examine the normality distribution for all data sets. The results indicated that all data sets were normally distributed ($p > .05$). In addition, homogeneity of variance was examined through Levene's test and was not violated ($F = .208$, $p = .813$). The homogeneity of regression slopes was confirmed, indicating that ANCOVA can be performed to examine the impacts of the proposed approaches ($F = .452$, $p = .639$). Table 8 shows the ANCOVA results of collaborative knowledge building for the three groups. The findings revealed that there were significant differences in collaborative knowledge building across the three groups ($F = 28.43$, $p < .001$). Furthermore, post hoc analysis was performed through the

LSD test to examine the specific differences across the three approaches. The results indicated that the collaborative knowledge building of the AATDF groups was significantly better than that of the AATD and TOCL groups.

As shown in Table 7, the interview results indicated that the AATDF approach better promotes collaborative knowledge building than the AATD approach. All the interviewees from the AATDF group reported that the analysis results stimulated them to coconstruct knowledge (100%). They also reported acquiring new knowledge and skills based on the analysis results and personalised feedback (86%). For example, one interviewee believed that “Our group often makes up for deficiencies and acquires new knowledge after comparing our topic path with the expected topic path. We really like it”. In contrast, the interview results revealed that the proportions of promoting collaborative knowledge building were lower for the AATD groups than for the AATDF groups.

Table 8
ANCOVA results of collaborative knowledge building

Groups	N	Mean	SD	Adjusted mean	SE	df	F	Post hoc
(1) AATDF group	63	780.42	149.70	780.37	35.12	2	28.43^{***}	(1) > (2)
(2) AATD group	63	539.17	159.18	539.18	35.13			(1) > (3)
(3) TOCL group	63	411.48	169.39	411.52	35.12			(2) > (3)

$^{***}p < .001$

Analysis of the SSR of behavioural patterns

Tables 9, 10, and 11 present the adjusted residuals of the AATDF, AATD and TOCL groups respectively. Target behaviour occurs significantly more often than expected by chance when the adjusted residual is larger than 1.96 (Bakeman & Quera, 2011). Figure 7 shows the SSR behavioural sequence transition diagrams of the AATDF, AATD and TOCL groups.

The results indicated that nine significant SSR behavioural sequences occurred in the AATDF group. As shown in Figure 7, OG→MP indicates that learners make plans after orientating goals. MP→OG indicates that learners orientate goals again after making plans. MP→MP indicates that learners make plans continually. MP→ES indicates that learners enact different strategies after they make plans. ES→MC indicates that learners monitor and control the OCL progress after they enact strategies. MC→MC indicates that learners monitor and control continually. ER→ER indicates that learners evaluate and reflect continually. ER→AM indicates that learners adapt metacognition after they evaluate and reflect. AM→ES indicates that learners enact different strategies after they adapt metacognition.

In contrast, only seven significant SSR behavioural sequences occurred in the AATD group: OG→OG (orientating goals repeatedly), OG→MP (making plans after orientating goals), MP→MP (making plans repeatedly), MP→ES (enacting strategies after making plans), ES→MC (monitoring and controlling after enacting strategies), ER→ES (enacting strategies after evaluating and reflecting) and ER→ER (evaluating and reflecting repeatedly). In addition, only six repeated SSR behavioural sequences occurred in the control group: OG→OG (orientating goals repeatedly), MP→MP (making plans repeatedly), ES→ES (enacting strategies repeatedly), MC→MC (monitoring and controlling repeatedly), ER→ER (evaluating and reflecting repeatedly) and AM→AM (adapting metacognition repeatedly). Furthermore, there were three significant SSR behavioural transition sequences that occurred only in the AATDF group (see Table 12): MP→OG, ER→AM and AM→ES. This finding indicated that orientating goals, enacting strategies and adapting metacognition were crucial SSR behaviours for successful OCL.

As shown in Table 7, all the interviewees from the AATDF group reported that they could monitor the OCL progress, enact strategies and adapt goals and plans based on the analysis results. They could also jointly regulate themselves according to the analysis results (95%). The analysis results also contributed to improving efficiency and increasing confidence (95%). For instance, one interviewee told us, “Our group often monitors collaborative learning progress and regulates ourselves based on the analysis results. If there is off-topic information or superficial discussion, we immediately concentrate on the task and discuss it in depth". Another interviewee said, "The analysis results contribute to improving efficiency. We were so confident when we found the analysis results of our group were so perfect". In contrast, the interview results revealed that the proportions of promoting SSR were lower for the AATD groups than for the AATDF groups.

Table 9
Adjusted residuals of the AATDF group

Starting behaviour	Subsequent behaviour					
	OG	MP	ES	MC	ER	AM
Orientating goals (OG)	1.48	2.06*	-1.53	0.46	-0.98	-0.79
Making plans (MP)	2.83*	3.99*	3.73*	-1.75	-3.56	-2.60
Enacting strategies (ES)	-0.45	1.14	-1.85	2.26*	-2.24	0.67
Monitoring and controlling (MC)	1.43	-0.05	-1.27	2.73*	-2.04	-1.42
Evaluating and reflecting (ER)	-3.06	-3.84	-0.56	-3.98	7.36*	3.44*
Adapting metacognition (AM)	-1.68	-1.53	2.65*	-0.42	0.21	0.07

*$p < .05$

Table 10
Adjusted residuals of the AATD group

Starting behaviour	Subsequent behaviour					
	OG	MP	ES	MC	ER	AM
Orientating goals (OG)	6.22*	2.36*	-0.37	-2.32	-1.61	-0.53
Making plans (MP)	1.94	4.89*	2.82*	-3.19	-3.46	-0.59
Enacting strategies (ES)	-1.00	-0.43	-0.48	3.55*	-2.72	-1.69
Monitoring and controlling (MC)	-1.58	-0.84	-2.55	1.10	1.61	1.73
Evaluating and reflecting (ER)	-1.88	-3.79	2.38*	-1.79	5.13*	-0.50
Adapting metacognition (AM)	-0.45	-0.86	-0.64	1.16	-0.55	0.82

*$p < .05$

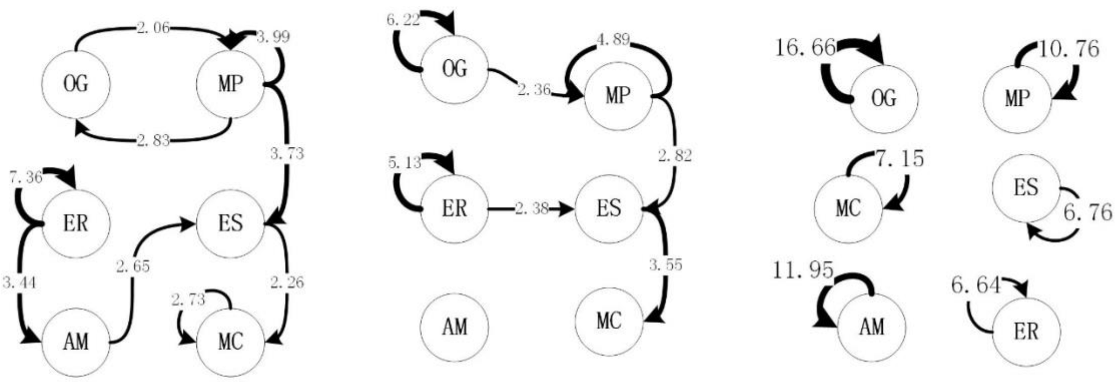
Table 11
Adjusted residuals of the TOCL group

Starting behaviour	Subsequent behaviour					
	OG	MP	ES	MC	ER	AM
Orientating goals (OG)	16.66*	0.68	-0.71	-3.88	-2.03	-0.73
Making plans (MP)	-0.72	10.76*	-0.96	-4.18	-2.88	-1.76
Enacting strategies (ES)	-1.50	-3.43	6.76*	-2.61	0.84	-0.66
Monitoring and controlling (MC)	-3.42	-1.79	-3.74	7.15*	-2.20	-1.99
Evaluating and reflecting (ER)	-0.52	-4.51	-0.59	-1.20	6.64*	1.82
Adapting metacognition (AM)	-0.72	-1.74	-0.04	-0.57	-1.00	11.95*

*$p < .05$

Table 12
Significant SSR behaviour sequences that occurred only in the AATDF group

Starting behaviour	Subsequent behaviour					
	OG	MP	ES	MC	ER	AM
Orientating goals (OG)						
Making plans (MP)	MP→OG					
Enacting strategies (ES)						
Monitoring and controlling (MC)						
Evaluating and reflecting (ER)			ER→AM			
Adapting metacognition (AM)					AM→ES	



The behavioural transition diagram of AATDF group

The behavioural transition diagram of AATD group

The behavioural transition diagram of TOCL group

Figure 7. SSR behavioural transition diagram of the AATDF, AATD and TOCL groups

Discussion and conclusions

This study proposed and validated the impacts of the AATDF approach on group performance, collaborative knowledge building, and SSR in OCL. The results indicate that the AATDF approach has more significant and positive impacts on group performance, collaborative knowledge building and SSR than the AATD and TOCL approaches.

Effects on group performance

This study found that the AATDF approach significantly improves group performance compared with the AATD and TOCL approaches. The possible reasons lie in the following factors. First, compared with the AATD approach, the AATDF approach automatically detects topic features through LDA, which encouraged each group to be aware of the difference between the actual topics and the expected topics. The interview results also indicate that the expected topics are considered learning goals and representational guidance. Cheng et al. (2020) revealed that learning goal orientation is significantly related to learning performance. Representational guidance is an effective guidance strategy to facilitate OCL performance (C. M. Chen et al., 2021). Second, the groups using the AATDF approach were able to browse the topic distributions of other groups, which increased intergroup awareness to stimulate reflection and optimisation of group products. This result is in line with that of Y. Peng et al. (2022), who found that intergroup awareness contributes to improving group performance. Third, the interview results also indicate that the students from the AATDF group perceived the usefulness of the AATDF approach for improving group performance. The AATDF approach can generate meaningful learning analytics results; therefore, students have positive perceptions of the AATDF approach. Lu et al. (2017) proposed that learning analytics can improve learning performance to a large extent.

Effects on collaborative knowledge building

The present study found that the AATDF approach significantly improves collaborative knowledge building compared with the AATD and TOCL approaches. There are several possible reasons for the positive findings. First, the groups using the AATDF approach were able to browse the analysis results of topic distributions and features, which served as a shared reference. Shin et al. (2018) revealed that shared references are essential for fostering productive knowledge building. Second, the AATDF approach automatically analyses the topic distributions of individuals, each group and all groups, which provides more information for group awareness. Group awareness can effectively promote collaborative knowledge building during OCL (Y. Li et al., 2021). Third, the interview results reveal that the participants perceived the AATDF approach to be useful for promoting collaborative knowledge building. This finding was corroborated by Ghazal et al. (2020), who found that students' perceptions play a significant role in promoting collaborative knowledge building.

Effects on SSR

This study revealed that the AATDF approach significantly improves SSR compared to the AATD and TOCL approaches. Several reasons may explain the results. First, the AATDF approach automatically analyses topic distributions and features, which created shared space and representation. Shared space and representation can promote SSR (Järvelä et al., 2015). Second, the AATDF approach clearly demonstrated the expected topics, which is considered a group goal orientation to facilitate SSR. Lim and Lim (2020) revealed that goal orientation can promote regulation during collaborative learning. Third, the AATDF approach provides more group awareness information about topic distribution and features than the AATD and TOCL approaches, which promotes SSR. Strauß and Rummel (2021) revealed that group awareness can promote shared regulation during collaborative learning. Finally, the interview results confirm that the participants perceived the usefulness of the AATDF approach for promoting SSR. The design of the AATDF approach is in line with that of Järvelä et al. (2016), who proposed that a well-designed technological tool can promote SSR. Therefore, the participants in the AATDF group could better conduct SSR than those in the AATD and TOCL groups.

Implications

The present study has several important implications for practitioners and researchers. First, the AATDF approach demonstrates that detecting topic distribution and features can help learners quickly grasp the whole picture of online discussion content. Analysing topic distributions helps identify hot topics and off-topic information as well as the cognitions, metacognitions, behaviours and emotions associated with topics change during OCL. Detecting topic features contributes to comparing the differences between what the teachers expected and what the learners actually discussed. Learners can make use of the analysis results and real-time feedback to improve learning performance. Providing learning analytics results can significantly increase learning performance (Hwang et al., 2017).

Second, the AATDF approach integrated the analysis results of topic distributions and features, which contributed insights into designing and optimising collaborative learning tasks as well as providing earlier adjustment of methods or learning resources to improve collaborative learning performance. Practitioners and researchers can optimise collaborative learning activity design based on the analysis results of topic distributions and features, such as optimising learning tasks, interaction strategies, learning resources and assessment methods. For example, if there are negative emotions related to some topics, the learning tasks and learning resources may need to be adjusted to prevent the learners from feeling too frustrated or the assigned tasks from being too difficult. If there is a lack of reflection and evaluation related to some topics, then interaction strategies or assessment methods may need to be optimised accordingly to promote reflection and evaluation.

Third, the present study revealed that DNNs are more efficient than traditional machine learning methods in terms of analysing topic distributions. This result also echoes that of Shan et al. (2020), who found similar results. DNNs have the inherent ability to extract high-level features and overcome the shortcomings of traditional machine learning methods (W. Liu et al., 2017) to achieve superior performance in many domains. However, the disadvantages of DNNs include a lack of transparency, explainability and trust, which lead to poor large-scale application of DNNs in some domains (Rudin, 2019). As a cutting-edge technique, explainable DNNs can improve the transparency, robustness and reliability of DNNs (Ras et al., 2022). Therefore, researchers and developers can develop explainable DNNs to facilitate OCL in the future.

Limitations and future studies

This study has several limitations. First, this study involved students completing one OCL task in one learning domain. Caution should be taken when generalising the results to other learning domains. Future studies should examine the AATDF approach in other learning domains. Second, the current AATDF approach presented topic distributions and features only in short-term OCL. We suggest that future studies analyse distributions and features through long-term and large-scale experiments.

Author contributions

Lanqin Zheng: Conceptualisation, Investigation, Writing – original draft, Writing – review and editing; **Lu Zhong:** Data curation, Investigation, Formal analysis, Writing – review and editing; **Yunchao Fan:** Data curation, Writing – review and editing.

Acknowledgements

This study is funded by the International Joint Research Project of Huiyan International College, Faculty of Education, Beijing Normal University (ICER202101).

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Please cite as: Zheng, L., Zhong, L., & Fan, Y. (2023). An automated analysis of topic distributions and features approach to promoting group performance, collaborative knowledge building and socially shared regulation in online collaborative learning. *Australasian Journal of Educational Technology*, *39*(3), 114-132. https://doi.org/10.14742/ajet.7995