International Journal of Distance Education Technologies
Volume 22 • Issue 1

Effects of Different Leadership Styles on Cognitive Engagement in Online Collaborative Learning

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ABSTRACT

The collaborative learning approach as a universal teaching strategy is widely used in online learning. It is proven that the group leader has an important impact on group collaborative knowledge construction in online collaborative learning (OCL). However, limited research is available on how leadership styles influence a group universal teaching strategy is widely used in online learning this study, the authors adopted lag sequential analysis, epistemic network analysis, and social network analysis to explore the influence of divergent and convergent leadership styles on cognitive engagement in OCL groups. Compared with convergent leadership, divergent leadership strengthened online collaborative cognitive engagement through significant organizer and manager roles, triggered high-quality cognitive behavior transformation within the group, and promoted the balanced development of learners' cognitive structure.

KEYWORDS

Group Leader, Online Collaborative Learning, Learning Style, Cognitive Engagement

INTRODUCTION

Online learning is increasingly used to link learners without the constraints of time or space. Online collaborative learning (OCL) is an effective teaching strategy for progressive group discussion due to the accessibility of online learning communities, platforms, and other tools. In addition, teachers can guide synchronous or asynchronous cooperation and communication among students from different regions. While research has demonstrated that OCL can guide learners' cognitive engagement through social interactions (Heflin et al., 2017), a lack of face-to-face interaction can cause problems related to shallow learning, low team cohesion, and a weak collaborative atmosphere (Bóbó et al., 2022).

The group leader, an important role within OCL, has a positive impact on online collaborative discussions. The leader's interventions can facilitate the development of metacognitive skills of online collaborative learners (Dong et al., 2017), playing a mediating role in inducing and managing the cognitive engagement of the group and determining the level of knowledge sharing, construction,

DOI: 10.4018/IJDET.337964
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and creation of learners (Aalst, 2009). Regardless of the OCL design, the group leader is regarded as an important resource to improve cognitive engagement.

Researchers have conducted extensive analyses from the perspective of cognitive engagement models, quantification methods, and influencing factors to motivate the cognitive engagement of learners in OCL (Antonietti et al., 2023; Xu et al., 2020). Learning style, characteristic of the learner, reflects personal preferences when processing information (Reynolds et al., 2020). Learning style is closely related to cognitive engagement (while little is noticed in OCL).

Historically, teachers have believed that designing learning strategies and selecting teaching materials according to students' learning styles can enhance differing learning needs and learning effectiveness (Sugiharto, 2015). To further explore the role of learning styles, researchers have tried to establish an implicit link between learning style and learning process (Idkhan & Idris, 2021; Solarte et al., 2018). Some scholars have investigated the effects of learning style on learning behaviors and outcomes (Zeichner, 2019). These studies can guide teachers to propose corresponding improvement strategies based on individual style differences. However, more in-depth research is needed on the role of leader style, especially in group cognition at the level of instructional design and organization. To bridge the gap, researchers must explore the influence of leadership styles on group cognitive engagement in OCL.

Interaction content during OCL reflects the cognitive level and interaction quality of learners (Zhang et al., 2022), providing insight into cognitive engagement. To explore the potential relationship between leadership learning styles and group cognitive engagement, in this study the authors introduced a cognitive framework to investigate leadership learning styles on the cognitive process, cognitive structure, and role-play function in OCL. Then, the authors used the quasi-experimental method to explore the influence of leadership styles on group cognitive engagement. The main research questions were as follows:

1. What is the effect of different leadership styles on group cognitive processes in OCL?
2. What is the effect of different leadership styles on group cognitive structure in OCL?
3. How do different leadership styles regulate the effects of group cognition in OCL?

RELATED RESEARCH

Literature focuses on the leader's cognitive function, presents the Kolb learning style model, and reflects on the effects of cognitive and learning styles to facilitate the proposed research questions.

Cognitive Function of the Group Leader in Online Collaborative Learning

The group leader supports and manages online collaborative activities, rather than achieving the basic learning task. Regarding the influence of learning outcomes, the group leader improves the high-level knowledge construction in collaborative groups and facilitate teamwork performance (Sun et al., 2017). Dunbar et al. (2018) explored the relationship between group leaders and learning performance, finding that group leaders contribute to high learning scores and better performance.

Role assignment strategies are important factors that directly promote high levels of cognitive engagement (Gašević et al., 2015). For example, the leader can play the moderator and summarizer roles, having significant effects in promoting high levels of knowledge construction (Wever et al., 2010).

Different leadership styles, however, cannot be ignored. Kahai et al. (2013) explored the relationship between transformational and transactional leadership and collaborative learners' cognitive engagement, showing that the transformational leader is inclined to promote learners' cognitive engagement. Min et al. (2020) examined the relationship between leadership styles and motivation to engage in behaviors; their results noted a stronger association between behavioral engagement and transactional leadership styles.

These studies evidenced that the group leader in OCL can facilitate effective group cognitive improvement. They showed that different leadership styles produce different learning outcomes. Still, the following limitations remained: 1) Despite these results were derived from the analysis of external performance outcomes, the cognitive implicit role between the group leader and group members requires more research; 2) these studies revealed the role of the group leader, but they neglected ways in which the group leader can establish roles.

Kolb Learning Style Model

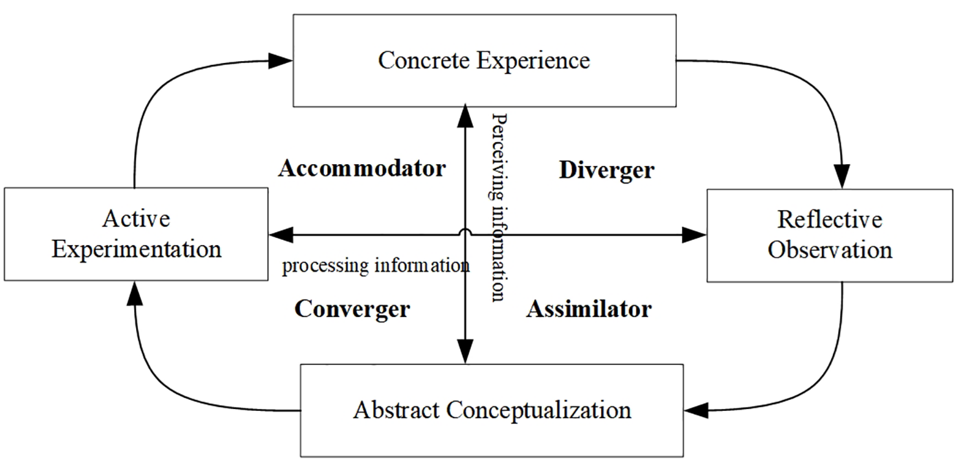
Learning style refers to a relatively stable and unique way of processing information as preferred by the learners in the learning process (Sugiharto, 2015). Researchers have classified learning styles from various perspectives, such as the Felder-Silverman learning style model (Felder & Silverman, 1988), the Pask learning style model (Gregorc, 1979), and the Kolb learning style model (Kolb, 1984). Owing to applicability and precision, the Kolb model best matches the online teaching setting (Răducu & Stănculescu, 2021). Therefore, the authors adopted it in this study.

Kolb proposed that the complete learning process is built on the perceiving and processing of information. It includes a concrete experience, reflective observation, abstract conceptualization, and active experimentation, and learner models as diverger, assimilator, converger, and accomodator (Figure 1). The Kolb learning style model provides new perspectives, revealing significant differences in learning styles and learning preferences (Kolb & Kolb, 2005). Generally, divergers prefer imaginative and active styles, favoring concrete experiences and reflective observations during interpersonal communication. Accommodators favor concrete experiences and active practice; they excel at learning from practical experience. Convergers prefer active time and abstract generalization; they have strong logical thinking skills, as well as a solid grasp of abstract concepts and knowledge. In addition, convergers are good at dealing with problems encountered in practice. Finally, assimilators prefer abstract generalization and reflective observation styles; they are good at condensing information and making it logical.

Effects of Learning Styles on Cognitive Engagement

Most research has shown that different learning styles have a significant impact on learners' learning effectiveness. For example, Wuryan and Yufiarti (2017) noted that learning styles have an interactive

Figure 1. Kolb LEARNING STYLES MODEL



effect on students' writing. Shaw (2012) suggested that learning styles affect learning performance. However, these experimental results failed to identify the process and structure of cognitive behaviors in knowledge construction. Thus, more researchers have begun to explore the influence of learning styles by mining educational data.

First, researchers are exploring differences in task handling methods. Compared to active learners, contemplative learners were found to take less time to complete tasks. Their learning behaviors change over time (Van Waes et al., 2014). When comparing the reading/writing learning style of visual learners, it was found that these learners obtain their information from visual channels. In addition, they deal with text and image problems (Huang, 2019).

Second, researchers have been studying differences in the role of style regulation. Learning styles affect the subjective presence and cognitive load in the learning process (Huang et al., 2020); thus, active/reflective learning styles influence learner skill transfer. Specifically, active learners exhibit interactive behaviors that promote learning (Hu et al., 2021). Research has also shown that divergers and convergers are significantly higher in the use of retelling strategies when compared with accommodators (Yang et al., 2015).

In brief, these studies demonstrate that learning styles serve as important elements that influence learning. They can, in turn, provide important methods for regulating and optimizing learners' cognitive engagement.

The above studies focus on the effects of learning style differences on individual learners. However, the research does not delve into how different learning styles impact the group cognitive interaction process.

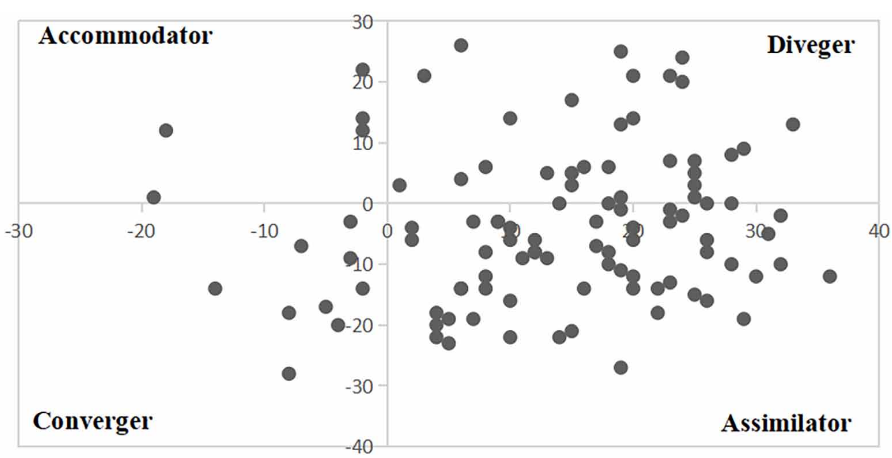
METHODS

Research Context

The authors carried out this study in "Modern Educational Technology," a 10-week course at a normal university in China, during fall 2022. The students were dedicated to a future in the teaching field. The required course aimed to improve the information technology literacy of normal students to meet the teaching needs of future education.

Before the experiment, the researchers asked the 104 course learners to complete a questionnaire survey in order to rationalize their grouping. The authors used Kolb's learning style inventory as a self-assessment tool for discriminating learning style preferences (Kolb & Kolb, 2005). The statistical results showed the number of learning style distribution (Figure 2): Convergers (n = 9, 8.7%),

Figure 2. Learning STYLE DISTRIBUTION



assimilators (n = 60, 57.8%), accommodators (n = 5, 4.8%), and divergers (n = 30, 28.8%). According to existing research, divergers and convergers have more pronounced learning style preference characteristics (Gregorc, 1979). Therefore, the auhtors selected the divergent and convergent styles to conduct the research.

Participants

According to the learning style distribution, the authors selected 54 students who participated in this study. Firstly, five divergers and five convergers as group leaders within the divergent and convergent groups, respectively. The authors drew on a large amount of relevant literature to confirm the reasonableness of the sample size (Chang, 2023; Chen et al., 2021; Kurucay & Inan, 2017). Subsequently, to eliminate the influence of group member learning style differences, the authors randomly assigned four to five assimilators to each group as members. Thus, they could ignore the influence of group members' styles on overall learning style tendencies. Finally, there were five groups (n = 26) of divergent groups led by divergers and five groups (n = 28) of convergent groups led by convergers. All were voluntarily involved in the experiment's course setting.

Three-Stage Collaborative Learning Process Design

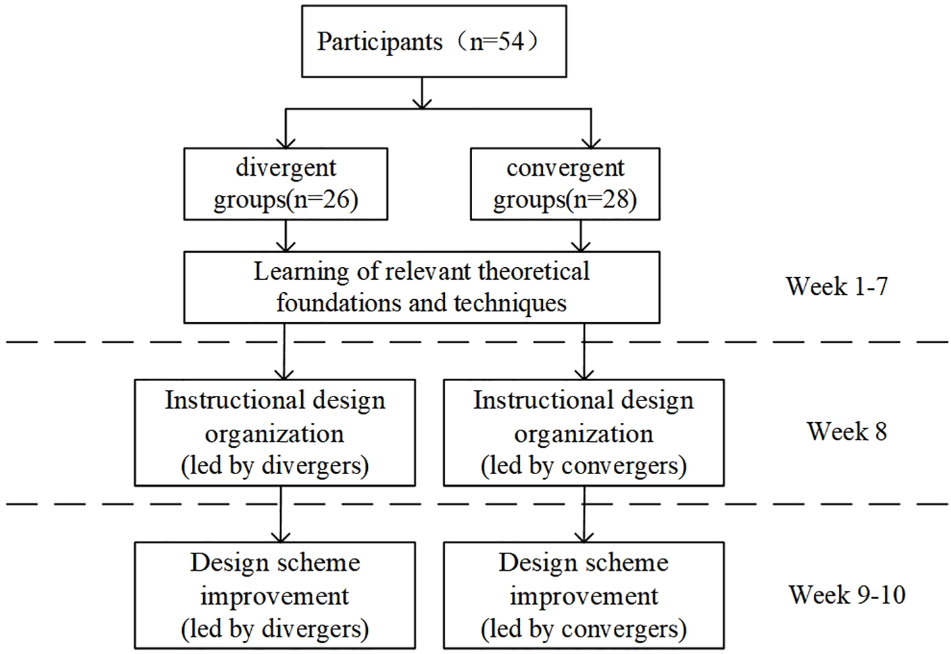
In this study, the authors used online collaborative platforms with the ability to upload learning materials and conduct online lectures to help students with online learning. They used QQ software to provide a free exchange during each group, connecting collaborative members. Students could share resources, solve problems, and advance the learning process with collaborative knowledge construction. The researchers established 10 QQ groups.

Referring to Gibson's (2001) collective cognitive model, the group leader organizes intragroup communication in the OCL process and triggers the group's cognitive behavior through individual members' and others' views. This classical model has shown potential in promoting the change and optimization of the cognitive structure, integrating views to jointly promote the completion and presentation of the learning work.

Based on this theory, the authors designed a three-stage collaborative learning process to facilitate the students' cognitive interaction (Figure 3). The experiment included practical activity and instructional design. The process lasted 10 weeks. The instructional design practice was conveyed and learned after seven weeks of the semester in the online course via group work. The details of the process are as follows:

- Learning Relevant Theoretical Foundations and Techniques: The students learned the relevant theoretical foundations and techniques during weeks 1 through 7. After seven weeks of learning, the students understood concepts and theories related to the integration of technology and education. After the analysis of the chapter test results, no significant difference in the prior knowledge level occurred among groups.
- Conducting Instructional Design Organization: In week 8, the researchers distributed the students to divergent and convergent groups. The students were required to learn in an online platform. According to the teaching objectives and rules, both groups combined the complete learning of the knowledge points independently for one week. This included learning materials, instructional design templates, determining themes, and completing the instructional design scheme.
- Examining Design Scheme Results: In weeks 9 through 10, the researchers required each group to take inner-discussed and give their recommendations, to reveal the shortcomings of their design scheme. In turn, the group members revised their instructional design work according to team comments. After the revision was complete, the students uploaded their group's strongest design scheme to the learning platform for the teacher's grade.

Figure 3. OCL process



Cognitive Engagement Analysis Model

To deepen the process of cognitive engagement, Chi and Wylie (2014) proposed the ICAP cognitive framework, which combines learners' implicit cognitive mental processes with explicit behavior. The ICAP framework provides an important theoretical basis for insight into learners' cognition in collaborative knowledge construction (Zhang et al., 2020). Research also suggests that students who play the role of active constructors will engage in active behaviors. Those with passive behaviors are often ignored (Zhao et al., 2014). Thus, in this study, the authors analyzed the cognitive engagement analysis model from the perspective of the active, constructive, and interactive. To ensure effectiveness, the authors finalized the coding scheme by combining the communication characteristics of the learners in this study and expert recommendations (Table 1).

Data Collection and Analysis

At the end of the experiment, the authors employed Excel to collect content interaction data of each group in the Tencent QQ software. To ensure the reliability of the coding results, two graduate students received coding training. The researchers determined the content for coding inconsistencies through mutual consultation. Then, they completed the coding work independently via two coders. Finally, a Kappa test for coding consistency showed kappa = 0.86 > 0.7.

The consistency indicated that it can be used for subsequent cognitive engagement analysis. During the data analysis, the researchers used multiresearch methods to analyze the cognitive process, cognitive structure, and role analysis of group leaders, respectively, as follows:

- Cognitive Process Analysis: The authors used lag sequential analysis (LSA) to analyze the sequential relationships group discussion content. LSA could mine cognitive behavioral transition sequences of different groups. To determine whether the sequence of behavioral transition reached statistical significance (the adjusted residual results, namely, the Z-values of each

Table 1. Coding scheme based on the ICAP framework

Classify	Dimensions	Description	Examples	Code
Active	Repeat	The learner explicitly repeats or quotes information already covered in the material.	Learning evaluation is mainly the evaluation of students' learning effectiveness and teachers' teaching.	A1
	Emphasize	The learner emphasizes a certain part of the content.	This part is the focus, so the reasons can be refined a bit more.	A2
	Summary	The learner summarizes the material or discussion.	Summary: The important and difficult points are not specific enough.	A3
Constructive	Expound	The learner articulates ideas or perspectives through detailed explanations, resource support or personal experience.	I think it would be more organized to write about this event in terms of how it happened and its effects.	B1
	Ask	The learner asks a new question based on their perceptions.	Do we need to add classroom questions to the instructional design?	B2
	Compare or link	The learner compares different cases to provide argument analysis of arguments or share links to external resources.	In contrast, this program did a much better job, with tables and stuff, clear content, and extended group discussions.	B3
	Respond	The learner responds to questions based on their perceptions.	I am setting up a situation where the students can take part in it.	B4
Interactive	Establish	The learner further establishes ideas based on the views of others.	I agree with the two students above, and I have a few more points to add.	C1
	Support	The learner agrees with the views of others.	Support! History classes are also important for values guidance!	C2
	Defend	The learner defends others because they hold different views.	I do not support this topic. There is not much to learn about this.	C3

behavior transition, $z > 1.96$), the authors carried out LSA in GSEQ 5.1. This method is used to reveal the cognitive process from multiple angles, such as key behavioral transition sequences (Bakeman & Gottman, 1997).

- Cognitive Structure Analysis: The authors used the epistemic network analysis (ENA) to visualize the accumulated relations between cognitive elements through network representations (Shaffer et al., 2016). In this study, the ENA web clearly presented the differences in the cognitive structural characteristics between the divergent and convergent groups.
- Regulating Effects of Different Leadership Styles: Social network analysis (SNA) is an analytical technique that quantifies the interactivity among and within a network of actors/nodes. The authors used SNA to discover how different leadership styles moderate group cognitive engagement. The researchers selected centrality measures to characterize the organizational and managerial roles of group leaders. The in-degree measured the management ability of the group leader. The higher value signified stronger management ability. The out-degree measured the organizational ability of the group leader. The higher value signified stronger organizational ability (Ruan, 2017).

RESULTS

The results showed the details of differences in the cognitive process, cognitive structure, and role of leaders in groups, respectively.

Group Cognitive Processes Analysis

Table 2 presents the number of codes of divergent and convergent groups after two stages of experiments. The results showed the number of cognitive engagement coding in the divergent groups (517) and convergent groups (408), indicating that divergent leadership promoted higher cognitive engagement in the collaborative learning process. In detail, the divergent groups have higher cognitive engagement than the convergent groups in most dimensions, especially in the active (74:48) and constructive dimensions (338:255). This indicates a significant difference in the use of cognitive strategies between the divergent and convergent groups.

To further analyze the differences in cognitive processes, the authors used LSA to explore the cognitive behavioral transition of the groups. To visualize the process of the significant behavioral sequences, the researchers generated behavior transition diagrams for the two groups that occurred during the online discussion (Figures 4 and 5).

Figures 4 and 5 show that the behavior paths of the two groups are significantly different. There are also the paths that promote the occurrence of members' knowledge construction. Behavior path B2 (ask) → B4 (respond) is more significant in both groups, implying that group members often followed up and provided relevant responses when students asked questions. Thus, the two groups share a positive atmosphere of OCL. Behavior path B1 → C2 (expound → support) means that, when

Table 2. Content interaction data encoding

Stage	Groups	Active			Constructive				Interactive			Total
		A1	A2	A3	B1	B2	B3	B4	C1	C2	C3	
Instructional design organization	Divergent	11	5	16	62	52	10	73	11	38	12	290
	Convergent	1	1	5	44	42	1	64	9	38	15	220
Design scheme improvement	Divergent	6	3	33	54	35	9	43	6	32	6	227
	Convergent	5	2	34	37	25	6	36	5	33	5	188
Total	Divergent	17	8	49	116	87	19	116	17	70	18	517
	Convergent	6	3	39	81	67	7	100	14	71	20	408

Figure 4. Behavioral transition diagram of divergent groups

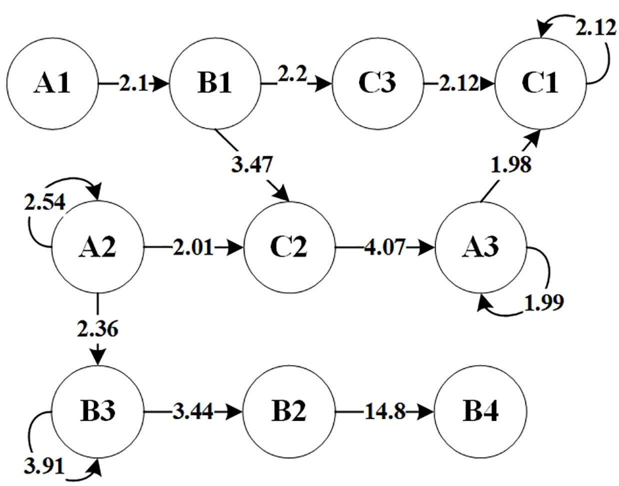
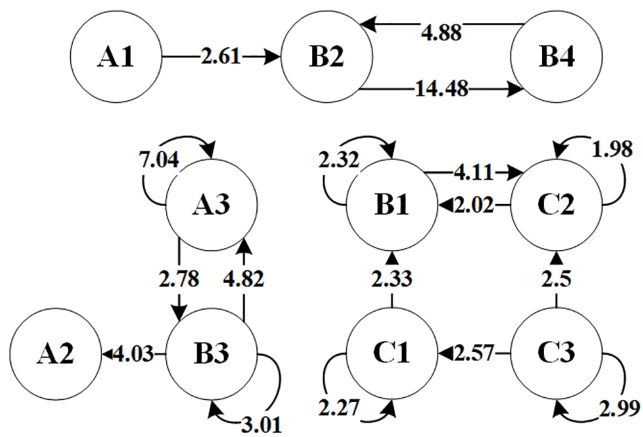


Figure 5. Behavioral transition diagram of convergent groups



students express views, other group members express support or compliance. In other words, others are less likely to express disagreement, when students discuss cases and arguments. This may imply that learners are actively engaged in knowledge construction through cognitive collisions.

According to the behavioral transition diagrams (Figure 3), the results showed that the divergent groups promote cognition establishment through deeply extended behavior paths. The path of "A1 → B1 → C3 → C1" (repeat → expound → defend → establish) indicates that, when students tend to repeat the question before expounding their views, other members may express disagreement from different views. For example, if students propose a controversial idea, the leader organizes and participates to ensure that members can express their divergent ideas. The path of "C2 → A3 → C1" (support → summary → establish) indicates that, after passing the consensus on an issue, members will summarize the results and build their ideas. The path of "A2 → B3 → B2 → B4" (emphasize → compare or link → ask → respond) indicates that members emphasize what they think needs attention and share links to provide reference ideas. The other members ask questions and conduct an in-depth analysis.

The convergent groups in Figure 4 show the maintenance of cognitive occurrence through simple behavior paths. In this regard, the path of "A1 → B2 → B4" (repeat → ask → respond) means that students tend to repeat ambiguous content before asking for help. In turn, no specific meaning-building activity occurs after the response. For example, students often post confusing content into the chat group. They ask other members for solutions to the problem, then receive responses from others instead of giving further positive feedback. The path of "A3 → B3 → A2" (summary → compare or link → emphasize) indicates that members generate corresponding discussions around the summary content. However, the students tend to reinforce the conclusion without any extension.

The behavioral analysis uncovers specific intentions during interactions. A higher frequency of interaction means that learners are more motivated to participate (Yang & Chen, 2023). The divergent groups' behavior transition in the deep construction dimensions shows more significant paths. The frequent conversion between different dimensions also indicates that the divergent groups are inclined to deep knowledge construction and the efficient transfer of information. The convergent groups are more manifested in the cognitive behavior transition of the shallow dimension, such as the active dimension.

Group Cognitive Structure Analysis

To compare the differences in cognitive structure between the two groups, the researchers used ENA to determine epistemic-network characteristics. Figure 6 shows the ENA networks between divergent and convergent groups. The dots represent the cognitive network centroids of each learner. The squares are the mean centroids of all students in the group, which are all projected into a two-dimensional confidence interval. The results show a clear separation between the two centroids, indicating that the students in the divergent and convergent groups differ in cognitive structure during the discussion.

The authors used a two-sample t-test to explain this variability. The results in Table 3 show a significant difference between the divergent groups (M = -0.26) and convergent groups (M = 0.22) in the X dimension (p = 0.00 < 0.05). No significant differences occur in the Y dimension (p = 1.00 > 0.05). Thus, the author could conclude that the different leadership styles altered the formation of cognitive structures in OCL groups.

To deeply reveal the cognitive structure differences between the two groups, the authors demonstrated the cognitive structure diagram of the divergent groups (Figure 7) and convergent groups (Figure 8). In the cognitive network, the 10 nodes correspond to the 10 coded different cognitive

Figure 6. Mean of the plotted points for divergent groups (dark color) and convergent group (light color)

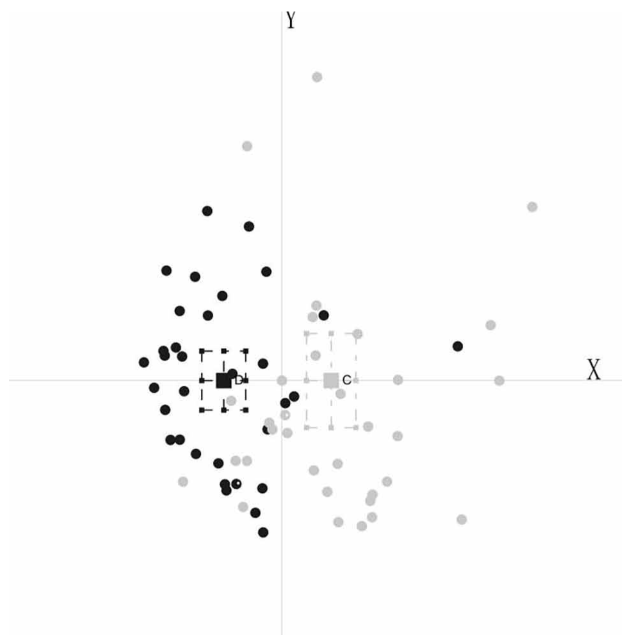


Table 3. Double sample t-test results

Groups	X						Y					
	Mean	SD	N	*t*	Effect Size (d)	p	Mean	SD	N	*t*	Effect Size (d)	p
Divergent Groups	-0.26	0.26	26	-6.59	1.53	0.00*	0.00	0.37	26	0.00	0	1.00
Convergent	0.22	0.22	28				0.00	0.65	28			

Note. *p<0.05.

Figure 7. Cognitive network structure diagram of divergent groups

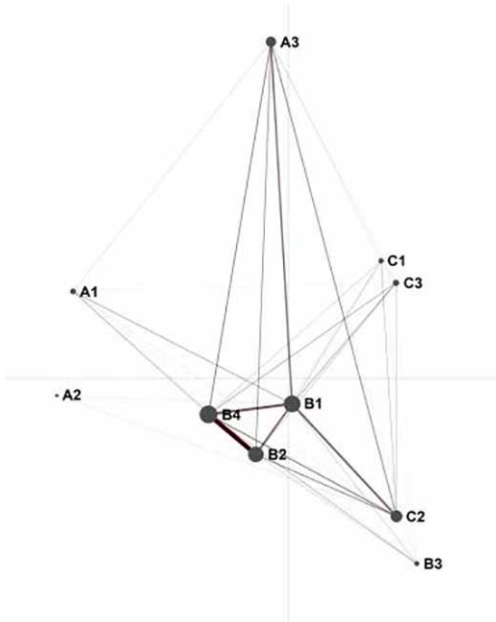
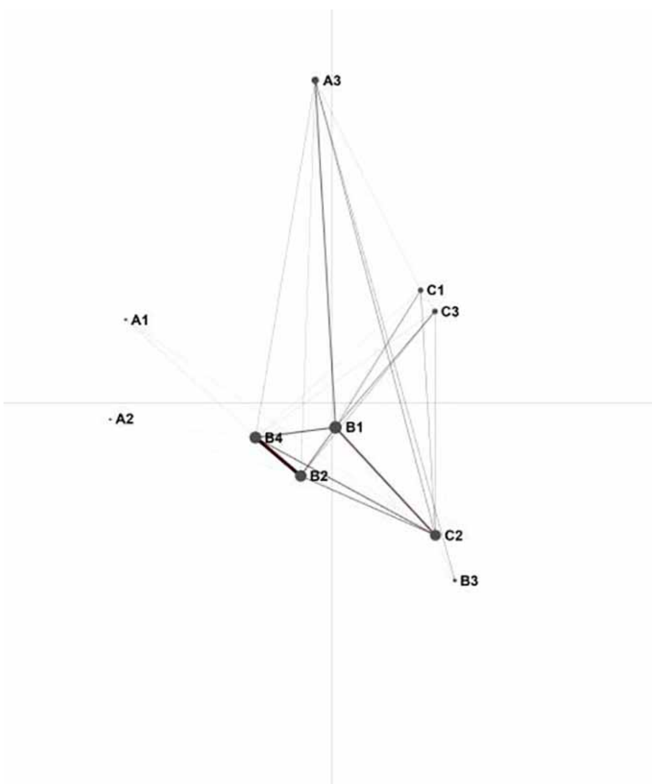


Figure 8. cognitive network structure diagram of convergent groups



coding elements. Generally, the comparison of the two diagrams reveals that, in the breadth of knowledge elements connections, the divergent and convergent groups' connections are similar and cover almost all dimensions. In the cognitive elements, connection strength between the divergent and convergent groups has some differences. A main difference is that A1 (repeat) and C1 (establish) are frequently used and connected in the divergent groups, but not in the convergent groups. This result provides evidence that the divergent groups repeat explicitly specific content, building effective and relevant cognition.

To observe this difference, the researchers drew the subtracted network (if there are overlapping lines between the two groups of cognitive elements, the color of the stronger connected group will eventually appear). Figure 9 shows that most of the connections belong to the divergent groups (dark color). The convergent groups (light color) have a slight advantage in the connections between summary and compare or link (A3 - B3). Divergent groups are, therefore, more efficient in knowledge construction and have a better cognitive structure during the OCL process. The convergent groups' feature structure is slightly simple, indicating a weak and shallow cognitive structure.

Leadership Regulating Analysis

The authors used SNA to measure the social attributes of different roles (Table 4). In terms of the out-degree between divergent groups (leaders M = 22.00, group members M = 9.62, p = 0.006) and convergent groups (leaders M = 14.80, group members M = 7.87, p = 0.045), the leaders' mean

Figure 9. Subtracted network

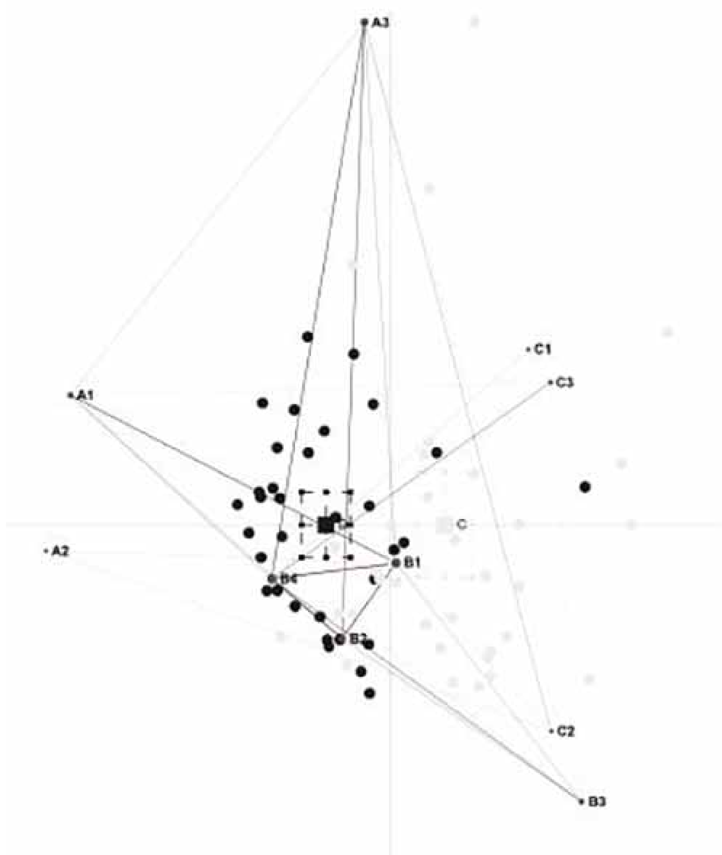


Table 4. Difference of point-degree centricity

Groups	Social attributes		Leaders	Group members
Divergent	Out-degree	Mean	22	9.62
		p	0.006*	
	In-degree	Mean	15.60	11.14
		p	0.251	
Convergent	Out-degree	Mean	14.80	7.87
		p	0.045*	
	In-degree	Mean	13.00	8.26
		p	0.087	

Note. *p<0.05.

values are both significantly higher than the group members. This indicates that the leaders were more active than the group members in the interacting process. This shows the organizational function. In terms of in-degree between the divergent groups (leaders M = 15.60, group members M = 11.14, p = 0.251) and convergent groups (leaders M = 13.00, group members M = 8.26, p = 0.087), the leaders' mean values are both higher than the group members. However, there was no significant difference. Compared to group members, leaders have a stronger influence on the group interaction process and the management function is gradually established. Overall, the out-degree and in-degree values of divergent leadership are higher than convergent leadership. Thus, the organizational and management functions of divergent leaders are more obvious.

To further explore the regulating effects of leadership styles on group cognition in OCL, the researchers conducted a correlation analysis between the degree centrality of the leader and members' cognitive behavior (Table 5). The positive interaction of the leader makes the group members more willing to express their views and easily obtain support and recognition from other members. This induces members to actively ask, compare or link resources among members.

The convergent leaders' out-degree is significantly correlated with the cognitive behaviors of summary, compare or link dimensions, indicating that, although the convergent leaders have certain organizational functions, this has weakened in mobilizing the enthusiasm of cognitive interaction between members, so that group members show more low-order cognitive behaviors such as summary and compare or link. In addition, divergent leaders' in-degree is significantly correlated with cognitive behaviors of expound and ask, indicating that leaders accentuate their management functions by expanding interaction strategies. The in-degree of convergent leaders is only significantly correlated with the cognitive behaviors of emphasize, indicating that the influence of the leaders is more manifested in the management of the task process.

Table 5. Correlation analysis between social network attributes and cognitive behaviors

Groups	Social attribute	Dimension			
Divergent	Out-degree	Expound 0.971**	Ask 0.988**	Compare or link 0.949*	Support 0.976**
	In-degree	Expound 0.921*		Ask 0.899*	
Convergent	Out-degree	Summary 0.925**		Compare or link 0.887**	
	In-degree	Emphasize 0.989**			

Note. *p<0.05, **p<0.01.

DISCUSSION

Divergent Leadership Promoted High-Quality Behavior Transformation

Different learners' styles produce different behavioral sequences in the learning process (Wu & Hou, 2015). The authors observed a similar result also in this study, showing different behavioral sequences between the divergent and convergent groups. From the perspective of cognitive codes, the active and constructive behaviors of the divergent groups were significantly higher than the convergent groups. For example, the number of expound behaviors (116 times) was significantly higher than in the convergent groups (81 times), indicating that the divergent leaders could promote group cognitive engagement and actively mobilize members to express their views. From the perspective of behavioral transition, group members may have a stronger desire to socialize due to the positive interaction of divergent group leaders. For example, the behavior path of "B1→ C3→ C1" in divergent groups indicates that after students actively express their views. Other members can respond in a timely and clear attitude rather than blindly agree. In contrast, the behavior path of convergent groups "B1 → C2" was significant. This may be because the convergent leaders were not good at sociability (Ata & Cevik, 2019), so they did not fully mobilize the enthusiasm of the group members. Meanwhile, resulting in other members did not engage in specific meaning-construction activities when members expressed opinions. Overall, in terms of cognitive behaviors, the divergent groups showed more collaborative interaction and meaningful constructs than the convergent groups.

Divergent Leaders Helped Learners Build Balanced Cognitive Structures

In this study, the authors found that the cognitive structure of the divergent group is richer and more balanced than the convergent groups, indicating that divergent leaders can effectively promote the OCL of a cognitive network structure. The ENA revealed network models of epistemic criteria, showing the structure of group epistemology in terms of epistemic criteria (Chang, 2023). Previous studies had found that different guidance styles affect learners' knowledge construction and thinking ability cultivation, which is generally consistent with the authors' conclusions in this study (Kreunen et al., 2018). From the perspective of cognitive network density, the overall connection between the knowledge elements of the divergent groups is closer. The cooccurrence of cognitive elements in the convergent groups is weak, and the connections are relatively sparse. From the perspective of cognitive structure, the divergent groups' network structure is more complete and uniform. Thus, multidimensional cognitive collaboration can develop among collaborative learners. However, the convergent groups' network structure includes locality characteristics. It also lacks a connection with the deep interaction dimension. This may be because divergent leaders tend to group cooperation and observation (Xia et al., 2019). In turn, they can discover new ideas in time and actively guide the members to conduct in-depth discussions. This suggests that divergent leaders can be effective in facilitating deep knowledge construction for collaborative learners.

Role Functions of Divergent Leaders are More Prominent

In this study, the authors found that the leaders played the leadership and coordination roles in the internal network of the collaborative group. However, the divergent leaders showed more significant management and organizational functions than the convergent leaders. Studies have shown that divergent leaders play the core role in the idea generation stage, serving as active advocates in discussions and motivating member participation (Li & Zhang, 2016). In the process of cognitive engagement, the positive interaction of divergent leaders led to more cognitive behaviors of expound, ask, compare or link and support in the group. The convergent leaders triggered more summary and compare or link behaviors. Comparing differences shows that divergent leaders were more experienced in organizational interaction. In addition, the management function of the divergent leaders triggered more expound and ask behaviors, while the convergent leaders promoted more emphasize behavior. This indicates that the divergent leader promoted a deeper meaning knowledge construction of the group. In turn, the convergent leaders promote the cognitive engagement of the group more in the low-level active behavior. The divergent leaders can promote the high-level knowledge construction and active interaction dimension of the group, improve the quality of interaction, and gradually establish the role of the manager.

CONCLUSION

The group leader's special role in collaborative learning contributes to group cognitive engagement and facilitates group cognitive engagement by organizing and managing collaborative members. Manolis et al. (2013) pointed out that the Kolb model profiles learners from the perspective of the learning process, guiding the learning and understanding of the rules. Compared with convergent leadership, in this study the authors found that divergent leadership strengthened online collaborative cognitive engagement with significant organizer and manager roles, triggered high-quality cognitive behavior transformation in the group, and promoted the balanced development of learners' cognitive structure. This study not only enriches the theoretical research on learners' cognitive engagement in OCL, but also provides application guidance for teachers to design OCL strategies. Therefore, based on the conclusions in this study, the authors suggest teachers to design OCL activities, such as strengthening the role of the group leader to ensure efficient OCL, focusing on divergent leadership to promote deep cognitive participation, and maintaining a diversity of group styles to address multiple types.

This study had also limitations. First, the authors only explored the effects of leaders on group cognitive engagement. Therefore, future research should cover emotional and behavioral engagement in OCL. Second, current content-based encoding is mostly manual annotation. Moreover, manual coding methods require excessive energy and time. They can also cause low or poor accuracy with the increasing scale of online group interaction data. Therefore, future work should include designing an automated and precise classification of interactive texts for OCL. Third, the sample sizes in this research were inadequate. Hence, more participants will have to be included in future studies.

REFERENCES

Aalst, J. V. (2009). Distinguishing knowledge-sharing, knowledge-construction, and knowledge-creation discourses. *International Journal of Computer-Supported Collaborative Learning*, *4*(3), 259–287. doi:10.1007/s11412-009-9069-5 PMID:32214914

Antonietti, C., Schmitz, M. L., Consoli, T., Cattaneo, A., Gonon, P., & Petko, D. (2023). Development and validation of the ICAP Technology Scale to measure how teachers integrate technology into learning activities. *Computers & Education*, *192*, 104648. doi:10.1016/j.compedu.2022.104648

Ata, R., & Cevik, M. (2019). Exploring relationships between Kolb's learning styles and mobile learning readiness of pre-service teachers: A mixed study. *Education and Information Technologies*, *24*(2), 1351–1377. doi:10.1007/s10639-018-9835-y

Bakeman, R., & Gottman, J. M. (1997). *Observing interaction: An introduction to lag sequential analysis* (2nd ed.). Cambridge University Press. doi:10.1017/CBO9780511527685

Bóbó, M. L., Campos, F., Stroele, V., David, J. M., Braga, R., & Torrent, T. T. (2022). Using sentiment analysis to identify student emotional state to avoid dropout in e-learning. *International Journal of Distance Education Technologies*, *20*(1), 1–24. doi:10.4018/IJDET.305237

Chai, Y. L., Chen, X. D., & Rong, X. J. (2019). CSCL online asynchronous dialogue analysis and improvement strategy from perspective of shared monitoring and regulation: A case of "inquiry learning.". *Chinese E-education Research*, *40*(5), 72–80. doi:10.13811/j.cnki.eer.2019.05.010

Chang, H. Y. (2023). Scaffolding online peer critiquing to develop students' epistemic criteria of data visualization. *Computers & Education*, *203*, 104863. doi:10.1016/j.compedu.2023.104863

Chen, S., Ouyang, F., & Jiao, P. C. (2021). Promoting student engagement in online collaborative writing through a student-facing social learning analytics tool. *Journal of Computer Assisted Learning*, *38*(1), 192–208. doi:10.1111/jcal.12604

Chi, M. T. H., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist*, *49*(4), 219–243. doi:10.1080/00461520.2014.965823

Dong, Y. T., Bartol, K. M., Zhang, Z. X., & Li, C. W. (2017). Enhancing employee creativity via individual skill development and team knowledge sharing: Influences of dual-focused transformational leadership. *Journal of Organizational Behavior*, *38*(3), 439–458. doi:10.1002/job.2134

Dunbar, R. L., Dingel, M. J., Dame, L. F., Winchip, J., & Petzold, A. M. (2018). Student social self-efficacy, leadership status, and academic performance in collaborative learning environments. *Studies in Higher Education*, *43*(9), 1507–1523. doi:10.1080/03075079.2016.1265496

Felder, R. M., & Silverman, L. K. (1998). Learning and teaching styles in engineering education. *Journal of Engineering Education*, *78*(7), 674–681.

Galikyan, I., & Admiraal, W. (2019). Students' engagement in asynchronous online discussion: The relationship between cognitive presence, learner prominence, and academic performance. *The Internet and Higher Education*, *43*, 100692. doi:10.1016/j.iheduc.2019.100692

Gašević, D., Adesope, O., Joksimović, S., & Kovanović, V. (2015). Externally-facilitated regulation scaffolding and role assignment to develop cognitive presence in asynchronous online discussions. *The Internet and Higher Education*, *24*, 53–65. doi:10.1016/j.iheduc.2014.09.006

Gibson, C. B. (2001). From knowledge accumulation to accommodation: Cycles of collective cognition in work groups. *Journal of Organizational Behavior*, *22*(2), 121–134. doi:10.1002/job.84

Gregorc, A. F. (1979). Learning/teaching styles: Potent forces behind them. *Educational Leadership*, *36*, 234–237.

Heflin, H., Shewmaker, J., & Nguyen, J. (2017). Impact of mobile technology on student attitudes, engagement, and learning. *Computers & Education*, *107*, 91–99. doi:10.1016/j.compedu.2017.01.006

Hu, Y. L., Chang, X. Y., & Wu, B. (2021). The influence of immersive virtual reality on skill transfer: The moderating effect of learning style. *Chinese Journal of Distance Education*, *39*(2), 63–71.

Huang, C. L., Luo, Y. F., Yang, S. C., Lu, C. M., & Chen, A. S. (2020). Influence of students' learning style, sense of presence, and cognitive load on learning outcomes in an immersive virtual reality learning environment. *Journal of Educational Computing Research*, *58*(3), 596–615. doi:10.1177/0735633119867422

Huang, T. C. (2019). Do different learning styles make a difference when it comes to creativity? An empirical study. *Computers in Human Behavior*, *100*, 252–257. doi:10.1016/j.chb.2018.10.003

Idkhan, A. M., & Idris, M. M. (2021). Dimensions of students learning styles at the university with the Kolb learning model. *International Journal of Environment. Engineering and Education*, *3*(2), 75–82. doi:10.5281/ZENODO.5340456

Kahai, S., Jestire, R., & Huang, R. (2013). Effects of transformational and transactional leadership on cognitive effort and outcomes during collaborative learning within a virtual world. *British Journal of Educational Technology*, *44*(6), 969–985. doi:10.1111/bjet.12105

Kolb, A., & Kolb, D. (2005). *The Kolb Learning Style Inventory, version3.1:2005 technical specifications*. Hay Group, Experience Based Learning Systems.

Kolb, D. A. (1984). Experiential learning: Experience as the source of learning and development. *Journal of Business Ethics.* https://www.learningfromexperience.com/images/uploads/process-of-experiential-learning.pdf

Kreunen, K. M., Bossche, P. V. D., Hoven, M., Klink, M. V. D., & Gijselaers, W. (2018). When leadership powers team learning: A meta-analysis. *Small Group Research*, *49*(4), 475–513. doi:10.1177/1046496418764824 PMID:30008542

Kurucay, M., & Inan, F. A. (2017). Examining the effects of learner-learner interactions on satisfaction and learning in an online undergraduate course. *Computers & Education*, *115*, 20–37. doi:10.1016/j.compedu.2017.06.010

Li, W. H., & Zhang, Y. Y. (2016). The empirical research on the impacts of learning styles to the online collaborative learning process. *Chinese Modern Educational Technology*, *26*(6), 94–100.

Manolis, C., Burns, D. J., Assudani, R., & Chinta, R. (2013). Assessing experiential learning styles: A methodological reconstruction and validation of the Kolb Learning Style Inventory. *Learning and Individual Differences*, *23*(1), 44–52. doi:10.1016/j.lindif.2012.10.009

Min, K. K., Lee, I. H., & Wang, Y. (2020). How students emerge as learning leaders in small group online discussions. *Journal of Computer Assisted Learning*, *36*(5), 610–624. doi:10.1111/jcal.12431

Răducu, C. M., & Stănculescu, E. (2021). Adaptability to online teaching during Covid-19 pandemic: A multiple mediation analysis based on Kolb's theory. *International Journal of Environmental Research and Public Health*, *18*(15), 8032. doi:10.3390/ijerph18158032 PMID:34360324

Reynolds, Q. J., Gilliland, K. O., Smith, K., Walker, J. A., & Beck Dallaghan, G. L. (2020). Differences in medical student performance on examinations: Exploring score variance between Kolb's Learning Style Inventory classifications. *BMC Medical Education*, *20*(1), 423. doi:10.1186/s12909-020-02353-5 PMID:33176776

Ruan, Y. J. (2017). *Research on the structure of students' interaction network in e-learning space*. School of Education Information Technology, Central China Normal University.

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

Shaw, R. S. (2012). A study of the relationships among learning styles, participation types, and performance in programming language learning supported by online forums. *Computers & Education*, *58*(1), 111–120. doi:10.1016/j.compedu.2011.08.013

Shi, Y. F., Tong, M. W., & Long, T. T. (2021). Investigating relationships among blended synchronous learning environments, students' motivation, and cognitive engagement: A mixed methods study. *Computers & Education*, *168*, 104193. doi:10.1016/j.compedu.2021.104193

Solarte, M., Ramírez-Velarde, R., Alario-Hoyos, C., Ramírez-González, G., & Ordóñez-Eraso, H. (2018). Kolb's learning styles, learning activities and academic performance in a massive private online course. In I. Batyrshin, M. Martínez-Villaseñor, & H. Ponce Espinosa (Eds.), *Advances in soft computing, MICAI 2018, lecture notes in computer science* (Vol. 11288, pp. 327–341). Springer., doi:10.1007/978-3-030-04491-6_25

Sugiharto. (2015). The effect of cooperative learning model and Kolb learning styles on learning result of the basics of politics. *Journal of Education and Practice, 6*(21), 1—12.

Sun, J. J., Anderson, R. C., Perry, M., & Lin, T. J. (2017). Emergent leadership in children's cooperative problem solving groups. *Cognition and Instruction*, *35*(3), 212–235. doi:10.1080/07370008.2017.1313615

Van Waes, L., van Weijen, D., & Leijten, M. (2014). Learning to write in an online writing center: The effect of learning styles on the writing process. *Computers & Education*, *73*, 60–71. doi:10.1016/j.compedu.2013.12.009

Wever, B. D., Keer, H. V., Schellens, T., & Valcke, M. (2010). Roles as a structuring tool in online discussion groups: The differential impact of different roles on social knowledge construction. *Computers in Human Behavior*, *26*(4), 516–523. doi:10.1016/j.chb.2009.08.008

Wu, S. Y., & Hou, H. (2015). How cognitive styles affect the learning behaviors of online problem-solving based discussion activity: A lag sequential analysis. *Journal of Educational Computing Research*, *52*(2), 277–298. doi:10.1177/0735633115571307

Wuryan, & Yufiarti. (2017). The effect of teaching methods and learning styles on capabilities of writing essays on elementary schools students in East Jakarta. *Educational Research Review, 12(*12), 635—642. 10.5897/ERR2017.3187

Xia, X. L., Li, H. J., & Chen, W. (2019). Research on the influence of learning style on learning effectiveness. *Chinese Contemporary Vocational Education*, *6*, 80–87. doi:10.16851/j.cnki.51-1728/g4.20191129.006

Xu, B., Chen, N. S., & Chen, G. (2020). Effects of teacher role on student engagement in WeChat-based online discussion learning. *Computers & Education*, *157*, 103956. doi:10.1016/j.compedu.2020.103956

Yang, H. B., Liu, D. Z., & Yang, R. K. (2015). The relationship between learning interest, self-efficacy, learning strategy and grade: A study on middle school mathematics learning based on Kolb learning style. *Chinese Educational Science Research*, *247*(10), 52–57.

Yang, T. C., & Chen, J. H. (2023). Preservice teachers' perceptions and intentions regarding the use of chatbots through statistical and lag sequential analysis. *Computers and Education: Artificial Intelligence*, *4*, 100119. doi:10.1016/j.caeai.2022.100119

Zeichner, O. (2019). The relationship between extrovert/introvert attributes and feedback on students' achievements. *International Journal of Distance Education Technologies*, *17*(2), 1–17. doi:10.4018/IJDET.2019040101

Zhang, S., Gao, Q. Q., Sun, M. Y., Cai, Z. H., Li, H. H., Tang, Y. L., & Liu, Q. T. (2022). Understanding student teachers' collaborative problem solving: Insights from an epistemic network analysis (ENA). *Computers & Education*, *183*, 104485. doi:10.1016/j.compedu.2022.104485

Zhang, S., He, J. M., Shang, W. C., Xia, D., & Hu, Q. (2020). Cognitive engagement analysis model for collaborative knowledge construction and its application in online learning. *Chinese Journal of Distance Education*, *38*(4), 95–104.

Zhao, H. H., Sullivan, K. P. H., & Mellenius, I. (2014). Participation, interaction, and social presence: An exploratory study of collaboration in online peer review groups. *British Journal of Educational Technology*, *45*(5), 807–819. doi:10.1111/bjet.12094

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