VISUALIZATION OF COMPUTER-SUPPORTED COLLABORATIVE LEARNING MODELS IN THE CONTEXT OF MULTIMODAL DATA ANALYSIS

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Reception: 06/11/2022 **Acceptance**: 01/01/2023 **Publication**: 23/01/2023

Suggested citation:

M., Jianqiang, C., Wanyan, L., Biyuan, L., Shixin and Z. Jun (2023). **Visualization of computer-supported collaborative learning models in the context of multimodal data analysis**. *3C Empresa. Investigación y pensamiento crítico, 12(1)*, 87-109. https://doi.org/10.17993/3cemp.2023.120151.87-109

ABSTRACT

Deep learning evaluation is a new direction formed by the intersection of multiple domains, and the core issue is how to visualize collaborative learning models to motivate learners. Therefore, this paper realizes real-time knowledge sharing and facilitates learners' interaction through computer-supported collaborative learning (CSCL) technology. In this paper, we collect, label, and analyze data based on five modalities: brain, behavior, cognition, environment, and technology. In this paper, a computer-supported collaborative learning process analysis model is developed under the threshold of multimodal data analysis. The model is based on roles and CSCL for intelligent network collaboration. This paper designs and develops an interactive visualization tool to support online collaborative learning process analysis. In addition, this paper conducts a practical study in an online classroom. The results show that the model and the tool can be effectively used for online collaborative learning process analysis, and the test model results fit well. The entropy index of the test model took a value of about 0.85, and about less than 10% of the individuals were assigned to the wrong profile. During the test, the participation of participants gradually increased from 5% to about 25%, and the participation effect improved by about 80%. This indicates the strong applicability value of the computer-supported collaborative learning process analysis model under the multimodal data analysis perspective.

KEYWORDS

multimodality; computer-supported collaborative learning; visualization; process analysis model; online classroom

 https://doi.org/10.17993/3cemp.2023.120151.87-109

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1. INTRODUCTION

Computer-supported collaborative learning (CSCL) is the theory and practice of learners supported by computer network technology for the purpose of improving learning performance. It enables collaborative cognition, exchange of emotions, and development of collaborative skills in shared activities and interactions. In online collaborative learning supported by technology, learners are able to ask questions to a greater extent. They are able to express ideas clearly, exchange ideas with each other, and share information. They can negotiate meaning. Ultimately, learners are able to improve their collaborative learning skills. They can promote the development of their cognitive skills and critical thinking [1]. Studies have shown that good collaborative learning will have a positive effect on learning outcomes [2]. However, the most central issue of collaborative learning in current research is how to visualize models and thus motivate learners. Moreover, deep learning evaluation is a new direction formed by the intersection of multiple domains. It can collect and build a deep learning database and create a deep learning evaluation analysis model. Ultimately, it can achieve the purpose of optimizing educational evaluation.

In the field of research and practice, there is a growing interest in computer-supported collaborative learning (CSCL). An educational practice in which students form learning groups and learn through social interaction via computers or the Internet [3].CSCL can take place in classroom or online learning environments and can be synchronous or asynchronous [4]. However, there are still many substantial problems with collaborative learning [5]. For example, learners have uneven participation in the learning process, lack of deep interaction, and biased support tools. Since collaborative learning is a complex social process. Learners in CSCL are different individuals. They have unique personality, cognitive, and affective characteristics. They do not actively and voluntarily collaborate with other members [6]. Individual differences and diversity, as well as the complexity of the learning environment, may negatively affect cognition, emotion, and motivation. During collaboration, it is difficult for learners to collaborate on complex problems or concepts through high-quality cognitive mapping, active interaction, and sharing [7]. sotani, Mizoguchi, and Jaques et al [8-9] argued that to improve collaboration in CSCL settings, students' engagement needs to be increased to increase their interaction rate. This implies that issues such as the allocation of responsibilities and resources and the mode of interaction need to be addressed. There is variation in learners' interactive engagement in CSCL, but it is not clear what causes this variation [10]. It has been suggested that differences in engagement during interaction may stem from students' motivation to participate in CSCL [11]. Therefore, a new generation of researchers has begun to seek to identify the causes and mechanisms hidden behind the positive collaborative outcomes. They focus on the process of collaborative interaction among members and try to analyze the collaborative learning process in depth. They understand the internal mechanisms by which effective collaboration occurs and build long-lasting analytical models. In recent years, due to the main properties of deep learning, it is increasingly used to solve several 3D visual problems [12-16], and these collaborative learning analytical models are based on different theoretical

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perspectives such as cognition or metacognition, knowledge construction, and critical thinking. The models construct various analytical frameworks oriented towards artifacts, contexts, interactions, and knowledge development. Based on different theoretical perspectives, the analytical frameworks also cover elements such as participants, interaction behaviors, cognitive and metacognitive, affect, learning output, social support, and topic space. Models have focused on different aspects of collaborative learning. Some models emphasize the importance of social interaction for collaboration. Some models focus on elements of collaboration related to interaction such as engagement, affect, and structural features of interaction (size, density, intensity). For example, the models proposed by Fahy [17] and Veldhuis [18]. Some models emphasize the important role of cognition in collaborative analysis. Some models focus on factors related to cognitive involvement, considering whether new ideas are presented in the discussion, whether the problem space is clarified, etc., such as Henri [19] and Newman [20]. There are also models that emphasize the importance of conversational behavior and focus on elements such as questions, answers, arguments, and comments, such as the analytical model constructed by Zhu [21]. However, knowledge construction in groups in collaborative learning is a process in which multiple factors are organically combined and interact with each other. Collaborative learning has the limitation of narrow perspective in examining the process of collaborative learning from a single side. From the analysis of the literature, though, researchers have tried to construct as comprehensive a dimension as possible to analyze the collaborative learning process. There are also researchers who have enhanced their understanding of the internal mechanisms of collaboration and the process of knowledge construction. For example, Li Yanyan's [22] model uses knowledge construction as the theoretical basis and messages as the minimum unit of analysis. The model quantitatively analyzes the collaborative learning process from three aspects: topic space, topic intention, and social network. the model of Paul [23], on the other hand, is based on knowledge construction theory and explores the collaborative learning process based on content analysis from three aspects: cognitive, social, and motivational. However, in general, the model construction and analysis of multidimensional perspectives are still incomplete and scarce. Moreover, along with the continuous development of the online collaborative learning environment, the model needs to be constantly revised and improved in new scenarios. Models to fit the analytical requirements of online collaborative learning. In this paper, after comparing numerous existing collaborative learning models such as: Web-based 1CAI model [24], Intermet-based intelligent teaching system ITS, and intelligent agent-based model of online collaborative environment [25], it is found that each of these virtual learning environment models is constructed with defects. Some models are limited to only two roles, teacher and student, and students are in a passive state. Some models emphasize the active role of students, but ignore the collaboration between teachers and the role of teachers as learners. The models are poorly interactive, lack intelligence, and do not allow for good collaborative learning. Considering that the roles of teachers and students participating in collaborative learning are dynamic and changing in CSCL, we introduced the role mechanism. Therefore, according to the current research base and research questions. In this

https://doi.org/10.17993/3cemp.2023.120151.87-109

paper, we collect, label, and analyze data based on five modalities: brain, behavior, cognition, environment, and technology, based on a deep learning database. In this paper, deep learning evaluation based on multimodal data is implemented and improved in terms of automating data collection, integrating predictive models, deepening educational applications, unifying mechanisms, and enhancing decision wisdom. This paper realizes real-time knowledge sharing and promotes interactive mutual assistance of learners through computer-supported collaborative learning (CSCL) technology. This paper establishes a model for analyzing the process of computer-supported collaborative learning in the context of multimodal data analysis. Based on this model, an interactive visualization tool is designed and developed to support online collaborative learning process analysis, and a practical study is conducted in an online classroom.

In this paper, we propose and build an intelligent network collaboration model RICLU based on role and CSCL, which focuses on role-based interaction, collaboration and negotiation mechanisms among multiple agents in a collaborative learning environment. The intelligent Agent takes on a role in learning on behalf of the client user and interacts with other users and the management Agent on the server side. This is a dynamic and open virtual learning environment, which better reflects the characteristics of autonomy, interactivity, collaboration and distribution transparency. This paper provides a good model for online education. In particular, the introduction of multi-role mechanism better reflects the personalization of user learning while promoting extensive cooperation among users.

2. ROLE-BASED AND CSCL MODELS FOR COLLABORATIVE WEB-BASED LEARNING

2.1. APPLICATION OF ROLE MECHANISM

A role is a unity of responsibilities and rights and has four attributes: responsibilities, rights, activities and agreements. As a reasonable criterion for classifying things, roles are abstracted by grouping participants according to their skills, abilities and other elements of the activity. A single participant may fill multiple roles. A class of roles can also be filled by multiple users. A collaborative organization can be considered as a collection of roles. There are specific relationships between roles. In the collaborative process, a role is an active, relatively independent abstraction unit. A role has a certain goal and can perform a series of operations in a sequential manner. At different moments, roles can be in different states. A role R is usually defined as a mapping f: (O,Ts)→action. O is the object on which the role acts. Ts is the task to be performed. Action is the action of the object. The role-based collaboration process is defined as a binary: P:=<Role, Relation>. Role denotes the set of role spaces, and Relation denotes the collaborative relationship between roles.

The CSCL-based web-based learning environment is a distributed web-based system. Users are located on the client side. Intelligent Agents represent users in their

https://doi.org/10.17993/3cemp.2023.120151.87-109

learning roles. Interacts with other users and the server-side Management Agent. Teachers and students are the most basic roles. Group managers, system managers, resource managers, and message carriers assist in learning as secondary roles to achieve better interactivity. All these roles are performed by the Smart Agent. Each role has different authority according to its task: Management Agent controls and manages all collaborative activities, shared resources, network communication, etc. in the virtual environment; Collaboration Group Agent manages the activities of all members of the group; Resource Management Agent manages the resource repository; Routing Agent is responsible for inter-member messaging. In the role-based and CSCL collaborative learning model, the following relationships exist among the roles: active relationship (equal relationship). The relationship between the collaborative agents is equal, and there is no controlling party and controlled party. They can engage in free learning and mutual learning. For example, the interactions between Student Agent and Student Agent and between Teacher Agent and Teacher Agent during group learning and free discussion are equal. They all have equal access to resources and privileges. One of the collaborators is the controlling party, who is responsible for management and supervision. The other party is the controlled party, whose actions are constrained by the control of one of the subjects. For example, the interaction between the Teacher Agent and the Student Agent reflects the relationship between teaching and learning. The Teacher supervises the students and guides them in their learning. The Environment Management Agent is the master when interacting with other subjects, and the other subjects are the controlled parties. For example, the Student Agent requests services from it (registration, access to a group, access to a repository, exit). The passive relationship is also manifested in the collaborative learning between the Group Agent and the Member Agent, where the latter is controlled by the former.

2.2. MODEL FRAMEWORK

From the perspective of application, collaborative learning can be divided into 3 layers: resource layer, functional layer, and management layer. The resource layer provides a large amount of basic resource data for building the learning environment, including text, audio and video, and WWW. These resources form the basic databases such as the book database, audio and video database, and test bank. The functional layer provides a friendly user interface to interact directly with learners and realize specific application functions. Such as electronic forums, online groups, e-mail, real-time video playback and evaluation of students' learning effects. The management implements effective monitoring of resource data in the resource layer and ensures data security. It performs daily maintenance of the functions in the learning environment and manages the basic information of registered students and teachers.

These management functions can be implemented through software and hardware. Four types of Agents in collaborative learning can be defined based on three characteristics of Agents: Autonomy, Cooperation, and Learning: Cooperative Agent, Learning Agent, Interface Agent, and Decision Agent. It establishes negotiations with

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other Agents and performs limited role learning. The Learning Agent emphasizes autonomy and learning. It observes the user's behavior, learns from the patterns it finds, and takes actions based on the user's preferences. The Interface Agent retrieves information intelligently. It finds data automatically and quickly. Decision Agent automatically performs tasks using intelligent mechanisms. It helps the user to learn.

The model is represented by a seven-tuple: F=(A,R,T,Task,Source,D,K). Where A is the set of Agents involved in the environment. A is represented by their internal identifier Aid. r = {Teacher, Student, Manager, Facilitator}, is the set of roles. t = {T1,T2,...Tn} is the set of collaborative groups $Ti(1 \leq i \leq n)$. Task is a set of collaborative tasks, indicating the tasks that each role in the group completes together. source is a collection of system resources, including multimedia database, courseware library, test bank, etc. D represents the database, describing system information such as student management information, resource management information, teacher information, etc. K is the knowledge base, which stores the collaboration rules and guides the collaborative learning activities of the collaborative groups. Based on the role analysis, the model defines Interface Agent (Student Agent and Teacher Agent), Routing Agent, Group Agent, Management Agent, and CORBA-based Object Requirements Agent, where Interface Agent is the functional layer. The Group Agent and the Management Agent belong to the management layer. CORBA-based Object Requirements Agents belong to the resource layer. Agents collaborate with each other over a network (Internet, Intranet or small local area network). Learners can take on the role of teachers or students. Common Object Request Broker Architecture CORBA can provide security services, naming services, lifetime services and external services. This facilitates distributed computing applications in a network environment and effectively describes the dynamic nature of the Agent. This is a better representation of object-oriented features. Combining the functions and roles of each Agent, a unified model is used to describe the basic framework and internal structure of the Agent in the network environment. The intelligent Agent in the model is defined as a nine-tuple: Ag=(M,A,R,B,I, D,V,K,T). M - describes the activities such as methods, executable behaviors and processes that the Agent has. A - describes the type of Agent, the intent to perform the activity and the status information of the cohort collaborators. R - Describes the role of the Agent in a collaborative activity. B - describes the Agent's personal workspace. It is the equivalent of a network blackboard and stores interaction information. I - Reasoning and problem processing system, which controls the behavior of the Agent. It is responsible for the interpretation and execution of domain knowledge, pattern matching, interaction information processing, and result evaluation. D - The basic elements and data sets of the problem solving domain. V - describes the domain knowledge (models, rules) and collaborative interaction communication behavior. K - a knowledge system consisting of domain-specific knowledge. It includes algorithms, models, generative rules and semantic networks, etc. T - the communication mechanism with other Agents. Each Agent performs the following functions in the model:

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(1) Interface Agent: Interacts with other Agents on behalf of learners. It exchanges requests, goals, resources, commitments, etc. to achieve the purpose of collaborative learning. It includes user interface layer, semantic understanding layer, operation layer and interaction layer. The operational layer includes behavior control, goal or rule base, information retrieval and reasoning engine. The operational layer corresponds to the belief set and knowledge base of the Agent. It learns the mindset of the user (teacher or student) and understands their preferences. It automatically perceives the learning environment and makes requests to other Agents (e.g., to the administrative Agent to register, exit, enter a group, request a resource, etc.). The Teacher Agent has the same functions as the Student Agent, and in the role of the Teacher, it is responsible for making decisions about teaching and learning issues, making inquiries about teaching and learning situations, and controlling and monitoring the Student Agent.

(2) Group Agent: A special kind of interface agent who supervises the activities of the members of the collaborative group and coordinates their activities as necessary. Tutor all members during group instruction. Responsible for the distribution of speaking rights during free discussion. It is responsible for assigning and coordinating tasks when learning together. It can be elected by the Interface Agent or assigned by the Management Agent. It is created when a group is created and disappears when a task is completed. When intergroup learning occurs, it acts as a representative of the group and negotiates with other group Agents about joint intentions.

(3) Management Agent: It is responsible for coordinating and supervising the activities of members and the allocation of resources in the entire dynamic environment, and any request for resources must be approved by it. It is the super user of the learning environment, and any Agent can communicate with it directly. It is connected to the Resource Module for data storage and retrieval. It can assign a member as a group leader and assign teachers to individual and group instructional activities. It can also record relevant information (including user joins, logins, processing interactions, collaboration information, student information, teacher information).

(4) Routing Agent: Responsible for communication between Interface Agent, between Group Agent and Member Agent, and between Group Agents. He is responsible for passing resource requests, task requests, goals, negotiation requests, information feedback, etc. It can also communicate directly with the Management Agent. It has mobility and is a mobile Agent.

(5) CORBA-based Object Requirements Agent: It follows the CORBA specification and provides CORBA-based public request services, and is connected with resource repositories (multimedia repository, courseware repository, test repository, answer repository), databases (student management information, teacher information, collaborative activity information), and knowledge repositories (collaborative rule repository and goal planning repository). The Management Agent accesses the repository by making resource access requests to it. It can also read, write, and update the database and knowledge base.

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2.3. DESCRIPTION OF THE COLLABORATION PROCESS

Collaborative learning includes individual instruction, group instruction, free discussion, and joint learning (collaborative lesson preparation and collaborative practice). In group instruction, the Teacher Agent is the controlling party, supervising and guiding the learning activities of each Agent. Free discussion uses the group Agent's web board as the workspace. The group uses a voice mechanism for collaboration. All members have equal relationships and are learners. However, each member is supervised and managed by the Group Agent. In joint learning, the Teacher Agent breaks down the learning task into subtasks. These subtasks are performed by a number of group members, with each task corresponding to a role. The assignment of tasks is based on a combination of assignment and voluntariness. Each member chooses whether to accept the task according to his or her ability and willingness.

The mechanisms of co-operative learning are conflict and competition, self-explanation, internalization, apprenticeship, shared cognitive tasking, and shared rules. We take co-learning as an example. Combining the above mechanisms and role mechanisms, a formal description of collaborative learning is given. The language system V uses predicates to represent collaborative interaction activities, and defines the interaction activities in task assignment as follows:

State (Ai): indicates the state of a member Agent Ai in the collaborative group. There are three kinds of states: idle (idle), waiting (waiting), and busy (working).

Ask (T, A_i, T_i): Teacher Agent T asks if A_i can complete the task T_i.

Cando (T, A_i, T_i):Ai tells T that it can do the task T_i alone.

Notcand (o T, A_i, T_i): A_i tells T that it cannot complete the task T_i alone.

Assig (n T, A_i, T_i): T assigns the task T_i to A_i.

Needhelp (T, A_i, A_j, T_i): A_i can complete the task assigned to it by T only with the help of A_j.

Askhelp (T, A_i, A_j, T_i): A_i asks A_j for help in completing the task assigned to it by T.

Help (T, Ai, A_j, T_i): A_j is willing to help A_i to complete the task assigned to it by T.

Refusehelp (T, A_i, A_j, T_i):A_j refuses to help Ai to complete the task assigned to it by T.

Do (A_j, A_j, T_i): A_j and A_j work together to complete the task T_i.

Report (A_i,T,result): A_i submits the execution result to T.

For a given task Ti, the interactions in the task assignment process are described by the following algorithm:

FOR each team member Agent A_i

IF State (A_i)=idle

{Ask (T, A_i,T_i);

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IF Cando (T, A_i,T_i)

{Assign (T, A_i, T_i); Stat (e A_i)= busy; return; }

ELSE

IF Needhelp (T, A_i, A_j, T_i)

{State(A_i)=waiting;

REPEAT

Askhelp (T, A_i, A_j, T_i);

UNTIL (find an A_j, satisfying: Help (T, A_i, A_j, T_i), or ask all A_j);

IF find A_j Do (A_j, A_j, T_i) that satisfy the condition;

ELSE {State (A_i)=idle; return;}}}

3. VISUAL COLLABORATIVE LEARNING ANALYTICS MODEL CONSTRUCTION

3.1. CSCL-KBS LEARNING ANALYSIS MODEL

Although there are many models on collaborative learning analysis, however, existing research still lacks a systematic and global perspective to overview the dimensions of collaborative process analysis [26]. A review of the current literature on collaborative learning process analysis. We were able to identify some new research perspectives that are gradually gaining attention in the study of collaborative learning process analysis. One of the important aspects is the research on knowledge processing in the collaborative learning process. Knowledge processing plays an important role in the collaborative process [27]. Knowledge processing is concerned with the process of knowledge creation and generation in collaborative learning. This process allows learners to organize knowledge into coherent structures and to generate new knowledge using existing knowledge. Studies have shown that the measurement of knowledge processing can measure whether a cluster is successfully engaged in collaborative problem solving [28]. Another important aspect is the research on social relationships in collaborative learning. Numerous studies point out that active online participation is a key factor in the success of student learning. In online collaborative learning, individuals in a group interact effectively for the common learning goals of the group. Social relationships among members can influence the process and quality of knowledge construction [29]. In addition, the analysis of behavioral patterns of collaborative processes is an important topic of current CSCL research. Group members accomplish activities with specific goals through interaction. This can be seen as consisting of a series of intentional interaction behaviors. Abstracting the sequence of interactions of these behaviors can lead to different behavioral patterns. The different behavioral patterns reflect the collaborative interaction strategies embodied by the collaborative group during the interaction activities.

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In order to provide a comprehensive portrayal of learning analysis in CSCL. On the basis of the findings of Li et al. [22]. This paper proposes an improved multidimensional analysis model. The model explores student knowledge construction in collaborative learning discussion activities. The model contains three analytical dimensions: knowledge processing (K), behavioral patterns (B), and social relationships (S). The model is designed for three different levels of study: individual, group, and community. The model is named as KBS model.

3.2. ANALYTICAL MODEL-BASED TOOL DESIGN AND PRACTICE

3.2.1. PARTICIPATION ANALYSIS

It is quite obvious that the basic activity in collaborative learning is to participate in discussions [30-31]. This in a way implies that the participants externalize and share the sense of information or knowledge. This is one of the most important manifestations of active interdependence of individuals. Social construction theory suggests that our knowledge and experience is not objectively "discovered". It is discussed, negotiated, and constructed by participants in group interaction. From the perspective of social construction theory, the process of understanding is not driven by natural forces. It is the result of the active, collaborative work of people in certain relationships. Therefore, participation in a collaborative group is the most basic requirement and behavior.

Researchers have argued that a participant's engagement can be measured by his/her interaction with peers or the teacher. Previous research has shown that participant engagement is a positive predictor of actual learning, individual retention in continuous learning, and learning satisfaction. In general, individual engagement in computer-supported collaborative learning refers to the number of individual perspectives the length of posts in the online environment or whether the perspectives are social rather than focusing on content creativity. Researchers have argued that the number of participants' perspectives is a better indicator of how engaged participants are in the computer-supported collaborative learning process. In this study a viewpoint is primarily a sentence of an individual.

Let C denote the sequence of viewpoints and C_r denote the tth viewpoint in the sequence. n denotes the length of the sequence of viewpoints. Since views vary over time, the variable 1 will be used to index individual views, also called "time" (the value of 1 ranges from 1 to n).

$$1 \le t \le n \tag{1}$$

Let P be a set of individuals. The variables a and b will be used to refer to any member (individual) of this set. To determine the initiator (or individual) of each viewpoint, we define the following participation function as shown in Equation (2):

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$$P_a(t) = \begin{cases} 1, \\ 0, \end{cases} \tag{2}$$

is denoted as 1 if participant a ∈ P contributes view c, and 0 otherwise. The participation function of any participant (a), can be defined as a sequence:

$$P_a = \{P_a(t)\}_{t=1}^{n} = \{P_a(1), P_a(2), P_a(3)_{,...,}, P_a(n)\} \tag{3}$$

where n is the same length as the sequence of viewpoints C. It takes the value 1 when participant a initiates the corresponding viewpoint in C, and 0 otherwise. Using this participation function, several useful descriptive measures of participation in the discussion can be defined in a relatively simple way. The number of points of view of any participant is:

$$\|Pa\| = \sum_{t=1}^{n} P_a(t) \tag{4}$$

In addition, during the discussion, participants may have "pandering" opinions. These are single-word opinion sentences such as "um", "ah", "yes", and "yes". Treating these as equivalent to longer sentences may result in higher participation by participants who are not seriously engaged in the discussion. This would affect the accuracy of the later analysis. Therefore, it is also necessary to calculate the length of the opinions expressed by the participants. The length W_a of any participant (a) expressing an opinion can be considered as:

$$\|W_a\| = \sum_{t=1}^{n} w_a(t) \tag{5}$$

where $W_a(\mathrm{t})$ is denoted as the length of opinions published by participant a at time t. and the total opinion length W is:

$$W = \sum_{1}^{k} \|W_a\| \tag{6}$$

where k is the number of individuals in the group. The participation of participants can be estimated by the sum of the relative proportions of their participation to the total number of participants and the relative proportions of the total number of words (its variation with rounds is shown in Figure 1):

$$\hat{p}a = \frac{\left(\frac{\|P_a\|}{n} \frac{\|W_a\|}{W}\right)}{2} \tag{7}$$

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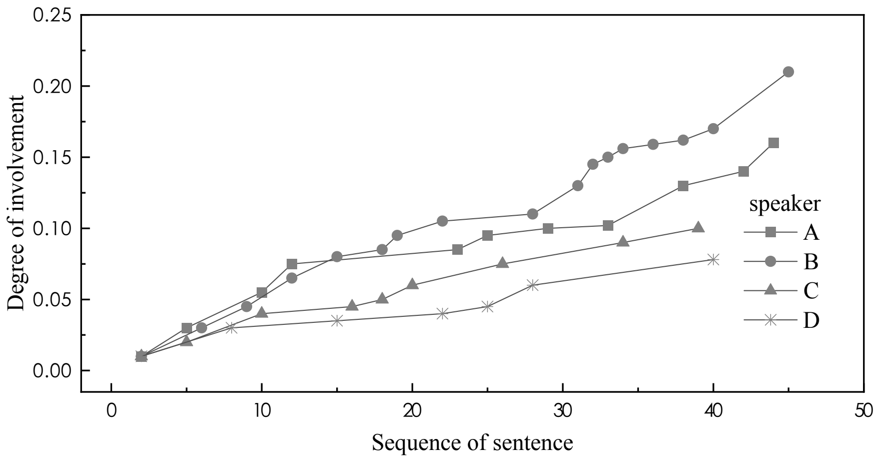

Figure 1 Changes in participant engagement over time

3.2.2. VISUALIZATION DESIGN AND RESULTS PRESENTATION

In the context of knowledge processing, knowledge and the connections between knowledge are important assessment criteria. Students form new knowledge structures by integrating and linking knowledge, thus facilitating knowledge processing. Therefore, it is important to be able to monitor in real time the development of key knowledge points during student discussions. This is important for teachers to keep track of the development of students' cognitive engagement and to effectively monitor the teaching process. In the operationalization analysis of knowledge processing, natural language syllabification techniques were used. The Chinese word-sorting system of CAS was used to keyword-sort the discussion texts during the collaborative process and identify the keywords during the students' discussions. This paper matches with the knowledge concept map provided by experts about the collaborative discussion problem. Meanwhile, this paper measures the cognitive involvement in the collaborative process from the perspective of cluster or student knowledge structure formation. As shown in Figure 2, the knowledge point development change map presents teachers with the development change and distribution pattern of cluster knowledge points from the time dimension. When the mouse hovers over a knowledge point, it also automatically shows back the content of the post where the knowledge point is located, the poster and the time of the posting. Using this visual information, teachers can help discover in-depth information about the process of group discussion. For example, how the group knowledge points were generated over time, whether any group had problems with off-topic or stagnant discussions, and whether relationships between knowledge points were established. This makes the development process of cognitive engagement easier to monitor. However, knowledge processing can only focus on cognitive engagement during collaborative discussions. This lacks a clear indication of the behavioral interactions of the cluster. The developmental changes in cognitive processes are influenced by the behavioral aspects of the cluster interactions themselves. Therefore, further, the visual presentation of behavioral patterns can be used to explore the strategies and patterns of students' behavioral interactions during collaborative knowledge construction.

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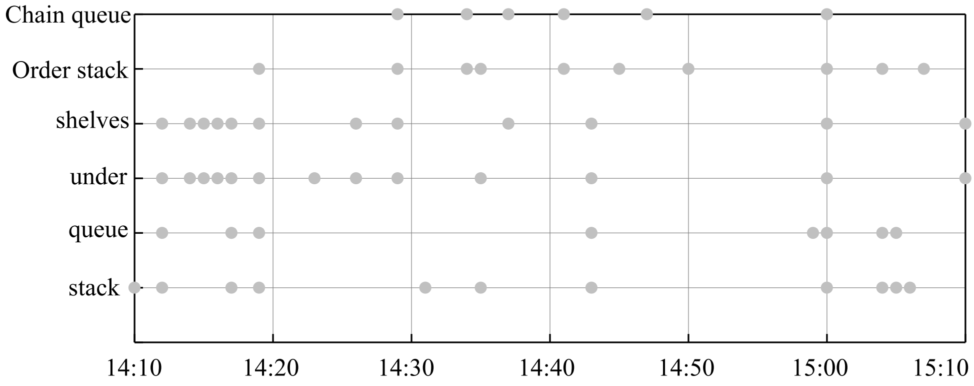
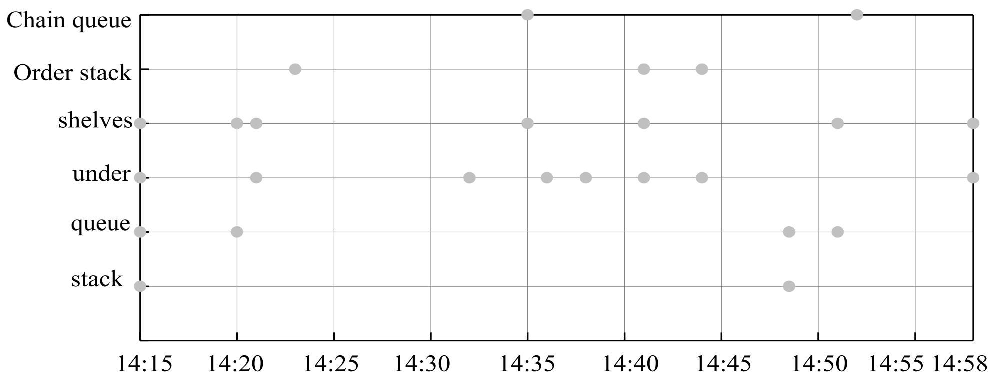


(a) Group 1



(b) Group 5

Figure 2 Development of knowledge points

In terms of behavioral patterns, to dig deeper into the influence of group behavioral patterns on students' collaborative learning. This paper investigates the characteristics of discussion-based online collaborative learning. In this paper, collaborative behaviors are coded into five first-level categories: presentation (C1), negotiation (C2), questioning (C3), management (C4), and emotional communication (C5), and each category is further refined into 14 second-level categories (C11: gives ideas/ options; C12: further explains ideas; C13: revises ideas/options; C14: summarizes ideas/options. C21: agrees; C22: Agree, give evidence/reference; C23: Disagree; C24: Disagree, give evidence.C31: Ask questions; C32: Ask follow-up questions. C41: Organize/assign tasks; C42: Coordinate management/reminders). Embed these codes in the posting area of the Moodle platform. The selection of behavioral categories can be made when students submit postings. This can support the automated processing of analytics tools. Finally, the association rule approach to data mining in learning analytics is used through the analytics system. This method calculates the probability that each behavior will be accompanied by the next behavior and the intensity of the next behavior, extracts behavior transition pairs that occur at high frequencies, and finally forms behavior sequence transition patterns. These behavior patterns characterize the different behavior patterns of the collaborative group in the collaborative interaction.

In terms of social relationship analysis, the analysis of social interactions will help teachers to better understand who are the central participants in the knowledge

https://doi.org/10.17993/3cemp.2023.120151.87-109

construction dialogue. It can see if there are some undesirable social relationships that can have an impact on the motivation for collaborative learning. The visualization diagram based on the interactions can graphically represent the characteristics of the interaction network structure. It can effectively support teachers in qualitatively analyzing the attributes of the interactive network structure and discovering whether there are distinct central, peripheral, and isolated figures in the network.

3.2.3. POTENTIAL PROFILE ANALYSIS

For potential profile models, the most important issue is to determine the number of their profiles. Currently, researchers still determine the model mainly based on its fit indices. These fit indices include the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and likelihood ratio test. The better the model fit is, the smaller the values of these indices are. In addition, the entropy index has a value range from 0 to 1. This can be used to measure the accuracy of the model in classifying profiles (classes). The higher the value is, the more accurate the classification is. For example, when it is 0.6, about 20% of the individuals may be classified into the wrong profiles (potential classes). While when Entropy=0.8, about less than 10% of the individuals were classified into the wrong profiles (potential classes). As shown in Figure 3, the model results fit well (when choosing a model, it is important to consider not only the statistical indicators but also the substantive significance of each class).

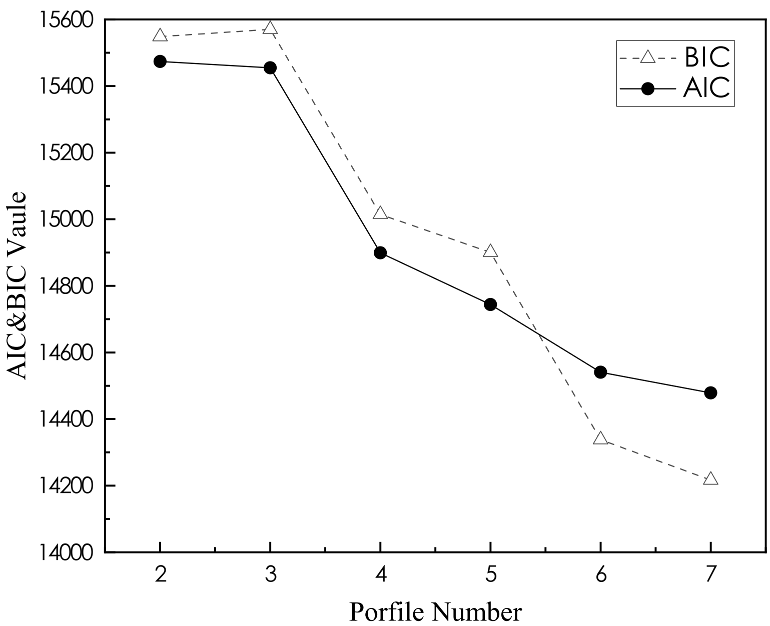


Figure 3 Fitting index gravel plot for potential profile analysis

For the model with six categories of potential profile analysis, the results showed that engagement differed significantly on participant categories ($F(6,164) = 74.22$, $p < 0.01$). Social influence differed significantly across participant categories ($F(6,164) = 76.80$, $p < 0.01$). Overall response rate was significantly different on participant categories ($F(6,164) = 97.89$, $p < 0.01$). Intrinsic correlation was significantly different across participant categories ($F(6,164)= 32.85$, $p<0.01$). Communication density

https://doi.org/10.17993/3cemp.2023.120151.87-109

differed significantly across participant categories ($F(6,164)= 86.89$, $p< 0.01$). Response rate was significantly different across participant categories ($F(6,164) = 86.89$, $p < 0.01$).

4. DISCUSSION OF PRACTICE RESULTS

Through the analysis of the three important dimensions in the model and the visualization of the results based on tool support, it can be seen that the use of learning analytics improves the subjective drawbacks of the mainstream manual coding-based analysis of the original collaborative learning process. The technique overcomes the shortcomings of manual analysis, which is time-consuming and laborious and can only be used for post-collaboration analysis, and provides implementation feedback on the collaborative process. The technique enhances the evaluation, feedback, perception and adaptation of collaborative learning. At the same time, the presentation of visualizations based on tool analysis transforms the data generated by the collaborative process into a friendly visual form. This brings to the fore some important features, patterns, and anomalies. Thus, visual presentation supported by analytical tools can be a key feature. It is used to gain insight into the learning process as well as to provide basic support for monitoring, feedback, and evaluation. It is important for teachers to monitor their teaching, researchers to uncover large-scale teaching patterns, and process evaluation.

4.1. PERCEPTIVENESS OF THE COLLABORATIVE ACTIVITY PROCESS

Model-based visual presentation can improve teachers' perception of the process of collaborative activities. When multiple groups are discussing online at the same time, it can be difficult for teachers to monitor problems with group collaboration in real time without the help of tools. With visual information, it is easier for teachers to identify problems such as digressions and stagnation in the discussion. Teachers can gain a deeper understanding of the discussion process. As can be seen from the comparative display of the two groups in Figure 2, Group 1 had more discussion on the six knowledge points selected by the teacher during the discussion time. There was no deviation or stagnation in the middle of Group 1. In contrast, the discussion in Group 5 was fragmented and disorganized, without establishing relationships among related knowledge points. Further, when the teacher hovers over a particular bullet point, the tool automatically displays more detailed information about that knowledge point. For example, which student mentioned the point at that point in time, and the original text content of their discussion of the point. With this information, teachers can more easily find out at what point the group entered into the discussion of a particular issue. It is also possible to discover how the group gradually builds knowledge-to-knowledge connections in the discussion that facilitate problem solving. In other words, presenting the distribution patterns of knowledge over time makes the traditional "black box" collaborative process of knowledge processing visible. This will provide teachers with sufficient information to better observe the discussion process.

It can provide additional evidence for researchers to conduct ongoing inquiry into the internal mechanisms of collaborative processes.

4.2. IMPACT OF VISUAL PRESENTATION ON THE PATTERN OF COLLABORATIVE ACTIVITIES

Model-based visual presentation can provide powerful support for exploring the patterns of collaborative activities. In large-scale online education scenarios, the visual presentation of behavioral sequence patterns in behavioral models can be used to flexibly explore the behavioral transition patterns of online collaborative activities. The visual presentation helps teachers gain deeper insight into the internal patterns of group interaction behaviors. In Group 1, the self-loop of C11→C11 during the collaborative discussion to complete the task shows that each member can continuously put forward his or her own point of view. Members actively think about the problem and express their suggestions. In addition, the transitions from C11→C32, C11→C23, and C11→C13 show that the members of Group 1 presented their ideas accompanied by further follow-up questions from other members, questioning with evidence, and revision to improve their ideas. This indicates that the members of the group were able to argue the issue sufficiently to keep moving the task forward to completion. Moreover, the transformation of C32→ C12 shows that when a member pursues a point of view, he or she is given a more detailed explanation by other members. This indicates that the group is very interactive. In contrast, after a member of group 5 raises a viewpoint, other members give questions (C11→C21), but the questions are not followed by corresponding explanations. c31→C11 and C32→C11 show that members of the group do not give explanations or revise their views after facing questions or follow-up questions, but continue to raise new views. From the later analysis of the content based on knowledge processing and the synthesis of the interaction structure, it is clear that Group 5 did not reach the pattern of deep interaction of questioning-pursuing-questioning. This is related to its group members' lack of attention to other people's viewpoints and the fact that group members' discussions are more about posting only rather than engaging in dialogue.

Extraction results using real-time behavioral sequence transformation provided by the tool. Teachers or researchers can conduct the mining of online collaborative learning behavioral patterns in various scenarios. For example, in terms of the characteristics of group behavior patterns, the behavioral characteristics of collaborative groups with regular patterns in the process of collaborative knowledge construction can be found. Their effects on knowledge construction can also be found. Also, the similarities and differences in behavioral patterns presented by high and low quality groups can be examined to help teachers explore important positive influences in high quality discussions as well as potential limitations present in low quality groups. This will provide a valuable reference for teachers to design better online collaborative activities and teaching strategies. Using real-time process information from the visualization tool, it can also be explored to obtain comparisons of differences in behavior patterns at different stages. By analyzing the different behavioral patterns of collaborative groups at the beginning, unfolding, and concluding

https://doi.org/10.17993/3cemp.2023.120151.87-109

stages of collaboration, the changes of behavioral development in the collaborative knowledge construction process can be explored. The results can provide a basis for exploring the internal mechanism of the knowledge construction process.

4.3. EVIDENCE SUPPORT FOR PROCESS EVALUATION

Model-based visual representations can provide comprehensive evidence to support process evaluation. Collaborative assignments within online classrooms often involve a large amount of participation and contribution. This makes monitoring and evaluation by tutors time-consuming, tedious, and error-prone. It is nearly impossible for tutors to manually process the hundreds of sequences of contributions in a discussion topic and the relationships between these contributions. As a direct consequence, most online learning environments use simple metrics based on the number of posts, reads, topics created, and average length of statements. These measures are very useful in capturing the dynamics of online collaborative activity. However, they ignore the essential feature of the need to continuously consider the process of knowledge construction. This does not serve the core of process-based evaluation of clusters. Thus, using the three dimensions of the multidimensional model to complement and explain each other will help teachers to comprehensively evaluate the group collaboration process in terms of multiple dimensions, including cognitive engagement, interactive behaviors, and social relationships.

By observing the behavioral transition pattern, it can be found that Group 5 mainly reflected more behavioral strategies of questioning or pursuing in the interaction pattern of behavior. However, group 5 did not show more meaningful negotiation processes such as arguing in the process of question reaching. Further, a deeper examination of the content revealed by the mouse locating knowledge points shows that Group 5 lacked sufficient motivation in the content of their statements to explain their views or to discuss alternative options. Group 5 prefers to seek ultimate help, such as being told the answer directly. In other words, the knowledge processing dimension was further combined. The analysis of the content provides an understanding of the micro-level of online collaborative discussions. Exploring the relationship between the influence of social network structure on knowledge construction can explore the internal causes affecting the effectiveness of collaborative learning from multiple dimensions. This can provide more robust evidence to support process evaluation.

5. CONCLUSION AND OUTLOOK

In this paper, we use computer-supported collaborative learning (CSCL) technology to share knowledge in real time and promote interactive learning. In this paper, we collect, annotate and analyze data based on five modalities: brain, behavior, cognition, environment and technology, and establish a model of computer-supported collaborative learning process analysis in the context of multimodal data analysis. The model is based on the intelligent network collaboration of roles and CSCL, and an interactive visualization tool is designed and developed to support the analysis of online collaborative learning process. In addition, this paper conducts a practical study in an online classroom. The study shows that the model and tool can be effectively used for online collaborative learning process analysis. It can help teachers monitor the discussion process in real time, identify problems in collaboration, and provide timely intervention and guidance. The following conclusions were obtained:

(1) In this paper, we elaborate the application of role theory in online learning environment, and propose a new intelligent CSCL model by combining the three-layer structure of application perspective. The model is personalized and intelligent, with good practicality, and well reflects the dynamic distribution of multiple roles in collaborative learning. Especially, the multiple roles of teachers in the environment better realize the unity of teaching and learning.

(1) The intelligent network collaboration model based on roles and CSCL is proposed in this paper. The model combines the theory of CSCL, intelligent agent technology and role theory, and has good application value. The model results fit well according to the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and likelihood ratio test. When the entropy index takes a value of about 0.85, about less than 10% of the individuals are assigned to the wrong profile.

(1) Model-based visualization enhances teachers' perception of the process of collaborative activities. It provides powerful support for exploring the patterns of collaborative activities and provides comprehensive evidence to support process evaluation. Visual presentation improves the effectiveness of monitoring the discussion process in real time. During the test, the participation of participants gradually increased from 5% to 25%, and the participation effect increased by about 80%.

In this paper, we study the interaction, cooperation and coordination among role-based multi-intelligent Agents from the perspective of multiple roles. This paper proposes and describes the collaboration and coordination mechanism among role-based intelligent agents. In particular, the role mechanism is studied in the application of open and dynamic network environment. The article greatly enriches the multi-agent system (MAS) theory. The mechanism, if combined with adaptive knowledge mining algorithms, will greatly contribute to the progress of distributed data mining research. The next step is to apply the role-based cooperation and coordination negotiation mechanism among intelligent agents and adaptive knowledge mining of intelligent agents to distributed data mining systems with knowledge orientation. This has good application prospects and is the direction we need to study in the future.

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