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Effects of Personalized Intervention on Collaborative Knowledge Building, Group Performance, Socially Shared Metacognitive Regulation, and Cognitive Load in Computer-Supported Collaborative Learning

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ABSTRACT: In recent years, the rapid development of artificial intelligence has increased the power of personalized learning. This study aimed to provide personalized intervention for each group participating in computer-supported collaborative learning. The personalized intervention adopted a deep neural network model, Bidirectional Encoder Representations from Transformers (BERT), to automatically classify online discussion transcripts and provide classification results in real time. Personalized feedback and recommendations were automatically generated from the classification results. A quasi-experimental research design was adopted to examine the effects of the proposed personalized intervention approach on collaborative knowledge building, group performance, socially shared metacognitive regulation, and cognitive load. Sixty-six college students participated in this study and were randomly assigned to the experimental and control groups. For online collaborative learning, students in the experimental group adopted the personalized intervention approach, whereas those in the control group used the conventional approach. Both quantitative and qualitative research methods were adopted to analyze data. The results indicated significant differences in the level of collaborative knowledge building and group performance between the experimental and control groups. Furthermore, the experimental group demonstrated more socially shared metacognitive regulation than the control group. There was no significant difference in cognitive load between the experimental and control groups. The results obtained from interviews were consistent with the quantitative data. The main findings together with the implications for practitioners are discussed in depth.

Keywords: Personalized intervention, Deep neural network, Collaborative learning, Knowledge building, Socially shared metacognitive regulation

1. Introduction

Computer-supported collaborative learning (CSCL) has been widely adopted in the field of education. CSCL is an effective pedagogical approach that aims to foster the social nature of learning (Jeong, Hmelo-Silver, & Jo, 2019), to co-construct shared understanding and intersubjective meaning making (Stahl, 2006). CSCL is sustained by group interaction to promote socialized learning (Hernández-Sellés, Muñoz-Carril, & González-Sanmamed, 2019). Most research topics in the field of CSCL center on discourse and pattern, factors influencing CSCL, methodology, scripting, scaffolding, and the development of CSCL environments (Tang, Tsai, & Lin, 2014). However, there is still a need to provide personalized intervention in CSCL. To achieve this, it is necessary to automatically analyze the large amount of data generated in CSCL. Previous studies adopted traditional machine learning methods to analyze CSCL data. For example, Mu, Stegmann, Mayfield, Rosé, and Fischer (2012) adopted such methods to automatically segment online discussion transcripts in CSCL. However, conventional machine learning methods depend heavily on human-designed features (Hadi, Al-Radaideh, & Alhawari, 2018) and there is a lack of semantic representations (Shan, Xu, Yang, Jia, & Xiang, 2020), which results in poor performance.

With the rapid development of modern artificial intelligence (AI), AI applications have attracted increasing interest in the field of education (Chen, Xie, & Hwang, 2020). One of the missions of AI in education is to provide personalized guidance, support, or intervention, based on learning status or characteristics (Hwang, Xie, Wah, & Gašević, 2020). However, the provision of personalized intervention to improve learning is still underdeveloped (Hsu, Chiou, Tseng, & Hwang, 2016). Furthermore, although previous studies have exploited conventional machine learning, little work has been done to adopt deep learning technologies in the field of education (Chen, Xie, Zou, & Hwang, 2020). Deep neural networks (DNNs), the type of neural networks used in deep learning, are now able to exceed human accuracy in many fields (Sze, Chen, Yang, & Emer, 2017).

To the best of our knowledge, studies on the real-time analysis of online discussion transcripts gathered during CSCL is very rare, and research on personalized intervention using modern AI techniques in the CSCL context remain lacking. Additionally, it was found that the use of technology may increase cognitive load (Wu, Huang, Su, Chang, & Lu, 2018). Moreover, the particular intervention could have an impact on socially shared regulation in CSCL context (Lin, 2018). It is very important to investigate the effects of personalized intervention on cognitive load and socially shared metacognitive regulation (SSMR), since few studies to date have examined the issues. Given the scarcity of related studies, this paper proposes a personalized intervention approach based on DNNs and examines the effects of this approach on collaborative knowledge building, group performance, socially shared metacognitive regulation, and cognitive load. The following research questions are addressed:

(1) Can the personalized intervention approach improve collaborative knowledge building, compared with the conventional online collaborative learning approach?
(2) Can the personalized intervention approach improve group performance, compared with the conventional online collaborative learning approach?
(3) Can the personalized intervention approach enhance SSMR, compared with the conventional online collaborative learning approach?
(4) Can the personalized intervention approach increase cognitive load, compared with the conventional online collaborative learning approach?

2. Literature review

2.1. Computer-supported collaborative learning

CSCL is concerned with how people learn together with the help of computers (Stahl, Koschmann, & Suthers, 2014). During CSCL, learners communicate and collaborate using digital tools to complete collaborative learning tasks together. CSCL has contributed significantly to enabling learners to acquire knowledge and improve skills (Chen, Wang, Kirschner, & Tsai, 2018). Recently, growing interest was paid to SSMR in CSCL context. SSMR is defined as learners' goal-directed, consensual, and complementary regulation of joint cognitive processes in collaborative learning (Iiskala, Vauras, Lehtinen, & Salonen, 2011). SSMR focused on the metacognitive regulatory episodes at the group level and played a very crucial role in CSCL (De Backer, Van Keer, & Valcke, 2020). Furthermore, CSCL emphasizes the co-construction of knowledge and skills by learners through social interaction (Dillenbourg, 1999; Chen et al., 2018). Therefore, social interaction is the crucial element of collaborative learning (Kreijns, Kirschner, & Jochems, 2003). In the CSCL context, large amounts of data are generated through social interaction, and these data need to be analyzed immediately to provide real-time feedback to learners.

Previous studies have adopted various methods to analyze the data generated during CSCL. For example, social network analysis has often been employed to analyze and visualize the relationships and patterns of interaction in CSCL (Dado & Bodemer, 2017). Epistemic network analysis has been adopted to analyze discourse data to model a cognitive network (Shaffer, Collier, & Ruis, 2016). Furthermore, a social epistemic network signature has been proposed to analyze the social and cognitive dimensions of collaborative learning (Gašević, Joksimović, Eagan, & Shaffer, 2019). In addition, content analysis is a commonly adopted technique for the analysis of discussion transcripts generated in CSCL (Strijbos, Martens, Prins, & Jochems, 2006). Content analysis has often been used to analyze knowledge construction (Gunawardena, Lowe, & Anderson, 1997), cognitive presence (Garrison, Anderson, & Archer, 2001), argumentation (Weinberger, Stegmann, Fischer, & Mandl, 2007), self-regulated learning in collaborative learning (Sobocinski, Malmberg, & Järvelä, 2017), and collective creativity (Tan, Caleon, Jonathan, & Koh, 2014). Moreover, lag sequential analysis has also been employed to analyze behavioural transition (Zheng, Li, Zhang, & Sun, 2019) and temporal differences (Lämsä, Hämäläinen, Koskinen, Viiri, & Mannonen, 2020). However, the aforementioned analysis method was conducted manually to perform lag analysis of discussion transcripts during CSCL. Therefore, it was very difficult to use the lag analysis results to provide real-time feedback and intervention. To progress to a deep understanding of the CSCL process, there is an urgent need to conduct real-time analysis to provide personalized intervention for learners.

2.2. Personalized intervention

Learning intervention is conceptualized as the design of supporting strategies and guiding activities to improve learning performance (Zhang, Fei, Quddus, & Davis, 2014). Early learning intervention was employed in the field of special education to provide remedial education for students with learning difficulties (Mesmer & Mesmer, 2008). Subsequently, researchers examined the effects of learning intervention in different learning settings. For example, Westenskow, Moyer-Packenham, and Child (2017) implemented one-on-one tutoring intervention in the classroom for pupils with low mathematics achievement and found that the intervention produced positive results. Hwang, Chang, Chen, and Chen (2018) engaged students in a four-week mobile learning intervention and found that they outperformed comparable students, in terms of learning achievements and learning motivation. Furthermore, Liu, McKelroy, Corliss, and Carrigan (2017) used the adaptive learning system to implement intervention, and found that adaptive learning intervention contributed to addressing the knowledge gap in chemistry. Hwang, Sung, Chang, and Huang (2020) developed a fuzzy expert system-based to implement adaptive learning intervention through analyzing the learners' cognitive and affective status.

Personalized intervention means that different learners receive different types of intervention, based on their learning status (Zhang, Zou, Miao, Zhang, Hwang, & Zhu, 2020). Early personalized intervention was implemented through instructors' observations. In recent years, the development of learning analytics has increased the power of personalized intervention. Teachers or staff can provide personalized intervention based on the results of learning analytics. For example, Yi et al. (2017) implemented personalized intervention through bulletin messages and email in an online learning environment. Zhang et al. (2020) enacted personalized intervention through individual interviews or sending learning reports, to improve academic performance and learning behaviours in a blended learning setting. Furthermore, Yang, Ogata, Matsui, and Chen (2021) believed that artificial intelligence is shifting from technology to humanity, which means that AI should shift from improving productivity to considering human conditions and having a human-oriented approach. Therefore, personalized intervention should shift from technology-oriented intervention to human-oriented intervention. Previous studies implemented interventions to facilitate collaborative learning through scaffolding (Shin, Kim, & Song, 2020), a digital educational intervention (Männistö et al., 2019) or a metacognitive intervention (Smith & Mancy, 2018). However, very few studies have conducted personalized intervention in the CSCL context. Moreover, there is still a lack of studies on personalized intervention based on modern AI technologies.

2.3. Modern artificial intelligence in education

AI can be defined as "computers that mimic cognitive functions that humans associate with the human mind, such as learning and problem-solving" (Russell & Norvig, 2009, p. 2). Traditional AI has usually adopted rule-based or statistical models for prediction (Chen et al., 2020). However, modern AI employs DNN techniques (Yosinski, Clune, Bengio, & Lipson, 2014). Since the development of modern AI, DNNs have been used in many domains, such as natural language processing, speech recognition, image recognition, decision making, and robotics (Hwang et al., 2020).

Typical DNN models include convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory network (LSTM) networks, and bidirectional long short-term memory (BiLSTM) networks. The CNN was proposed by LeCun, Bottou, Bengio, and Haffner (1998) and consists of an input layer, convolution layer, pooling layer, fully connected layer, and output layer. RNNs are designed to deal with (time) sequential data to represent relationships among data points (Schuster & Paliwal, 1997). Based on RNNs, LSTM networks are designed to overcome back-propagation problems; they include an input gate, forget gate, and output gate (Hochreiter & Schmidhuber, 1997). Because of their superior ability to preserve sequence information over time, LSTM networks have obtained strong results in a variety of sequence modelling tasks (Tai, Socher, & Manning, 2015). Furthermore, BiLSTM networks were proposed to overcome the shortcomings of LSTM; a BiLSTM network consists of LSTM units that operate in both directions to analyze the features of the future and the past (Graves & Schmidhuber, 2005).

These DNN models provide the potential for facilitating and optimizing learning in the field of education. For example, Xing and Du (2019) adopted a deep learning algorithm to predict MOOC dropout and provide personalized intervention for at-risk students. Wei, Lin, Yang, and Yu (2017) developed a convolution-LSTM-based model to conduct sentiment analysis of cross-domain MOOC forum postings. Jin, Li, Wang, Zhang, Lin, and Yin (2019) developed a drawing learning system, based on the generative adversarial network, to aid pencil drawing; they found that the system promoted the learners' interest in pencil drawing. Park, Mott, Min, Boyer, Wiebe, and Lester (2019) proposed a multistep deep convolutional generative adversarial network to generate educational game level for computer education. Nevertheless, to the best of our knowledge, very few studies have adopted DNNs in the field of CSCL. It should be noted that DNNs is designed for learning tasks with sequential data and DNNs achieved better performance than traditional machine learning (Prusa & Khoshgoftaar, 2017). Therefore, DNNs is very appropriate for online discussion text classification since the discussion transcripts can be represented as sequences of words. Thus, this study adopted DNNs to provide real-time analysis of online discussion transcripts and personalized intervention in online collaborative learning.

3. Personalized intervention based on a deep neural network model

This study evaluated a personalized intervention approach to improve collaborative knowledge building, group performance, and SSMR. This approach included three phases, namely data collection, data analysis, and personalized intervention. Figure 1 shows the framework of the proposed personalized intervention approach. In the first phase, participants completed the online collaborative learning task about computer networks. Figure 2 shows a screenshot of the online collaborative learning platform. All of the participants participated in online collaborative learning through the same platform, which also recorded the online discussion transcripts of all groups. To be noted that only learners in the experimental group can click the button of the latest progress to browse the analysis results.

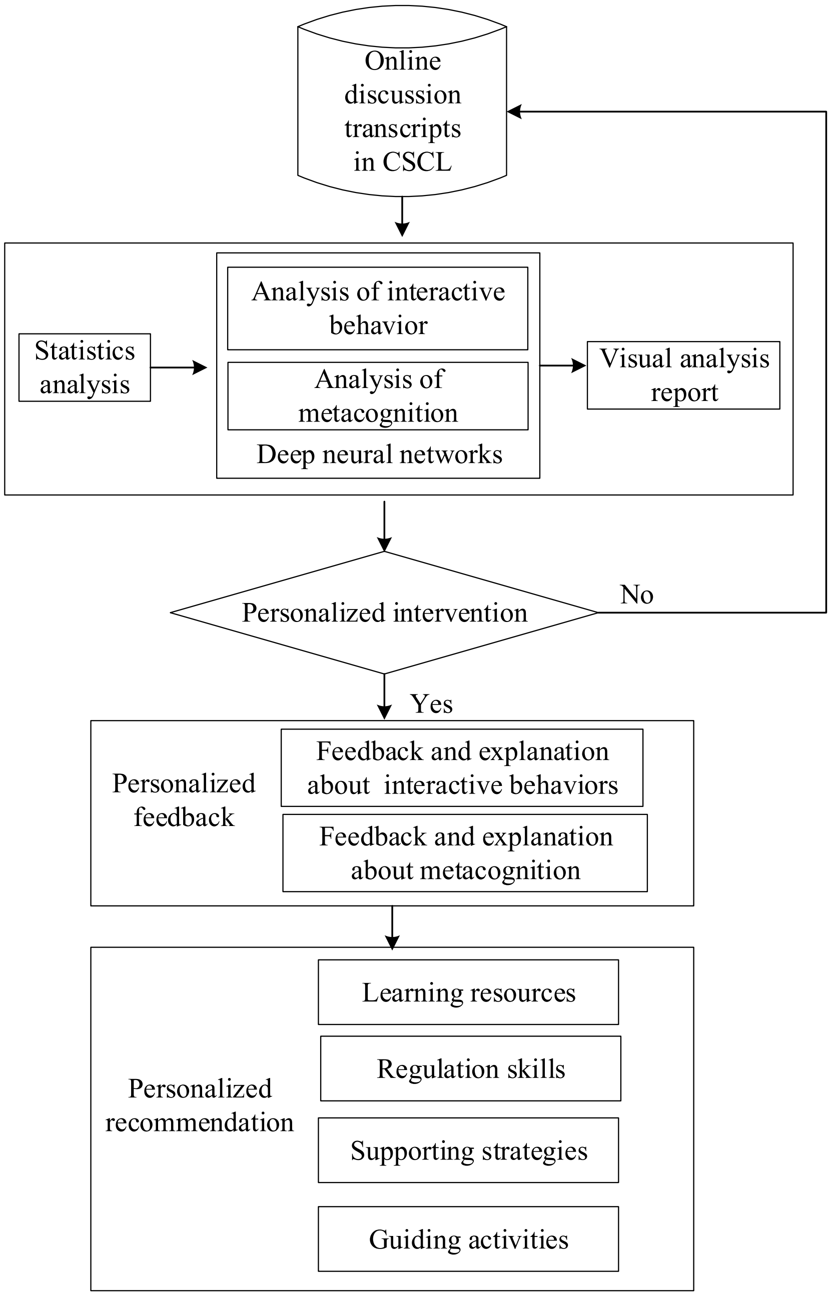


Figure 1. The personalized intervention framework

In the second phase, online discussion transcripts were analyzed in real time through statistical analysis and DNN analysis. The statistical analysis of social interaction included the analysis of the number of posts, duration, interaction frequency, and word cloud. In addition, online interactive behaviors and metacognition of the experimental groups were automatically classified by a DNN model. With regard to interactive behaviors, the online discussion transcripts of the experimental groups were automatically classified into five categories proposed by authors, namely knowledge building, regulation, support and agreement, asking questions, and off-topic information. With regard to metacognition, the online discussion transcripts were automatically classified into four categories adapted from Zheng (2017), namely planning, monitoring, reflection and evaluation, and off-topic information. The automatic classification results were displayed through a visualization chart and learners could browse at any time. The DNN model was Bidirectional Encoder Representations from Transformers (BERT), which was proposed by Devlin, Chang, Lee, and Toutanova (2019). BERT includes pretraining of deep bidirectional representations and fine-tuning with one additional output layer (Devlin et al., 2019). BERT is trained through the masked language modeling task and independently recovers the masked tokens (Minaee, Kalchbrenner, Cambria, Nikzad, Chenaghlu, & Gao, 2020). In previous studies, BERT achieved the best performance in text classification (González-Carvajal & Garrido-Merchán, 2020). In this study, BERT-Base in Chinese was selected as the pretrained model, 70% of the data were selected as the training set, and 30% were selected as the test set. The parameters were set as follows: the maximum sequence length was 128, the train batch size was 32, the learning rate was 5e-5, and the numbers of train epochs was 3. In addition, other models were used to compare the classification accuracy, as shown in Table 1. It was found that BERT achieved the highest accuracy in terms of interactive behaviors and metacognition classification. Figure 3 shows a screenshot of the statistical result on social interaction and the automatic classification results.

Figure 2. The screenshot of CSCL platform

In the third phase, personalized intervention was provided, based on the analysis results. When the analysis results exceeded the intervention thresholds, our system provided personalized group feedback and recommendations. Personalized group feedback included interactive behaviors and metacognition classification results of each group as well as explanations. For example, when the classification result about interactive behaviors showed that there was off-topic information, the system provided the personalized group feedback "Please focus on the collaborative learning task and don't discuss off-topic information." When there was more information about asking questions, the system provided the feedback "Please communicate with your peers to solve problems together. Go ahead!" In addition, when the classification result about metacognition revealed that there was little information about reflection and evaluation, the system provided the feedback "Please reflect and evaluate the collaborative learning progress and group product. Your group can refine the group product further." Figure 4 shows a screenshot of the personalized group feedback. Moreover, the personalized intervention also provided personalized recommendations and suggestions for learning resources, supporting strategies, and guiding activities. For example, when there were few messages about knowledge building, the system recommended and demonstrated learning materials and knowledge graphs about computer networks. When the classification result about metacognition revealed that there were few messages about planning, the system recommended the construction of a detailed plan about role assignment and scheduling. When the classification result about metacognition revealed that there was little information about monitoring, the system suggested that the group members should monitor and control the collaborative learning process further. Figure 5 and Figure 6 show screenshots of personalized recommendations.

Table 1. The accuracy of different models

Models	Classifications	Accuracy
BERT	Interactive behaviors	0.87
	Metacognition	0.89
LSTM	Interactive behaviors	0.63
	Metacognition	0.85
BiLSTM	Interactive behaviors	0.61
	Metacognition	0.85
Support Vector Machine	Interactive behaviors	0.65
	Metacognition	0.71
Logistic Regression	Interactive behaviors	0.64
	Metacognition	0.76

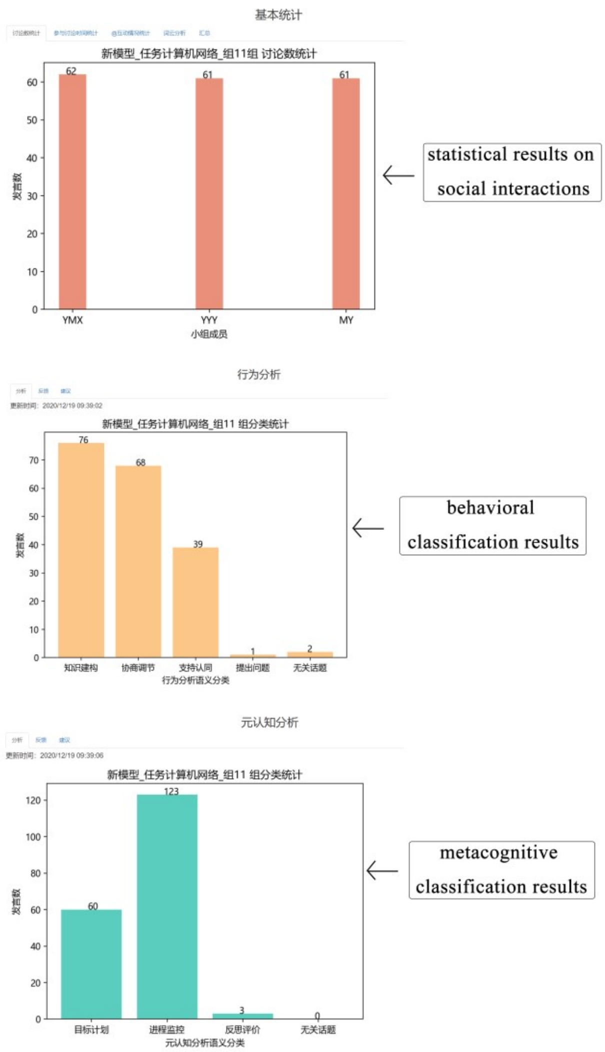
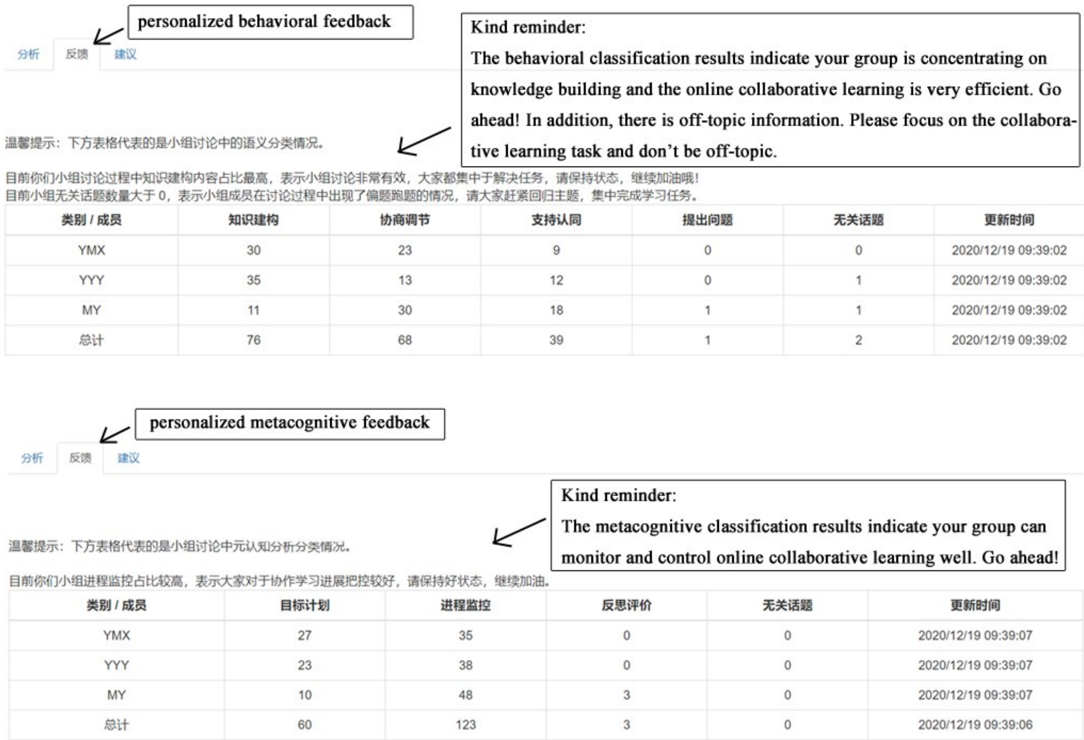


Figure 3. The screenshot of classification results



类别 / 成员	知识建构	协商调节	支持认同	提出问题	无关话题	更新时间
YMX	30	23	9	0	0	2020/12/19 09:39:02
YYY	35	13	12	0	1	2020/12/19 09:39:02
MY	11	30	18	1	1	2020/12/19 09:39:02
总计	76	68	39	1	2	2020/12/19 09:39:02

类别 / 成员	目标计划	进程监控	反思评价	无关话题	更新时间
YMX	27	35	0	0	2020/12/19 09:39:07
YYY	23	38	0	0	2020/12/19 09:39:07
MY	10	48	3	0	2020/12/19 09:39:07
总计	60	123	3	0	2020/12/19 09:39:06

Figure 4. The screenshot of personalized group feedback

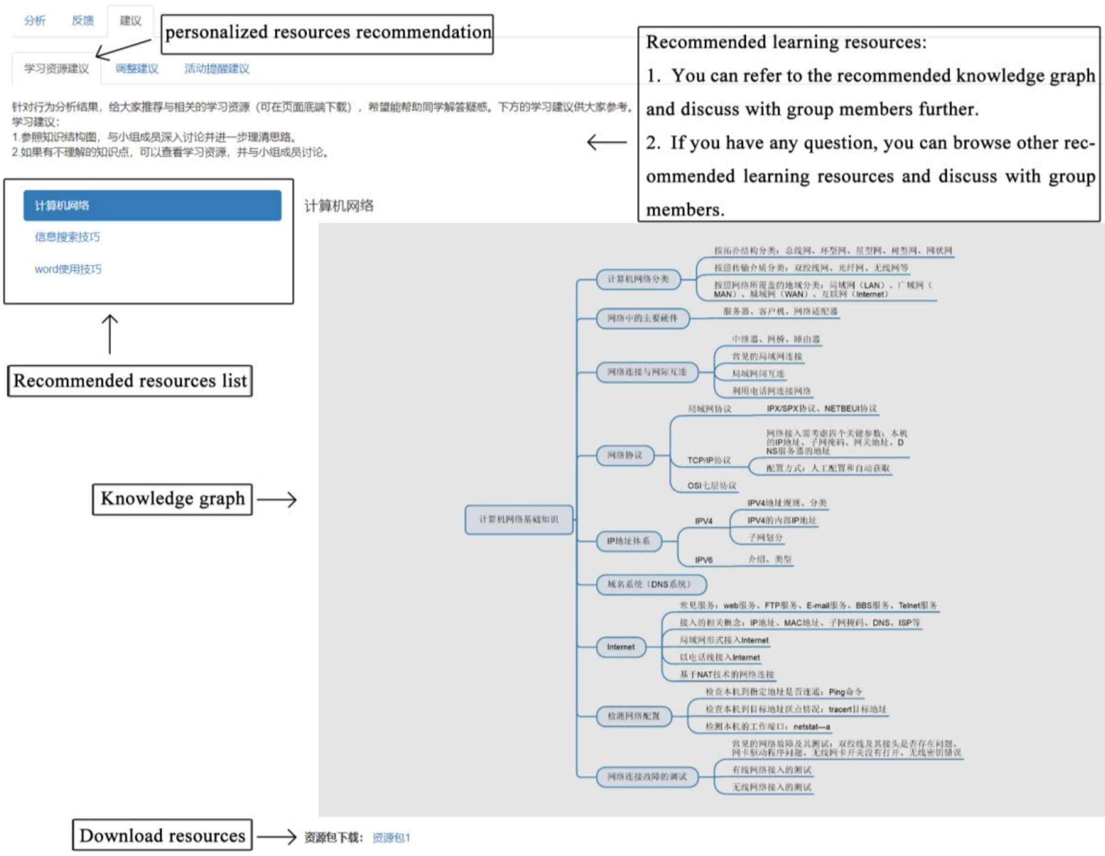


Figure 5. The screenshot of personalized resources recommendations

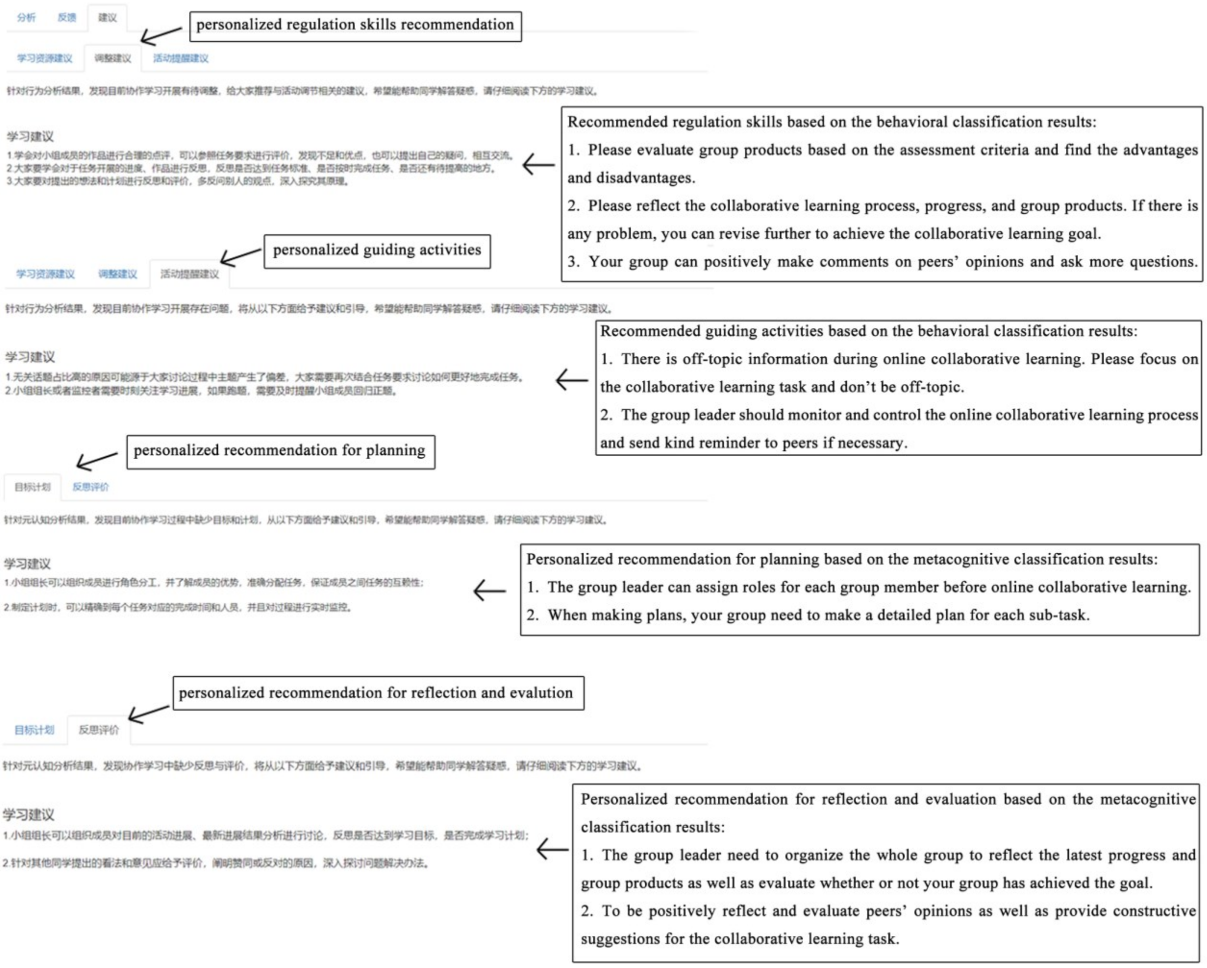


Figure 6. The screenshot of personalized recommendations

4. Method

4.1. Participants

The participants in the study were from a university in Beijing and were enrolled through posters on campus. Sixty-six college students participated, including eight males and 58 females, with an average age of 21. They majored in education, psychology, history, politics, AI, mathematics, physics, and chemistry, but all participants had prior knowledge about computer networks. All participants were randomly assigned to 11 experimental groups and 11 control groups. Each team contained three students who had not previously collaborated.

4.2. Experimental procedure

The experimental procedure included four phases. In the first phase, a pre-test about prior knowledge was conducted. The results of the pre-test indicated that there was no significant difference in prior knowledge between the experimental group and control group ($t = .68$, $p = .49$). In the second phase, the online collaborative learning platform was introduced and online collaborative learning was conducted for three hours. The experimental group and control group completed the same task, with the same duration. The only difference was that the participants in the experimental group conducted online collaborative learning using the personalized intervention approach, whereas those in the control group used the conventional online collaborative learning approach without personalized intervention. After completing the collaborative learning task, all groups submitted their main ideas and solutions in a Word document, as the group product. In the third phase, a post-questionnaire about cognitive load was completed for 10 minutes. Finally, a semi-structured focus group interview was conducted by two research assistants to understand participants' perceptions of the personalized intervention approach. Six experimental groups were randomly selected and each group participated in a 30-

minute interview in a lab. The interview outline included 10 questions about the personalized intervention approach. The sample interview question included "Do you think the personalized feedback and recommendations were helpful? Why?" The online collaborative learning task was as follows.

With the rapid development of the Internet, college students were encouraged to do pioneering work to serve society. XiaoWang wants to establish a company for online programming education. The first step was to construct a network for the company. Please help XiaoWang to complete the following tasks:

- How should the local network and wireless network be constructed, for the company and for each room? How should the connectivity of the network be tested?
- One day, the local network and wireless network become disconnected. How can they be fixed?
- To overcome fierce market competition, XiaoWang have to investigate the market and competitors. Please help XiaoWang to find and process information about online programming education, by writing a market research report.

4.3. Instruments

The research instruments included a pre-test and questionnaire about cognitive load. The pre-test aimed to examine whether the experimental group and control group had equivalent prior knowledge about computer networks. The pre-test consisted of 10 single-choice questions, four true-false questions, and three short answer questions with a total score of 100. The example items of the pre-test are "What is computer architecture?" and "Can you list the three applications of computer network?". The pre-test was developed by the teacher with more than 10 years' experience of teaching computer course. The pre-test was evaluated by the experienced teacher and a research assistant. The inter-rater reliability using kappa statistics was 0.83, indicating high consistency. This study did not adopt a post-test because collaborative learning performance was measured through the level of collaborative knowledge building and the group products. The cognitive load questionnaire was adapted from Hwang, Yang, and Wang (2013) and it included eight items with a Likert scale: three items that measured mental effort and five items that measured mental load. The reliability of the questionnaire was 0.91 (0.86 for mental load and 0.81 for mental effort). Example items of the cognitive load questionnaire are "The learning content in this learning activity was difficult for me" and "I need to put lots of effort into completing the learning tasks or achieving the learning objectives in this learning activity."

4.4. Data analysis method

The data analysis methods include the IIS-map analysis method, content analysis method, and sequential analysis method. To analyze the level of collaborative knowledge building, this study adopted the IIS-map analysis method proposed by Zheng, Yang, and Huang (2012). This method includes three steps, namely drawing the target knowledge graph, coding the online discussion transcripts, and calculating the level of collaborative knowledge building. The collaborative knowledge building level was equal to the activation quantities of all nodes. Two researchers coded the discussion transcripts of 22 groups. The inter-rater reliability using kappa statistics was 0.86, indicating high consistency. SSMR was analyzed based on the coding scheme adapted from Zheng, Li, and Huang (2017), and the analysis unit was a single SSMR episode. Table 2 shows the coding scheme for SSMR. The inter-rater reliability using kappa statistics achieved 0.83, indicating high consistency. The lag sequence analysis method was adopted to analyze the SSMR behavioural transition. The GSEQ 5.1 software developed by Quera, Bakeman, and Gnisci (2007) was employed to conduct behavioural sequence analysis. Moreover, group performance was evaluated, based on the scores of the group products. The assessment criteria were developed by the authors and are shown in Table 3. The inter-rater reliability using kappa statistics was 0.80, indicating high consistency. Finally, face-to-face interviews were recorded by audio and the accuracy of all of the interview data was verified by participants. Content analysis method was used by two research assistants to independently analyze the interview transcripts and group data into inductively categories. Then two assistants reviewed the content and discussed it to come to a consensus when they had conflicts.

Table 2. Coding scheme for socially shared metacognitive regulation

First-level category	Second-level category	Examples
Orienting goals (OG)	Task understanding (TS)	"The tasks require us to find solutions to setting up the local network and wireless network."
	Setting goals (SG)	"Our group need to complete the three subtasks together."
Making plans (MP)	Making plans about how to reach the goals, including selecting strategies and setting timelines (MP)	"We need to make a detailed plan about schedule, strategies, and role assignment."
	Negotiating the division of labor (ND)	"How can we assign roles?"
Enacting strategies (ES)	Advancing and explaining solutions (AE)	"Let's discuss how to test the connectivity of the network."
	Coordinating conflicts (CO)	"We have reached a face-saving compromise."
Monitoring and controlling (MC)	Monitoring or controlling the whole group's progress (MC)	"How is our group progressing?"
	Claiming (partial) understanding or comprehension failure (CC)	"We have not discovered how to fix the local network."
	Detecting errors or checking plausibility (DC)	"Our solution is not feasible at all."
Evaluating and reflecting (ER)	Evaluating current solutions (EV)	"The current solutions still need to be refined further."
	Reflecting on the group's goals and progress (RE)	"Our group product is perfect and we have completed the task."
Adapting metacognition (AP)	Making adaptations to goals, plans, or strategies (MA)	"We have to change our strategies."

Table 3. Assessment criteria for group product

Dimensions/Rating	16–20	15–11	6–10	1–5
Correctness (20)	Correct opinions and examples.	Correct opinions, but inappropriate examples.	Improper opinions or examples.	Wrong opinions and wrong examples.
Diversity (20)	The solutions and explanations were comprehensive and diverse.	The solutions and explanations were partly comprehensive and diverse.	The solutions and explanations were not diverse.	Solutions and explanations were lacking.
Originality (20)	The solutions and explanations were original and innovative.	The solutions and explanations were partly original.	The solutions and explanations lacked originality.	The solutions and explanations were copied from the Internet.
Completeness (20)	The solutions and explanations were complete and coherent.	The solutions and explanations were complete but not coherent.	The solutions were almost complete, but the explanations were incomplete and incoherent.	Both the solutions and explanations were incomplete.
Format (20)	The Word document was formatted perfectly regarding layout, style, background, color, fonts, type size, and row spacing.	The Word document was formatted well in terms of layout, color, fonts, type size, and row spacing.	The Word document was formatted well only in terms of fonts and type size.	The Word document format was completely disordered.

5. Results

5.1. Analysis of collaborative knowledge building

This study adopted a one-way ANCOVA (analysis of covariance) to examine whether there were significant differences in collaborative knowledge building between the experimental and control groups. First, the findings of a Kolmogorov–Smirnov test revealed that all datasets were normally distributed ($p > .05$). Second, the assumption of homogeneity of regression was not violated ($F = 0.01$, $p = .92$). Therefore, the one-way ANCOVA could be performed, with the pre-test as the covariant variable to exclude the effects of pre-test on collaborative knowledge building, the learning approach as the independent variable, and collaborative knowledge building as the dependent variable. Table 4 shows the ANCOVA analysis results. The results revealed a significant difference in collaborative knowledge building between the experimental and control groups ($F = 12.70$, $p = .002$). Moreover, the mean score of the experimental group was higher than that of the control group. Therefore, the learners who learned with the personalized intervention approach had a higher level of collaborative knowledge building than those who learned with the conventional approach. The eta squared value $\eta^2 = .40$ indicated a large effect size ($\eta^2 > .138$), according to Cohen (1988). Therefore, the personalized intervention approach had a beneficial effect in increasing the level of collaborative knowledge building. Figure 7 and Figure 8 show the knowledge graphs of an experimental group and control group, respectively. The number besides the node denoted the activation quantity. It is very obvious that the experimental group co-constructed a graph containing more knowledge and relationships.

Table 4. Summary of ANCOVA on collaborative knowledge building

Group	*N*	Mean	*SD*	Adjusted mean	*SE*	*F*	η^2
Experimental group	33	385.90	83.56	389.81	31.71	12.70**	.40
Control group	33	232.51	121.27	228.60	31.71		

Note. $^{**}p < .01$.

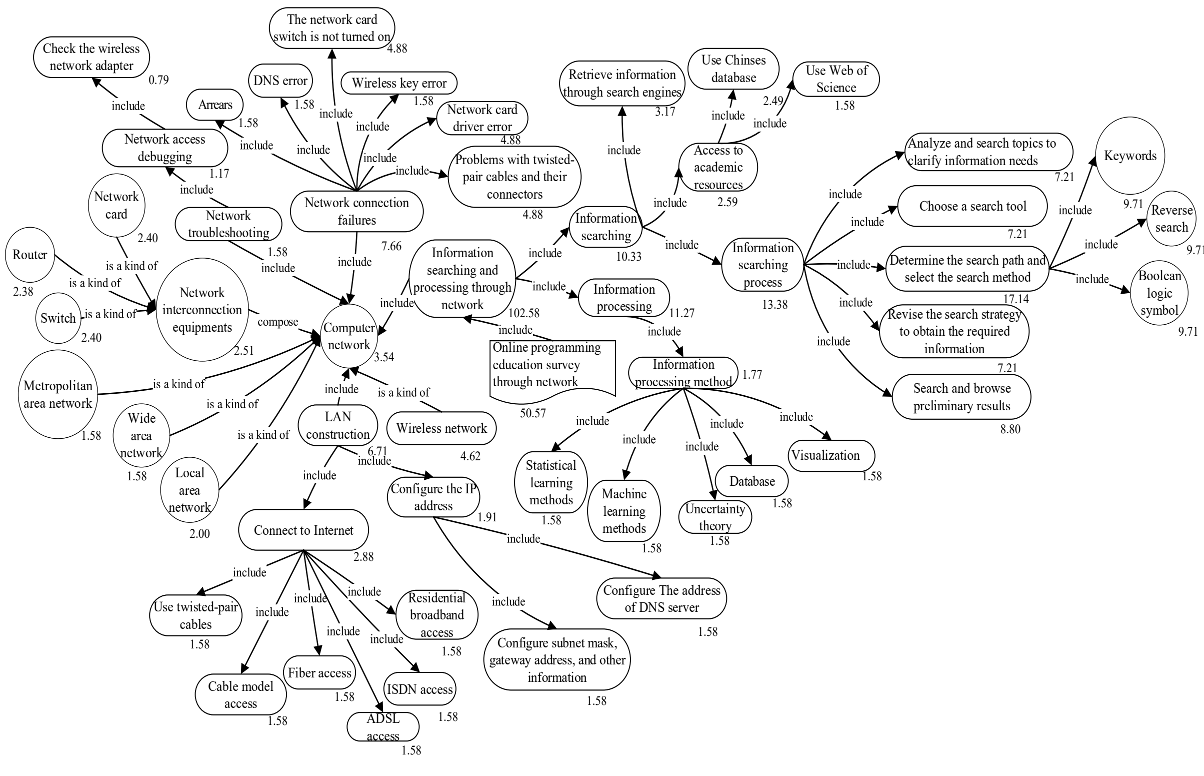


Figure 7. The knowledge graph of an experimental group

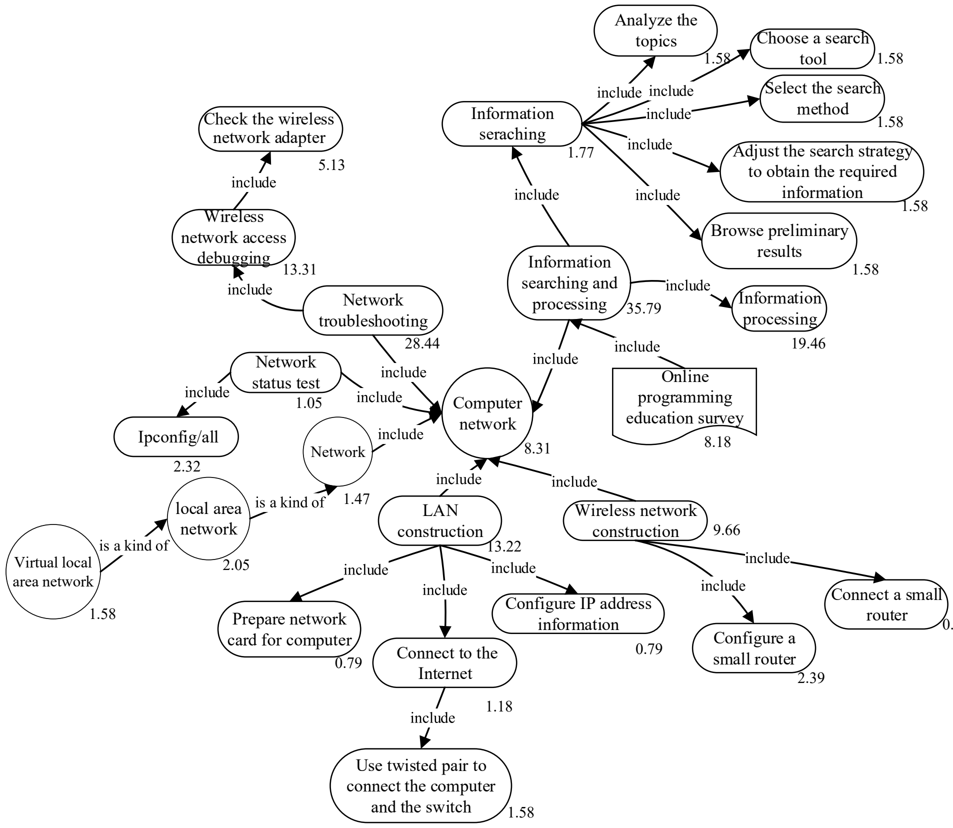


Figure 8. The knowledge graph of a control group

5.2. Analysis of group performance

The study also investigated the impacts of the personalized approach on group performance. The scores for the group products were used to evaluate group performance. The results of a Kolmogorov–Smirnov test confirmed that all datasets were normally distributed (p > .05). The assumption of homogeneity of regression was not violated (F = 1.309, p = .268), meaning that the one-way ANCOVA could be performed. As shown in Table 5, there was a significant difference in group performance between the experimental and control groups (F = 62.24, p = .000). The eta squared value η^2 = .766 indicates a large effect size (η^2 > .138). Therefore, the learners who learned with the personalized intervention approach achieved a higher group performance than those who learned with the conventional approach.

Table 5. Summary of ANCOVA on group performance

Group	N	Mean	SD	Adjusted mean	SE	F	η^2
Experimental group	33	85.00	4.09	84.90	2.06	62.24^{***}	.766
Control group	33	61.64	8.42	61.73	2.06		

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

5.3. Analysis of socially shared metacognitive regulation

Table 6 shows the descriptive statistics results of SSMR behaviors of the experimental and control groups. The lag sequential analysis method was adopted to analyze the SSMR behavioral transitions. Table 7 shows the results for the experimental group. The vertical direction in Table 7 indicates the starting behaviors and the horizontal direction indicates the subsequent behaviors. The z-score is used to evaluate the possible behavioral sequence transitions. A z-score greater than 1.96 indicates that the behavioral sequence has a significant level (Bakeman & Quera, 2011). As shown in Table 7, there were six significant behavior sequences: OG→MP, MP→MP, MP→ES, ES→MC, ES→AP, and MC→ER. Figure 9 shows the SSMR behavioral transition diagram for the experimental group. In contrast, for the control group, there were only three behavior sequences with a significant level, namely MP→MP, ES→ES, and MC→ER. Table 8 shows the results of the control groups and Figure 10 shows the SSMR behavioral transition diagrams of the control groups. Therefore, the behavioral transitions of the experimental groups were more diverse than those of the control groups. As shown in Table 9, there were three significant behavior sequences that only occurred in the experimental groups, namely MP→ES, ES→MC, and ES→AP. Therefore, enacting strategies, monitoring and controlling, and adapting metacognition were the crucial regulatory metacognitive behaviors for successful collaborative learning.

Table 6. The descriptive statistics results of SSMR behaviors

		OG	MP	ES	MC	ER	AP
Experimental group	*N*	10	40	136	127	30	10
	Mean	0.91	3.64	12.36	11.55	2.73	0.91
	SD	1.14	2.11	7.58	7.21	1.95	1.04
Control group	*N*	5	41	77	110	14	0
	Mean	0.45	3.73	7	10	1.27	0
	SD	0.82	2.83	5.46	6.96	1.19	0

Table 7. Adjusted residuals of the experimental group

Starting behavior	Subsequent behavior					
	OG	MP	ES	MC	ER	AP
Orientating goals (OG)	1.63	2.21*	-1.95	0.23	0.14	-0.56
Making plans (MP)	-1.04	2.36*	2.09*	-1.96	-1.49	-1.17
Enacting strategies (ES)	-0.08	0.06	-2.92	2.39*	-0.26	2.05*
Monitoring and controlling (MC)	0.84	-1.48	1.63	-1.63	2.08*	-1.74
Evaluating and reflecting (ER)	-0.82	-1.04	0.28	1.06	-0.92	0.29
Adapting metacognition (AP)	-0.50	-1.05	1.33	-0.44	-1.00	1.35

Note. $^{*}p < .05$.

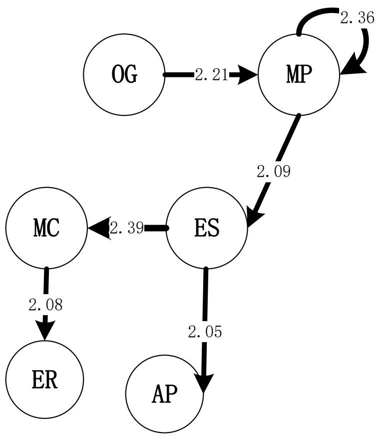


Figure 9. SSMR behavioural transition diagram of the experimental group

Table 8. Adjusted residuals of the control group

Starting behavior	Subsequent behavior					
	OG	MP	ES	MC	ER	AP
Orientating goals (OG)	-0.30	0.36	0.36	-0.24	-0.57	0.00
Making plans (MP)	0.41	2.98*	-1.24	-0.20	-1.77	0.00
Enacting strategies (ES)	-1.40	0.36	2.04*	-1.37	-0.92	0.00
Monitoring and controlling(MC)	1.22	-2.34	-0.72	1.04	2.06*	0.00
Evaluating and reflecting (ER)	-0.35	-1.10	-1.05	1.41	0.95	0.00
Adapting metacognition(AP)	0.00	0.00	0.00	0.00	0.00	0.00

Note. $^{*}p < .05$.

Table 9. Significant behaviour sequences that only occurred in the experimental group

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

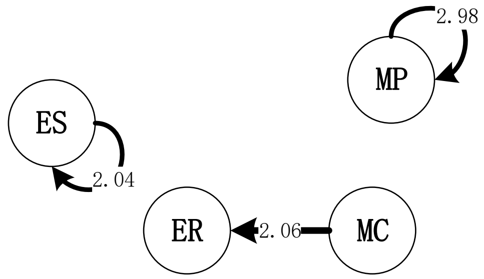


Figure 10. SSMR behavioural transition diagram of the control group

5.4. Cognitive load

The independent-samples t test was used to examine the difference in cognitive load. As shown in Table 10, there was no significant difference in cognitive load between the experimental and control groups (t = 1.50, p = .13). Furthermore, there were no significant differences in mental load (t = 1.22, p = .22) and mental effort (t = 0.54, p = .58) between the experimental and control groups. Therefore, all of the participants had similar perceptions concerning the collaborative learning tasks. The proposed personalized approach did not increase cognitive load on the participants of the experimental group.

Table 10. Independent sample t-test results of cognitive load

Dimensions	Group	N	Mean	SD	t
Cognitive load	Experimental group	33	4.50	1.33	1.50
	Control group	33	4.04	1.11	
Mental load	Experimental group	33	4.61	1.35	1.22
	Control group	33	4.23	1.13	
Mental efforts	Experimental group	33	3.20	0.57	0.54
	Control group	33	3.27	0.47	

5.5. Interview results

To gain a better understanding of participants' perceptions of the personalized intervention approach, six experimental groups were randomly selected for interview. The interview data were sorted into three categories. First, all of the interviewees believed that the personalized intervention approach was very helpful for increasing the level of collaborative knowledge building and improving group products. The main reason was that the personalized intervention approach could automatically classify discussion transcripts and provide personalized service based on the analysis results. Learners could keep track of the status and progress of collaborative learning by checking the analysis results. For example, one interviewee stated, "When our group check the latest progress and find that there is many off-topic information, we immediately go back to the collaborative learning task and build knowledge together." Another interviewee stated, "The feedback and suggestions are very helpful. The suggestions for learning resources and guiding activities contributed to our co-constructing knowledge together. We really appreciate it."

Second, all of the interviewees believed that the personalized intervention approach contributed to SSMR. The analysis results on interactive behaviors and metacognition informed learners in the experimental groups to regulate themselves. For example, one interviewee told us, "The analysis results on metacognition show that there is little information about reflection and evaluation. The system reminds us to reflect further on the collaborative learning process and the group product." Another interviewee said, "The metacognition classification results are helpful for SSMR. When our group finds the metacognition status of each group member, we can regulate ourselves immediately, based on the results."

Third, all of the interviewees believed that the personalized intervention approach did not increase cognitive load. For example, one interviewee said, "Our group members like to check the classification results to learn more about the collaborative learning progress. We really need it to regulate ourselves. There is no cognitive load." Another interviewee stated, "The personalized group feedback and suggestions are really necessary and we like to check them when we need. There is no cognitive load for us."

6. Discussion

This study examined the effects of the personalized intervention approach on collaborative knowledge building, group performance, SSMR, and cognitive load in CSCL. The personalized intervention approach was implemented automatically, based on the classification results performed by BERT. The results of the quasi-experiment indicated that the proposed personalized intervention approach significantly improved collaborative knowledge building, group performance, and SSMR behaviours. In addition, it did not increase learners' cognitive load.

6.1. Effects on collaborative knowledge building and group performance

The results of the ANCOVA analysis revealed that learners in the experimental groups outperformed those of the control groups in terms of collaborative knowledge building and group performance. This finding indicates that the personalized intervention approach can efficiently increase the level of collaborative knowledge building and improve the group products. There are several possible explanations for the findings. First, the personalized intervention approach performed the automatic classification of online interactive behaviours, which provided extra information about the progress of online collaborative learning. The classification of online interactive behaviours (showing the numbers of knowledge building, regulation, support, asking questions, and off-topic information) stimulated learners to co-construct knowledge in depth. When learners found that there was off-topic information, they would immediately return to collaborative knowledge building and complete the group products. In addition, the statistical results on social interaction also quantified the contribution of each group member, thereby increasing the group awareness of the members' status. As Yilmaz and Yilmaz (2020) concluded, increasing group awareness contributed to improving knowledge building.

Second, the personalized intervention approach provided personalized group feedback and explanations for each group. The formative feedback and explanations about online interactive behaviours and metacognition helped learners to gain a better understanding of the collaborative learning progress and problems. As Resendes, Scardamalia, Bereiter, Chen, and Halewood (2015) suggested, formative feedback promoted discussion moves to advance knowledge building. Furthermore, the support of the personalized intervention approach increased the sense of collective cognitive responsibility to ensure that the collaborative knowledge building and group products improved (Zhang, Scardamalia, Reeve, & Messina, 2009). Third, the personalized intervention approach provided individualized recommendations for each group. These suggestions, which included various types of learning resources, cases, support strategies, and guiding activities, improved the collaborative knowledge building and group products.

6.2. Effects on socially shared metacognitive regulation

This study found that the personalized intervention approach promoted SSMR behaviours. Learners who used the personalized intervention approach demonstrated more SSMR behaviours than those in the control groups. In addition, the study found that enacting strategies, monitoring and controlling, and adapting metacognition were the critical behaviours for promoting SSMR. There are several possible explanations for these findings. First, the metacognition classification results showed the numbers of planning, monitoring, and reflection and evaluation behaviours during collaborative learning, thereby directly promoting SSMR at the group level. Second, the statistical analysis of social interaction and the classification of interactive behaviours also contributed to SSMR. For example, when group members found that there was little interaction, they would increase interaction with peers. Third, personalized group feedback and recommendation further facilitated group metacognitive regulation and behavioural transition. This finding is consistent with that of De Backer, Van Keer, and Valcke (2016), who believed that feedback promoted groups' metacognitive regulation.

6.3. Effects on cognitive load

The study found that the proposed personalized intervention approach did not increase cognitive load for learners in the experimental group. Learners from the experimental group did not report feeling stressed when the personalized intervention was provided to support collaborative learning. The reason may be that learners checked the latest progress and personalized intervention only when they needed. Furthermore, the personalized intervention was considered very helpful for completing collaborative learning tasks. As Paas, Renkl, and Sweller (2003) revealed that learners' cognitive load can be controlled and reduced by using an effective instructional design. In addition, learners in the two groups completed the same collaborative learning task, with the same duration. Therefore, there was no significant difference in cognitive load between the experimental and control groups.

6.4. Implications

The rapid development of AI enables real-time analysis and personalized intervention to improve the performance of collaborative learning. The current study adopted a DNN model to automatically classify online collaborative learning transcripts and provide personalized intervention for each group. This study has several implications for teachers, developers, and practitioners.

First, teachers should provide personalized intervention to improve the performance of collaborative learning. With the aid of AI technology, data generated in online collaborative learning can immediately be analyzed automatically to provide personalized intervention. Types of intervention include supporting strategies, guiding activities, and recommended learning sources. Teachers or practitioners can also evaluate the impacts of personalized intervention on learning performance and perceptions. However, it should be noted that personalized intervention needs to be elaborately designed to achieve the desired effects (Liu et al., 2017).

Second, teachers and practitioners should pay attention to SSMR to achieve productive collaborative learning. It has been found that SSMR is positively related to learning performance (De Backer, Van Keer, & Valcke, 2020). Because learners may have difficulties with SSMR, teachers and practitioners can provide necessary training about SSMR skills before collaborative learning. For example, to improve SSMR, training should be provided in monitoring and controlling collaborative learning processes, as well as adapting metacognition.

Third, researchers and developers need to focus on the latest AI techniques to improve the accuracy of DNN models. For example, more work is required on enhancing the performance of BERT. Increasing training datasets also contributes to improving the accuracy of DNN models (Hestness et al., 2017). Fine-tuning strategies can be adopted to obtain optimized models that achieve better performance. In addition, developers should also develop new DNN models to be applied in different domains.

7. Conclusions

This study examined the effects of personalized intervention on collaborative knowledge building, group performance, SSMR, and cognitive load. The personalized intervention approach included automatic analysis of interactive behaviors and metacognition, providing personalized group feedback, and providing personalized recommendations. The findings revealed that the proposed personalized intervention approach significantly improved collaborative knowledge building, group products, and SSMR. The study highlighted the contributions of DNNs to providing real-time analysis and personalized intervention in CSCL. The main contribution of the study was to adopt a DNN model to implement personalized intervention in CSCL. The study broadened the understanding of how teachers and practitioners can be guided to provide personalized intervention in CSCL.

The study had several limitations and its results should be generalized with caution. First, the sample size was not large. Future studies will increase the sample size and datasets to improve the accuracy of the model and validate the proposed approach to personalized intervention. Second, the duration of the experiment was short. Future studies will conduct long-term experiments to provide powerful evidence about the personalized intervention approach. Third, the study examined the effects of the personalized intervention approach only on collaborative knowledge building, group performance, and SSMR. Future studies will examine the effects on other variables, such as collective efficacy, problem solving skills, and higher-order thinking skills.

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References

Bakeman, R., & Quera, V. (2011). *Sequential analysis and observational methods for the behavioral sciences*. Cambridge, U K: Cambridge University Press.

Chen, J., Wang, M., Kirschner, P. A., & Tsai, C. C. (2018). The Role of collaboration, computer use, learning environments, and supporting strategies in CSCL: A meta-analysis. *Review of Educational Research, 88*(6), 799–843. doi:10.3102/00346 54318 791584

Chen, X., Xie, H., & Hwang, G. J. (2020). A Multi-perspective study on artificial intelligence in education: Grants, conferences, journals, software tools, institutions, and researchers. *Computers and Education: Artificial Intelligence*, *1*,100005. doi:10.1016/j.caeai.2020.100005

Chen, X., Xie, H., Zou, D. & Hwang, G.-J. (2020). Application and theory gaps during the rise of Artificial Intelligence in Education. *Computers and Education: Artificial Intelligence*, *1*,100002. doi:10.1016/j.caeai.2020.100002

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Earlbaum Associates.

Dado, M. & Bodemer, D. (2017). A Review of methodological applications of social network analysis in computer-supported collaborative learning. *Educational Research Review*, *22*,159–180. doi:10.1016/j.edurev.2017.08.005

De Backer, L., Van Keer, H. & Valcke, M. (2016). Eliciting reciprocal peer-tutoring groups' metacognitive regulation through structuring and problematizing scaffolds. *The Journal of Experimental Education*, *84* (4), 804–828. doi:10.1080/00220973.2015.1134419

De Backer, L., Van Keer, H. & Valcke, M. (2020). Variations in socially shared metacognitive regulation and their relation with university students' performance. *Metacognition and Learning*, *15* (2), 233–259. doi:10.1007/s11409-020-09229-5

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies* (Vol. 1, pp. 4171–4186). Minnesota. Minneapolis. Retrieved from https://arxiv.org/abs/1810.04805

Dillenbourg, P. (1999). What do you mean by collaborative learning. In P. Dillenbourg (Ed.), *Collaborative-learning: Cognitive and Computational Approaches* (pp. 1–19). Oxford, England: Elsevier.

Garrison, D. R., Anderson, T. & Archer, W. (2001). Critical thinking, cognitive presence, and computer conferencing in distance education. *American Journal of Distance Education*, *15* (1), 7–23. doi:10.1080/08923640109527071

Gašević, D., Joksimović, S., Eagan, B. R. & Shaffer, D. W. (2019). SENS: Network analytics to combine social and cognitive perspectives of collaborative learning. *Computers in Human Behavior*, *92*, 562–577. doi:10.1016/j.chb.2018.07.003

González-Carvajal, S., & Garrido-Merchán, E. C. (2020). Comparing BERT against traditional machine learning text classification. Retrieved from https://arxiv.org/pdf/2005.13012.pdf

Graves, A., & Schmidhuber, J. (2005). Framewise phoneme classification with bidirectional LSTM networks. In *Proceedings of the 2005 IEEE International Joint Conference on Neural Networks* (Vol. 4, pp. 2047–2052). Montréal, Canada.doi:10.1109/ijcnn.2005.1556215

Gunawardena, C. N., Lowe, C. A. & Anderson, T. (1997). Analysis of a global online debate and the development of an interaction analysis model for examining social construction of knowledge in computer conferencing. *Journal of Educational Computing Research*, *17* (4), 397–431. doi:10.2190/7mqv-x9uj-c7q3-nrag

Hadi, W., Al-Radaideh, Q. A. & Alhawari, S. (2018). Integrating associative rule-based classification with Naïve Bayes for text classification. *Applied Soft Computing*, *69*, 344–356. doi:10.1016/j.asoc.2018.04.056

Hernández-Sellés, N., Pablo-César Muñoz-Carril & González-Sanmamed, M. (2019). Computer-supported collaborative learning: An analysis of the relationship between interaction, emotional support and online collaborative tools. *Computers & Education*, *138*, 1–12. doi:10.1016/j.compedu.2019.04.012

Hestness, J., Narang, S., Ardalani, N., Diamos, G., Jun, H., Kianinejad, H., Ali Patwary, M. M., Yang, Y., & Zhou, Y. (2017). Deep learning scaling is predictable, empirically. Retrieved from https://arxiv.org/pdf/1712.00409.pdf

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, *9*(8), 1735–1780. doi:10.1162/neco.1997.9.8.1735

Hsu, T.-Y., Chiou, C.-K., Tseng, J. C. R. & Hwang, G.-J. (2016). Development and evaluation of an active learning support system for context-aware ubiquitous learning. *IEEE transactions on learning technologies*, *9* (1), 37–45. doi:10.1109/tlt.2015.2439683

Hwang, G.-J., Chang, S.-C., Chen, P.-Y. & Chen, X.-Y. (2018). Effects of integrating an active learning-promoting mechanism into location-based real-world learning environments on students' learning performances and behaviors. *Educational Technology Research and Development*, *66* (2), 451–474. doi:10.1007/s11423-017-9567-5

Hwang, G. J., Sung, H. Y., Chang, S. C., & Huang, X. C. (2020). A Fuzzy expert system-based adaptive learning approach to improving students' learning performances by considering affective and cognitive factors. *Computers and Education: Artificial Intelligence*, *1*, 100003. doi:10.1016/j.caeai.2020.100003

Hwang, G.-J., Xie, H., Wah, B. W. & Gašević, D. (2020). Vision, challenges, roles and research issues of Artificial Intelligence in Education. *Computers and Education: Artificial Intelligence*, *1*, 100001. doi:10.1016/j.caeai.2020.100001

Hwang, G.-J., Yang, L.-H. & Wang, S.-Y. (2013). A Concept map-embedded educational computer game for improving students' learning performance in natural science courses. *Computers & Education*, *69*, 121–130. doi:10.1016/j.compedu.2013.07.008

Iiskala, T., Vauras, M., Lehtinen, E. & Salonen, P. (2011). Socially shared metacognition of dyads of pupils in collaborative mathematical problem-solving processes. *Learning and Instruction*, *21* (3), 379–393. doi:10.1016/j.learninstruc.2010.05.002

Jeong, H., Hmelo-Silver, C. E. & Jo, K. (2019). Ten years of computer-supported collaborative learning: A Meta-analysis of CSCL in STEM education during 2005–2014. *Educational Research Review*, *28*, 100284. doi:10.1016/j.edurev.2019.100284

Jin, Y., Li, P., Wang, W., Zhang, S., Lin, D., & Yin, C. (2019). GAN-based pencil drawing learning system for art education on large-scale image datasets with learning analytics. *Interactive Learning Environments*, 1–18. doi:10.1080/10494820.2019.1636827

Kreijns, K., Kirschner, P. A. & Jochems, W. (2003). Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: A Review of the research. *Computers in Human Behavior*, *19*(3), 335–353. doi:10.1016/s0747-5632(02)00057-2

Lämsä, J., Hämäläinen, R., Koskinen, P., Viiri, J. & Mannonen, J. (2020). The Potential of temporal analysis: Combining log data and lag sequential analysis to investigate temporal differences between scaffolded and non-scaffolded group inquiry-based learning processes. *Computers & Education*, *143*, 103674. doi:10.1016/j.compedu.2019.103674

Lecun, Y., Bottou, L., Bengio, Y. & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278–2324. doi:10.1109/5.726791

Lin, J. W. (2018). Effects of an online team project-based learning environment with group awareness and peer evaluation on socially shared regulation of learning and self-regulated learning. *Behaviour & Information Technology*, *37*(5), 445–461. doi:10.1080/0144929X.2018.1451558

Liu, M., Mckelroy, E., Corliss, S. B. & Carrigan, J. (2017). Investigating the effect of an adaptive learning intervention on students' learning. *Educational Technology Research and Development*, *65* (6), 1605–1625. doi:10.1007/s11423-017-9542-1

Männistö, M., Mikkonen, K., Vuopala, E., Kuivila, H. M., Virtanen, M., Kyngäs, H., & Kääriäinen, M. (2019). Effects of a digital educational intervention on collaborative learning in nursing education: A Quasi-experimental study. *Nordic Journal of Nursing Research*, *39*(4), 191–200. doi:10.1177/2057158519861041

Mesmer, E. M. & Mesmer, H. A. E. (2008). Response to Intervention (RTI): What teachers of reading need to know. *The Reading Teacher*, *62* (4), 280–290. doi:10.1598/rt.62.4.1

Minaee, S., Kalchbrenner, N., Cambria, E., Nikzad, N., Chenaghlu, M., & Gao, J. (2020). Deep learning based text classification: A Comprehensive review. *ACM Computing Surveys*, *54*(3), 1–40. doi:10.1145/3439726

Mu, J., Stegmann, K., Mayfield, E., Rosé, C. & Fischer, F. (2012). The ACODEA framework: Developing segmentation and classification schemes for fully automatic analysis of online discussions. *International Journal of Computer-Supported Collaborative Learning*, *7*(2), 285–305. doi:10.1007/s11412-012-9147-y

Paas, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent developments. *Educational psychologist*, *38*(1), 1–4. doi:10.1207/S15326985EP3801_1

Park, K., Mott, B. W., Min, W., Boyer, K. E., Wiebe, E. N., & Lester, J. C. (2019). Generating educational game levels with multistep deep convolutional generative adversarial networks. In *Proceedings* of *2019 IEEE Conference on Games (CoG)* (pp. 1–8). United Kingdom, London. doi: 10.1109/CIG.2019.8848085

Prusa, J. D., & Khoshgoftaar, T. M. (2017). Improving deep neural network design with new text data representations. *Journal of Big Data*, *4*: 7. doi:10.1186/s40537-017-0065-8

Quera, V., Bakeman, R. & Gnisci, A. (2007). Observer agreement for event sequences: Methods and software for sequence alignment and reliability estimates. *Behavior Research Methods*, *39* (1), 39–49. doi:10.3758/bf03192842

Resendes, M., Scardamalia, M., Bereiter, C., Chen, B. & Halewood, C. (2015). Group-level formative feedback and metadiscourse. *International Journal of Computer-Supported Collaborative Learning*, *10* (3), 309–336. doi:10.1007/s11412-015-9219-x

Russell, S. J., & Norvig, P. (2009). *Artificial Intelligence: A Modern approach* (3rd ed.). Upper Saddle River, NJ: Prentice-Hall.

Schuster, M. & Paliwal, K. K. (1997). Bidirectional recurrent neural networks. *IEEE transactions on Signal Processing*, *45*(11), 2673–2681. doi:10.1109/78.650093

Shaffer, D. W., Collier, W., & Ruis, A. R. (2016). A Tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. *Journal of Learning Analytics*, *3*(3), 9–45. doi: 10.18608/jla.2016.33.3

Shan, G., Xu, S., Yang, L., Jia, S. & Xiang, Y. (2020). Learn#: A Novel incremental learning method for text classification. *Expert Systems with Applications*, *147*, 113198. doi:10.1016/j.eswa.2020.113198

Shin, Y., Kim, D., & Song, D. (2020). Types and timing of scaffolding to promote meaningful peer interaction and increase learning performance in computer-supported collaborative learning environments. *Journal of Educational Computing Research*, *58*(3), 640–661. doi:10.1177/0735633119877134

Smith, J. M., & Mancy, R. (2018). Exploring the relationship between metacognitive and collaborative talk during group mathematical problem-solving–what do we mean by collaborative metacognition? *Research in Mathematics Education*, *20*(1), 14–36. doi:10.1080/14794802.2017.1410215

Sobocinski, M., Malmberg, J. & Järvelä, S. (2017). Exploring temporal sequences of regulatory phases and associated interactions in low- and high-challenge collaborative learning sessions. *Metacognition and Learning*, *12*(2), 275–294. doi:10.1007/s11409-016-9167-5

Stahl, G. (2006). *Group cognition: Computer support for building collaborative knowledge*. Cambridge, MA: MIT Press.

Stahl, G., Koschmann, T., & Suthers, D. (2014). Computer-supported collaborative learning. In R. K. Sawyer (Ed.), *The Cambridge Handbook of the Learning Sciences* (pp. 479–500). Cambridge University Press. doi:10.1017/CBO9781139519526.029

Strijbos, J.-W., Martens, R. L., Prins, F. J. & Jochems, W. M. G. (2006). Content analysis: What are they talking about? *Computers & Education*, *46*(1), 29–48. doi:10.1016/j.compedu.2005.04.002

Sze, V., Chen, Y.-H., Yang, T.-J. & Emer, J. S. (2017). Efficient processing of deep neural networks: A Tutorial and survey. *Proceedings of the IEEE*, *105*(12), 2295–2329. doi:10.1109/jproc.2017.2761740

Tai, K. S., Socher, R., & Manning, C. D. (2015). Improved semantic representations from tree-structured long short-term memory networks. Retrieved from https://www.aclweb.org/anthology/P15-1150.pdf

Tan, J. P.-L., Caleon, I. S., Jonathan, C. R., & Koh, E. (2014). A Dialogic framework for assessing collective creativity in computer-supported collaborative problem-solving tasks. *Research and Practice in Technology Enhanced Learning*, *9*(3), 411–437.

Tang, K.-Y., Tsai, C.-C. & Lin, T.-C. (2014). Contemporary intellectual structure of CSCL research (2006–2013): A Co-citation network analysis with an education focus. *International Journal of Computer-Supported Collaborative Learning*, *9*(3), 335–363. doi:10.1007/s11412-014-9196-5

Wei, X., Lin, H., Yang, L. & Yu, Y. (2017). A convolution-LSTM-based deep neural network for cross-domain MOOC forum post classification. *Information*, *8*(3), 92. doi:10.3390/info8030092

Weinberger, A., Stegmann, K., Fischer, F., & Mandl, H. (2007). Scripting argumentative knowledge construction in computer-supported learning environments. In F. Fischer, I. Kollar, H. Mandl, & J. M. Haake (Eds.), *Scripting Computer-Supported Collaborative Learning* (pp. 191–211). doi:10.1007/978-0-387-36949-5_12

Westenskow, A., Moyer-Packenham, P. S., & Child, B. (2017). An Iceberg model for improving mathematical understanding and mindset or disposition: An Individualized summer intervention program. *Journal of Education*, *197*(1), 1–9. doi:10.1177/002205741719700102

Wu, T.-T., Huang, Y.-M., Su, C.-Y., Chang, L., & Lu, Y. C. (2018). Application and analysis of a mobile e-book system based on project-based learning in community health nursing practice courses. *Educational Technology & Society*, *21*(4), 143–156.

Xing, W., & Du, D. (2019). Dropout prediction in MOOCs: Using deep learning for personalized intervention. *Journal of Educational Computing Research*, *57*(3), 547–570. doi:10.1177/0735633118757015

Yang, S. J., Ogata, H., Matsui, T., & Chen, N. S. (2021). Human-centered artificial intelligence in education: Seeing the invisible through the visible. *Computers and Education: Artificial Intelligence*, *2*, 100008. doi:10.1016/j.caeai.2021.100008.

Yi, B., Zhang, D., Wang, Y., Liu, H., Zhang, Z., Shu, J., & Lv, Y. (2017). Research on personalized learning model under informatization environment. In *2017 International Symposium on Educational Technology (ISET)* (pp. 48–52). IEEE. Retrieved from https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8005386

Yilmaz, R. & Yilmaz, F. G. K. (2020). Examination of the effectiveness of the task and group awareness support system used for computer-supported collaborative learning. *Educational Technology Research and Development*, *68*(3), 1355–1380. doi:10.1007/s11423-020-09741-0

Yosinski, J., Clune, J., Bengio, Y., & Lipson, H. (2014). How transferable are features in deep neural networks? In *Proceedings of the 27th International Conference on Neural Information Processing Systems* (Vol. 2, pp. 3320–3328). Retrieved from https://proceedings.neurips.cc/paper/2014/file/375c71349b295fbe2dcdca9206f20a06-Paper.pdf

Zhang, J. H., Zou, L. C., Miao, J. J., Zhang, Y. X., Hwang, G. J., & Zhu, Y. (2020). An Individualized intervention approach to improving university students' learning performance and interactive behaviors in a blended learning environment. *Interactive Learning Environments*, *28*(2), 231–245. doi:10.1080/10494820.2019.1636078

Zhang, J., Scardamalia, M., Reeve, R., & Messina, R. (2009). Designs for collective cognitive responsibility in knowledge-building communities. *The Journal of the learning sciences*, *18*(1), 7–44. doi:10.1080/10508400802581676

Zhang, Y., Fei, Q., Quddus, M., & Davis, C. (2014). An Examination of the impact of early intervention on learning outcomes of at-risk students. *Research in Higher Education Journal*, *26*, 1–12.

Zheng, L. (2017). *Knowledge building and regulation in computer-supported collaborative learning*. Singapore: Springer.

Zheng, L., Li, X., & Huang, R. (2017). The Effect of socially shared regulation approach on learning performance in computer-supported collaborative learning. *Educational Technology & Society*, *20*(4), 35–46.

Zheng, L., Li, X., Zhang, X., & Sun, W. (2019). The Effects of group metacognitive scaffolding on group metacognitive behaviors, group performance, and cognitive load in computer-supported collaborative learning. *The Internet and Higher Education*, *42*, 13–24. doi:10.1016/j.iheduc.2019.03.002

Zheng, L., Yang, K., & Huang, R. (2012). Analyzing interactions by an IIS-Map-based method in face-to-face collaborative learning: An Empirical study. *Educational Technology & Society*, *15*(3), 116–132.