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Research Article

Effects of heterogeneous complex-task sequencings on extraneous collective cognitive load, intrinsic motivation, and learning transfer in computer-supported collaborative learning

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ABSTRACT

Computer-supported collaborative learning is an instructional technique to solve complex tasks. One of the key factors to enhance collaboration is increasing the level of interdependence among the collaborators. This study was conducted to examine if the heterogeneous knowledge held by each member promoted by heterogenous instructional sequencings enhances the level of interdependence during collaboration. A quasi-experiment was conducted with college seniors preparing for their careers in a Shinhan University located in Gyeonggi-do, South Korea. The experiment consisted of two phases: one was, where students gained prior knowledge using homogeneous or heterogeneous complex-task sequencing. The other was, where they collaborated with each other using a computer-supported tool. The results showed the statistically significant difference between the two groups in terms of extraneous collective cognitive load, intrinsic motivation, and learning transfer. The collaborative groups of members, which utilized heterogeneous instructional sequencings during the individual learning phase showed relatively lower extraneous collective cognitive load, and higher intrinsic motivation in three consecutive collaborative sessions except for the first. As well as groups of members had higher learning transfer results. Implications and limitations were further discussed on results.

Keywords: collaborative learning, computer-supported collaborative learning, conservation of resource theory, collective cognitive load theory, complex-task instructional sequencings, intrinsic motivation

INTRODUCTION

Collaborative learning (CL) is a process by which learners are interdependent in acquiring skills and knowledge (Slavin, 2014). Modern learning trends has been shifted from individual learning to team learning to acquire professional knowledge (Hmelo-Silver & Chinn, 2016). This move recognizes the value of collaborative environments like project-based activities, which allow for individuals to integrate transactive memories (Weinberger et al., 2007), develop job-related skills (Zambrano et al., 2019b), and cultivate novel strategies for problem-solving.

However, collaboration does not always guarantee effective learning. In cases where not everyone contributes to collaboration, individuals may experience an unsatisfactory learning experience, wasting their precious time, effort, and cost (Zambrano et al., 2019a). In general, CL is particularly well-suited for ill-structured tasks (e.g., skill development, real-life problem solving) rather than structured tasks (e.g., memorization and reading comprehension) (Zambrano et al., 2019b). This implies that the problem space for CL should be broad enough to exceed the sum of individual cognitive resources (Kirschner et al., 2011), which aligns with what van Merriënboer and Kirschner (2017) defined as a *complex task*. Addition to this, since CL inevitably induces transactive costs while coordinating and communication with one another, effectively designing CL environment, where everyone can effectively contribute to the work is crucial.

According to collaborative cognitive load theory (CCLT), one of the key to successful CL outcomes is inducing a high level of interdependence among the members, which is the degree of which members rely on each other to solve shared goals (Kirschner et al., 2018). Interdependence in CL can be enhanced through the process of building trust among members and is classified into two distinct types: *outcome interdependence* and *means interdependence* (Janssen & Kirschner, 2020). *Outcome interdependence* occurs when team members engage in interactions focused on working collaboratively to achieve a common goal and complete a task. On the other hand, *means interdependence* involves interactions focused on exchanging different pieces of information among collaborators.

In this vein, an effective way to support *mean interdependence* is in a computer-supported collaborative learning (CSCL) environment, where resource exchange is facilitated among every collaborator through computer network. In a CSCL setting, learners can externalize their knowledge through artifacts and objects, allowing everyone to use shared embodied information (Kirschner & Erkens, 2013). This process reduces unnecessary transactive activities (Dado & Bodemer, 2017) and chances of overrating or underestimating the level of participant expertise (Engelmann & Hesse, 2010), promoting efficiency. Naturally enabling learners to monitor mutually among collaborators, individuals' knowledge can be verified by one another, establishing trust relationships (Fransen et al., 2011). This, in turn, enhances the collaborative dynamic, creating a foundation for a positive interdependent relationship that is essential for effective collaboration (Johnson & Johnson, 2009; Zambrano et al., 2019a).

The difference between CL and CSCL is not about the physical distance of the learning environment, but about the utilization of computer-supported tools to facilitate the process of collaboration (Dillenbourg et al., 2009). Collaboration is not merely achieved by forming members into teams and having them cooperate; rather, it requires meaningful sharing of learning experiences among members (Lange et al., 2021). Digital concept maps, as computer supported tools, can be used for learners to visually map out and share their conceptual knowledge efficiently. Meanwhile, collaborative complex tasks should be given for collaborators to integrate and coordinate their collective knowledge, skills, and attitudes. This approach has been limited by shared knowledge creating approach pursued in traditional design-based paradigms (e.g., Yang, 2023), and complex learning excluding skills and attitudes may not lead to meaningful outcomes (van Merriënboer & Kirschner, 2017). Therefore, in CL environment involving complex tasks, it is necessary to design methods that can integrate and coordinate the knowledge, skills, and attitudes of members. While there are various ways to enhance *means interdependence,* this study focuses on activating effective transactive memory in CL situations, stemming from a trust relationship during the process of problem-solving.

The purpose of this study is to examine if designing heterogeneous complex task sequencings during individual learning prior to CL phase can develop an effective CL environment. To this end, the experiment will be comprised of two phases: the first is, where members of groups acquire task-related knowledge by using homogeneous or heterogeneous complex-task sequencing, and the next is, where members collaborate to solve a complex task with concept map tools. It examines, firstly, extraneous collective cognitive load to determine whether knowledge, skills, and attitudes learned individually with heterogeneous sequencings can be effectively integrated and coordinated during CL phase. Secondly, it investigates intrinsic learning motivation during CL process to examine how well mean interdependence is formed among collaborators. Lastly, the study assesses learning transfer to determine if individual learning capabilities have been enhanced through complex CL. Based on research purpose, this study has three research questions.

RQ1. How does extraneous collective cognitive load differ during CSCL between groups learned with heterogenous complex-task sequencing, and groups learned with homogeneous complex-task sequencing?

RQ2. How does intrinsic motivation differ during CSCL between groups learned with heterogenous complex-task sequencing, and groups learned with homogeneous complex-task sequencing?

RQ3. How does learning transfer differ during CSCL between groups learned with heterogenous complex-task sequencing, and groups learned with homogeneous complex-task sequencing?

THEORETICAL BACKGROUND

Conservation of Resources Theory & Computer-Supported Collaborative Learning

CL supports effective learning activities by exchanging information between the working memories of the participants, which occurs when two or more members share cognitive efforts to achieve learning goals (Janssen & Kirschner, 2020). In CSCL situations, members can develop a collective cognitive structure in a transactive memory system, which represents a team-level information processing system that consists of individual memory systems (Wegner, 1987).

Hobfoll (1989) proposed conservation of resources theory that individuals seek to retain, protect, and enhance their resources, and when recognizing potential or actual loss of resources, they engage in proactive build-up behaviors, such as investing in resources to prevent further loss (Hobfoll, 1989). Resources are defined as anything necessary for achieving goals (Halbesleben et al., 2014), and in CSCL situations, time, effort, and knowledge invested in a transactive memory system can be considered as both collective and individual resources. Schneider et al. (2020) found that individuals who initially employed resources for collaboration tend to maintain or reinforce transactive activities to achieve goals. Thus, in CL situations, individuals are expected to keep investing resources to prevent loss and engage in build-up behaviors.

However, forming members into a team does not guarantee a strong transactive memory system (Gillies, 2016; Zambrano et al., 2019b). It is only when a high level of interdependence among members is formed that a firm transactive memory system can be promoted members (Weinberger et al., 2007), because a high level of interdependence facilitates active information exchange and transactive activities (Zambrano et al., 2019b). During these activities, teams actively invest resources and efforts (Janssen & Kirschner, 2020) because expanding individual resource pools with new knowledge motivates them to keep employing and building resources (Halbesleben et al., 2014; Hobfoll, 1989). On the other hand, teams experiencing low levels of interdependence, which can be seen as resource loss, may suffer from psychological distress (Halbesleben & Buckley, 2004). This can cause members to become passive and less willing to invest resources and effort (Paas & van Merriënboer, 2020), resulting in unfavorable CL outcomes. Thus, based on the theory, in order to ensure successful CL, this study hypothesizes that facilitating interdependence is the key to motivating members to actively invest and exchange their resources.

Collaborative Cognitive Load Theory

One key goal of effective instructional design is to manage the level of cognitive load during the learning process, which will enable learners to acquire novel knowledge efficiently (Kirschner et al., 2006). From this aspect, CCLT provides the underlying principles on how to foster a productive CL environment by considering human cognitive architecture (Kirschner et al., 2018). The theory entails the concept of a *mutual cognitive interdependence* principle, which infers collective working memory, a shared mental space created by members of a group through communication and coordination (Kirschner et al., 2018). This study is designed to meet the three basic principles of CCLT.

Collaborative cognitive load theory & complex task

The first principle of CCLT suggests that collaboration should be used when a task is complex enough to justify collaboration. The criterion for complexity is when there are greater elements than can be processed by individual working memory alone (Kirschner et al., 2018). In contrast, a low complexity task does not require *collective working memory*, for individual working memory alone is sufficient. This principle emphasizes a benefit of CL: every collaborator is able to perform more complex tasks than they could achieve alone because they share the mental burden.

Based on this principle, the collaborative task can be designed as an ill-structured task. van Merriënboer and Kirschner (2017) define the process of engaging with high-complexity, ill-structured types of learning as *complex learning*. For this type of learning, complex tasks should be given to integrate knowledge, skills, and attitudes, thereby facilitating the formation of a cohesive and coordinated schema (Frerejean et al., 2021; van Merriënboer & Kirschner, 2017). These coordinated schemas allow learners to generate potential solutions that are broadly and highly organized, by integrating the necessary knowledge from a common body of knowledge when addressing unstructured problems encountered in the real world (Frerejean et al., 2023). Therefore, complex tasks that induce the forming of such rich schemas imply that they need to deal with a substantial volume and breadth of content, requiring the development of partial schemas that progressively evolve into more refined and comprehensive schema.

In our designed experiment, groups of members were asked to draw up digital healthcare service proposals that requires members to integrate skills of data analysis and knowledge of digital healthcare services, and at the same time, utilize practical skills such as composing a formal document. This task is a complex task, for the task does not have structured answers and it requires learners to combine different domains of knowledge. In terms of CCLT, the complex task-to-be solved imposes sufficient intrinsic cognitive load on working memory, which is the mental effort demanded by the inherent complexity of a learning task. This makes the need for collaboration evident.

Collaborative cognitive load theory & digital concept map

The second principle of CCLT proposes that transactive activities among members should be optimized to minimize extraneous cognitive load in collaborative situations (Kirschner et al., 2018). Transactive activities refer to specific extra actions like communication and coordination for learners to agree on task-related strategies, divide tasks between participants, build upon each other's ideas, achieve consensus, and other activities (Baker, 2002; Fransen et al., 2013; Mayordomo & Onrubia, 2015; Popov et al., 2017). These actions have *cost* of collaboration, which generates extraneous cognitive load. Extraneous cognitive load is considered as mental effort imposed by instructional procedures; well-planned instructional design minimizes extraneous cognitive load for working memory to allow sufficient room germane to learning (Sweller et al., 2011; Sweller et al., 2019). In a similar vein, it is crucial to structure and control the communication and coordination when designing CL to reduce extraneous cognitive load (Kirschner et al., 2018).

Removing unnecessary interactions requires every participant's knowledge to be imputed to the others (Engelmann & Hesse, 2010). Imputing knowledge is related to the process called *grounding*, which is coordinating between the collaborators making them aware of the process and content of what they are doing (Clark & Brenna, 1991). Every participant should be well informed of what others do know or do not know, and thereby develop their knowledge at the team level. According to Engelmann and Hesse (2010), a CSCL tool that is particularly well-suited for fostering awareness of the information and knowledge each participant has is the concept map. Digital concept maps represent the knowledge held by individuals linked by nodes and visualized by showing the relations between the concepts.

This study therefore utilizes digital concept maps for participants to construct their knowledge after IL as it is expected to reduce transactive costs when establishing common ground during a collaborating session. Ultimately, based on CCLT, this tool may help reduce extraneous cognitive load imposed by transactive activities and promote productive collaboration.

Collaborative cognitive load theory & complex-task sequencing

The last principle of CCLT is that a collaborative setting should elevate the level of interdependence among the members in order to constitute a collective working memory efficaciously (Janssen & Kirschner, 2020). High quality interaction occurs when every member actively contributes to complete a collaborative work. When this happens, collaborators acquire knowledge from the areas of expertise of the other participants and rely on them for solving problems (Janssen & Kirschner, 2020). It increases germane collective cognitive load that directly contributes to learning. Based on CCLT, germane cognitive load is desirable, for this indicates that the cognitive structures of the learners are being constructed to improve performance (Kirschner et al., 2018; Zambrano et al., 2019b). To sum up, in a CL setting, a high level of interdependence promoted by active knowledge contribution induces the germane collective cognitive load that facilitates learning.

In a CSCL environment, degrees of interdependence can be managed by controlling mean interdependence. This allows learners to rely on one another to receive the different types of resources that they need for the task (Janssen & Kirschner, 2020). Therefore, it can be posited that CL becomes more efficient and effective when group members have different expertise and knowledge. A previous study also supported this hypothesis, showing that group members owning varied knowledge were more committed to learning (Nebel et al., 2017), which implies that cognitive load imposed due to active knowledge exchange between members elevated germane load. In order to examine the effect of heterogenous knowledge owned by each individual promoting collaboration, this study will use heterogeneous complex-task sequencings, which refers to using both the *simplifying conditions* and the *emphasis manipulation approach*, for students to acquire prior knowledge prior to collaboration.

Simplifying conditions & emphasis manipulation complex-task sequencing: Complex-task sequencing consists of a series of task classes, which aid learners to grasp the entire view of a complex-task, and the number of task classes can be as many as an instructor perceives to be necessary (van Merriënboer & Kirschner, 2017). In the simplifying conditions approach, the learners are taught to perform all the constituent skills synchronously, but when moving to the next task classes, the conditions under which the task is trained gradually become more complicated. In the emphasis manipulation approach, the learners practice a different set of constituent skills that are emphasized on each and every task class (Choi et al., 2019; van Merriënboer & Kirschner, 2017).

In cases, where a learner needs to master a complex task *searching for literature*, for instance, under simplifying conditions approach, a learner is first given a very simple task, where the search domain is well-defined, the results come in a few relevant articles, and the keywords to use are simple. As the learner goes through a series of task classes, the final mission will be more of a real-life task under which the search domain is vague and interdisciplinary, the results come up with various relevant and irrelevant articles, and the keywords to use are varied (van Merriënboer & Kirschner, 2017). In contrast, under the emphasis manipulation approach, a learner attempts different constituent skills on every single task class (Choi & Song, 2023). In each class, the learner will be instructed to learn how to define a search domain clearly, how to sort out relevant articles from the irrelevant, and how to pick up appropriate keywords to use. In conclusion, CL method for heterogeneous instructional sequencing in this study is shown in **Figure 1**. It shows the process of representing the learning from each instructional sequencing in a digital concept map in the IL phase, and then moving to CL phase. It reproduces the complex nature of the whole task sequencing, enabling members to solve the problem space through coordination and integration of their cognitive processes, while ensuring that the team's shared knowledge, skills, and attitudes are transferred to individual capabilities.

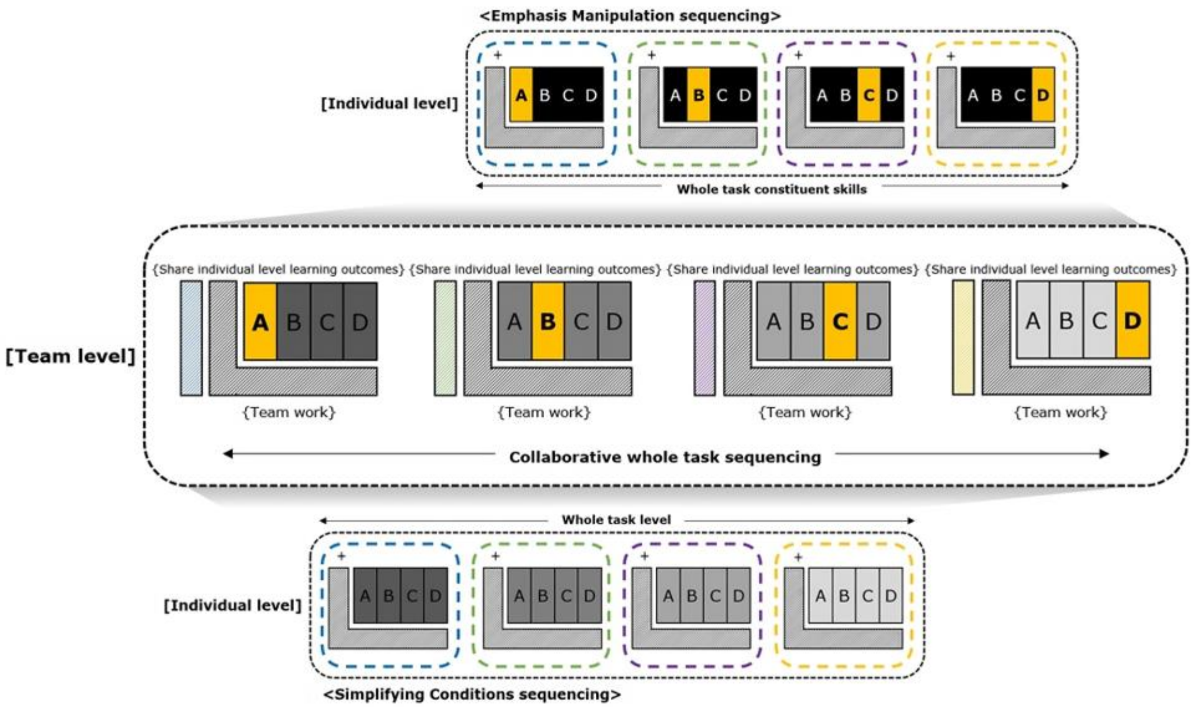

Figure 1. Designed model of individual & team learning (Source: Authors)

METHODS

Study Participants

The study was conducted on 60 college students in their 3rd to 4th year of study at Shinhan University in Gyeonggi-do, South Korea. These participants were selected based on their status as job seekers who possess a keen interest in the digital healthcare industry. They were a good fit for this experiment for they had looked for careers in the field of digital healthcare. Among the participants, 43 (71.7%) were male and 17 (28.3%) were female, with 16 (26.7%) in 3rd and 44(73.3%) in 4th. In all sessions, participants agreed to provide personal information for the study.

Study Design

The quasi-experiment conducted in this study aims to examine the effect of interdependence, which is derived from heterogeneous prior knowledge promoted by heterogeneous complex-task sequencings, on extraneous collective cognitive load, intrinsic motivation, and learning transfer. Figure 2 shows study design.

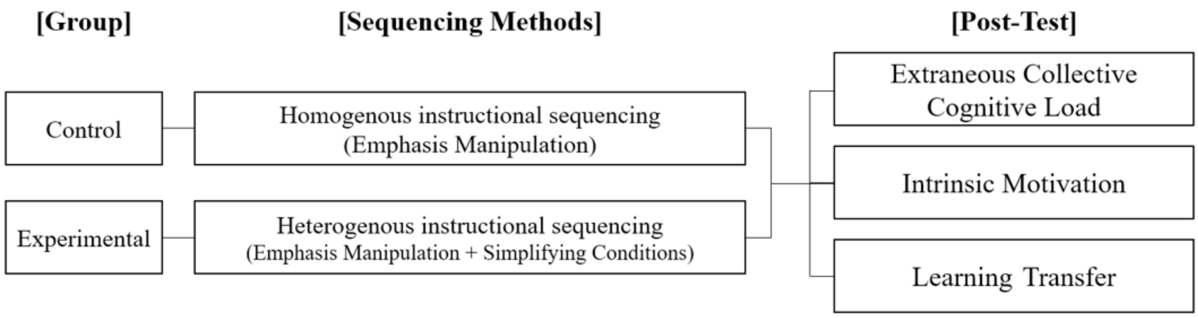

Figure 2. Study design model (Source: Authors)

In other words, the independent variable of the study is the number of complex-task sequencing types used for IL, and the dependent variables are extraneous collective cognitive load, intrinsic motivation, and learning transfer.

The specific design can be seen in the phases of IL and CL in **Figure 1**. This shows the design of the experiment, which consisted of two phases. First, at the individual level, learners acquired prior knowledge for problem solving in CL using one or both of the simplification condition and the emphasis manipulation approach (e.g., van Merriënboer & Kirschner, 2017). To be more specific, the experimental group was to gain prior knowledge by utilizing heterogeneous instructional sequencings: the emphasis manipulation and the simplifying conditions approach. Whereas, the control group was to learn only homogeneous instructional sequencings, which is the emphasis manipulation. Then, at a team level, team members represented their knowledge using concept maps and collaborated after to solve a complex task. Our hypothesis posited that the experimental group would demonstrate better collaborative performance with enhanced learning transfer, lower extraneous cognitive load, and raised intrinsic motivation.

Organizing Whole Tasks by Sequencing

The team learning task for CSCL was to *draw up a digital healthcare service proposal*. In order to instruct the materials at an individual level, two different complex-task sequencings were designed, each of them consisted of five task classes.

As shown in **Table 1**, for the simplifying conditions sequencing, individuals drew up a service development plan under a series of task instructions that gradually become complex. Whereas for the emphasis manipulation sequencing, learners focused on each different constituent skill set under each and every task class. Constituent skills that were needed for composing a service development plan are four: data analysis skills from open medical data, correlation, simple regression, and machine learning.

Table 1. Contents & composition of constituent skills by types of sequencing

C	DL	TS	Constituent skills				Contents of individual learning tasks by types of sequencing
			MRA	CA	SRA	MLA	
1	E	EM	√				Drawing up a service proposal focusing on market research analysis.
		SC	Sc				Digital healthcare service proposal should be composed of market research–review of licensing regulations–analysis of current development status & case studies–planning & proposal. Each content should be referred to page 1 (market research), 2&3 (licensing regulations), & 4 (current development status & case studies). Lastly, planning & proposal should be followed in an order of purpose of service, target, functions, & expected effect, as described on page 5.
2	M1	EM		√			Drawing up a service proposal focusing on correlation analysis.
		SC	SSC				Digital healthcare service proposal should be composed of market research–review of licensing regulations–analysis of current development status & case studies–planning & proposal. For market research, use news articles & forum materials on digital healthcare industry from last two years, & for licensing regulations, look up & utilize legislation, licensing, & renewal processes. For analysis of current development status & case studies, draw upon data regarding digital healthcare service cases from last two years. Lastly, planning & proposal should be followed in an order of purpose of service, target, functions, & expected effect.
3	M2	EM			√		Drawing up a plan focusing on simple regression analysis.
		SC	SCC				Based on current licensing regulations, market analysis from last two years, & development cases, digital healthcare service proposal should be drawn upon. Planning & proposal should be on information above.
4	D	EM				√	Drawing up a plan focusing on machine learning analysis.
		SC	CC				Digital healthcare service proposal should be drawn upon, considering market analysis, licensing regulations, & development cases. Planning & proposal need to be written with actual service development in consideration.
5	G	EM SC					Drawing up a marketing plan integrating all types of data analysis skills learnt.

Note. C: Category; DL: Difficulty level; TS: Types of sequencing; MRA: Market research analysis; CA: Correlation analysis; SRA: Simple regression analysis; MLA: Machine learning analysis; EM: Emphasis manipulation; SC: Simplifying conditions; E: Easy; M: medium; D: Difficult; G: General; Sc: Simple condition; SSC: Somewhat simple condition; SCC: Somewhat complex condition; & CC: Complex condition

Different types of complex-task sequencing aimed for learners to possess knowledge that were characteristically different from one another, even though it covered the same domain. The simplifying conditions intended for learners to grasp comprehensive knowledge of the whole-task, while the emphasis manipulation approaches led them to have profound understandings on each and every constituent skill.

Figure 3 shows the results of heterogenous instructional sequencing after IL according to the *categories 1-E* in **Table 1**, as represented by the digital conceptual tool Google Jamboard. It can be seen that the learner who learned with simplifying conditions learned a broader scope of the entire task, while the learner who learned with emphasis manipulation learned a narrower and deeper scope.

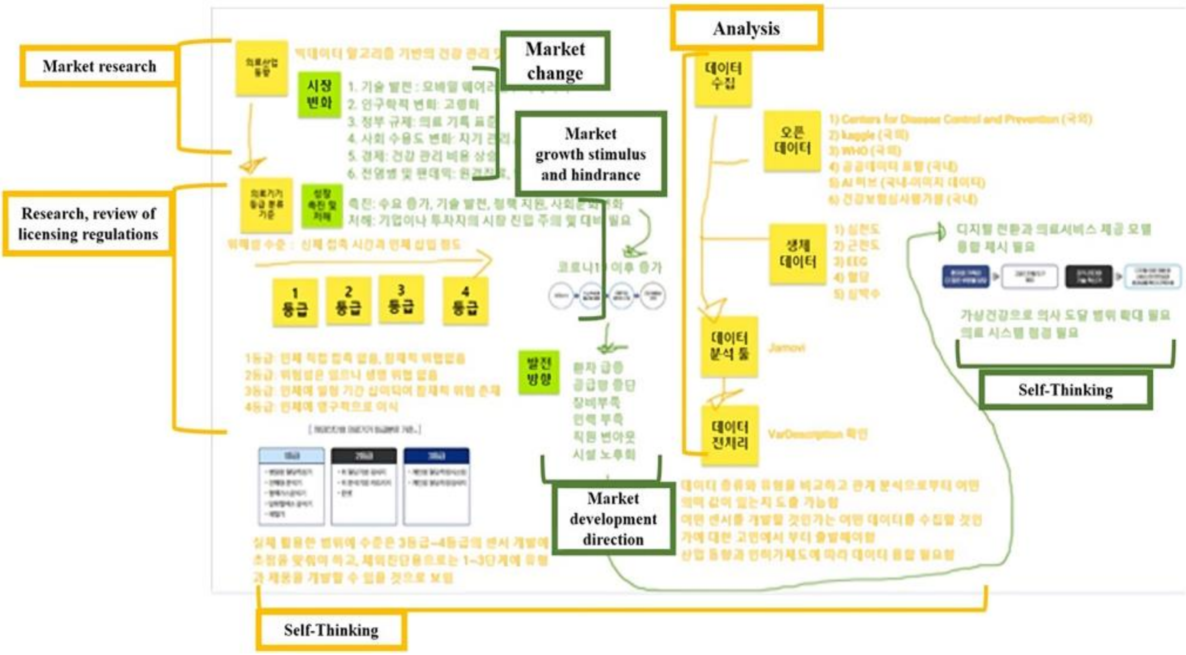

Figure 3. Digital concept map according to heterogeneous instructional sequencing (yellow: simplifying conditions & green: emphasis manipulation) (Source: Authors)

Learners who studied with simplifying conditions sequencing presented market research, review of licensing regulations, analysis, self-thinking, while learners who studied with emphasis manipulation sequencing presented market research (market change, market growth stimulus and hindrance, and market development direction), and self-thinking.

Measurement

The dependent variables to be measured include extraneous collective cognitive load experienced during CSCL situations, individuals' intrinsic motivation to engage in learning, and learning transfer to determine whether individuals apply what they have learned to their work.

Extraneous collective cognitive load test

To measure extraneous collective cognitive load, this study adopted the method employed by Retnowati et al. (2018), which measures individual's level of cognitive load, respectively and then add up to get an averaged collective cognitive load. For individual level of extraneous cognitive load, we used the measurement tool developed by Leppink et al. (2013). The questionnaire consisted of three items for extraneous cognitive load. The scale ranged from zero (strongly disagree) to 10 (strongly agree). Cronbach's alpha of this measure is .757.

Intrinsic motivation test

To assess intrinsic motivation, we used a tool developed by Ryan et al. (1990), which had been restructured from the intrinsic motivation inventory used in prior studies. The tool consisted of nine items: five items for enjoyment, two items for perceived comprehension, and two items for tension. The scale for each item ranged from one (strongly disagree) to seven (strongly agree). The contents of the items were modified to take collaborative situations into account. Cronbach's alpha of this measure is .860.

Learning transfer test

The learning transfer test was ensured to include all the constituent skills that were covered by both simplifying conditions and emphasis manipulation sequencings: market demand, licensing regulations, and the state of domestic development, and analysis skills from market research, correlation, simple regression, and machine learning. Cronbach's alpha of this measure is .804.

Participant's learning transfer was evaluated one month after the last training session (6th session). The measurement was a checklist designed for this study. The evaluation criteria and scores were determined according to the rubric in **Table 2**, which was developed by instructors and experts in digital healthcare content.

Table 2. Evaluation criteria for learning transfer measurement

C	Content	PA
1	Proposal includes 'market demand-licensing regulation-domestic development status & cases'. Uses social market data analysis, open medical data correlation, simple regression, & machine learning analysis. Considers service purpose, target, function, & expected effects in the proposal.	10
2	Proposal includes at least three components of 'market demand-licensing regulation-domestic development status & cases'. Employs at least three analyses from social market data, open medical data correlation, simple regression, & machine learning analysis. Considers at least three elements of service purpose, target, function, & expected effects in the proposal.	7
3	Proposal includes at least two components of 'market demand-licensing regulation-domestic development status & cases'. Utilizes at least two types of analysis from social market data, open medical data correlation, simple regression, & machine learning analysis. Considers at least two aspects of service purpose, target, function, and expected effects in the proposal.	5
4	Proposal includes one component of 'market demand-licensing regulation-domestic development status & cases'. Utilizes one type of analysis from social market data, open medical data correlation, simple regression, and machine learning analysis. Considers one aspect of service purpose, target, function, and expected effects in the proposal.	3
5	Proposal does not include 'market demand-licensing regulation-domestic development status & cases'. Does not use any of the listed analyses. Does not consider any elements of service purpose, target, function, or expected effects.	0

Note. C: Category & PA: Points assigned

The evaluation was carried out by two experts who have been working in the development of digital healthcare sensors and services for five years. For the results, where there were differences of opinion, the final evaluation was conducted with sufficient adjustments made until there were no disagreements.

Experimental Procedure

This study consisted of 30 groups, 15 of which was labeled as the experimental group and 15 as the control group. Each group consisted of two individuals. The experimental group (n=15) used two different types of sequencing for each individual, while the control group (n=15) used the same type of sequencing for both individuals. The study was conducted over a total of seven sessions, with each session taking place once a week, and the final session occurring one month later. Specific experimental procedure is shown in **Table 3**.

Table 3. Experimental procedure

S	Procedure		TA
	Homogenous sequencing group (control group)	Heterogenous sequencing group (experimental group)	(minutes)
S1	Orientation (introduction of this study & learning method)		10
	Formation of teams		15
	Instruction of using digital concept maps		45
S2-S6	Perform individual learning		50
	Break		10
	Visualizing knowledge using digital concept maps		15
	Perform team collaborative learning		30
	Extraneous cognitive load/intrinsic motivation test		5
S7	Learning transfer test		50

Note. S: Session & TA: Time assigned

In the first session, an introduction to this study and the learning method was provided, followed by team formation for CL. Additionally, instruction was given on how to use digital concept maps to visualize knowledge acquired from IL before CL. From the second to the sixth session, both groups engaged in IL by watching videos based on their respective sequencing approaches and were required to submit a digital-healthcare service proposal. While the same procedure was followed in each session, there were variations in the details according to the task classes (see **Table 2**). After taking a break to relieve cognitive resource depletion, participants represented their acquired knowledge on digital concept maps, and then collaborated in teams to draw up a digital healthcare plan using the information represented on the maps.

Collective cognitive load and intrinsic motivation were measured at the end of each session, and they were expected to be affected by interdependence formed while individuals collaborate using concept maps. The tests are conducted to examine the differences in each variable that occur between sessions. The seventh session took place at the end of the one month period, and learning transfer was evaluated. By having participants draw up a digital healthcare service proposal, we aim to assess meaningful learning effect regarding IL instructional sequencings for CSCL.

Analysis Method

The independent variable of this study is the complex-task sequencing types used for IL that constitutes team learning, and the dependent variables are extraneous collective cognitive load, intrinsic motivation, and learning transfer. To examine the differences in dependent variables between groups depending on the type of complex-task sequencing for each session, independent samples t-tests will be conducted, and data analysis was performed using SPSS 25.0 with a significance level of .05.

RESULTS

Results of Extraneous Collective Cognitive Load Between Groups on Sequencing Types

To investigate **RQ1**, the study analyzed extraneous collective cognitive load according to sequencing types–whether utilized homogeneous or heterogeneous instructional sequencings in IL phase. Prior to performing the independent samples t-tests, Levene's test for equality of variances confirmed the homoscedasticity assumption across all sessions, with no significant variance differences between groups at the .05 level. This validated the use of the t-test for assessing group differences in cognitive load. The results of variations in extraneous collective cognitive load are shown in **Table 4**.

Table 4. Results of extraneous collective cognitive load on sequencing types

S	Sequencing types	n	Levene's		t	Extraneous collective cognitive load			
			F	p		M	SD	p	ES (d)
1 (E)	Homogeneous sequencing	15	1.620	.21	.58	18.23	1.24	.570	
	Heterogeneous sequencing	15				18.00	.94		
	Total/mean	30				18.16	1.09		
2 (M1)	Homogeneous sequencing	15	.800	.78	2.47	17.93	.68	.020*	.89
	Heterogeneous sequencing	15				17.3	.73		
	Total/mean	30				17.62	.71		
3 (M2)	Homogeneous sequencing	15	3.790	.06	3.26	17.93	1.44	.003*	1.20
	Heterogeneous sequencing	15				16.53	.74		
	Total/mean	30				17.22	1.09		
4 (D)	Homogeneous sequencing	15	.605	.44	2.19	17.03	.81	.037*	.80
	Heterogeneous sequencing	15				16.27	1.08		
	Total/mean	30				16.65	.95		

Note. S: Session; n: Number of groups; M: Mean; & SD: Standard deviation

The study observed significant differences in extraneous collective cognitive load among groups based on the instructional sequencing types from the second to the fourth session, with exception of the first session. In the initial session, the extraneous cognitive load of the heterogeneous knowledge sequencing group (mean [M]=18, standard deviation [SD]=0.94) was slightly lower than the homogeneous group (M=18.23, SD=1.24), but this difference was not statistically significant (t[28]=0.58, p=0.57). In contrast, the second session showed a significant reduction in cognitive load for the heterogeneous group (M=17.3, SD=0.73) compared to the homogeneous group (M=17.93, SD=0.68), with a notable effect size of 0.89 (t[28]=2.47, p=0.02). Similarly, the third session revealed a significant decrease for the heterogeneous group (M=16.53, SD=0.74) with an effect size of 1.2 (t[28]=3.26, p=0.003). The fourth session continued this pattern, with the heterogeneous group showing a lower cognitive load (M=16.27, SD=1.08) and a significant effect size of 0.8 (t[28]=2.19, p=0.037). Overall, these findings suggested a consistent pattern of lower extraneous collective cognitive load in sessions employing heterogeneous knowledge sequencing compared to homogeneous sequencing.

Results of Intrinsic Motivation Between Groups on Sequencing Types

To address **RQ2** regarding the impact of sequencing types on intrinsic motivation by each session, an analysis was performed as presented in **Table 5**. The prerequisite of homoscedasticity for the independent samples t-test was verified through Levene's test across all sessions, with no significant group variance at the .05 significance level, fulfilling the condition for the t-test.

Table 5. Results of intrinsic motivation on sequencing types

S	Sequencing types	n	Levene's		t	Intrinsic motivation			
			F	p		M	SD	p	ES (d)
1 (E)	Homogeneous sequencing	15	2.330	.14	1.49	37.37	6.75	.148	
	Heterogeneous sequencing	15				40.57	4.88		
	Total/mean	30				38.97	5.82		
2 (M1)	Homogeneous sequencing	15	3.310	.08	2.02	39.63	4.97	.360*	.80
	Heterogeneous sequencing	15				43.03	3.33		
	Total/mean	30				41.33	4.15		
3 (M2)	Homogeneous sequencing	15	.515	.48	2.48	40.10	3.05	.020*	.90
	Heterogeneous sequencing	15				42.73	2.76		
	Total/mean	30				41.42	2.91		
4 (D)	Homogeneous sequencing	15	.008	.93	4.51	41.03	1.01	.000***	1.65
	Heterogeneous sequencing	15				42.63	.93		
	Total/mean	30				41.83	.97		

Note. S: Session; n: Number of groups; M: Mean; & SD: Standard deviation

The analysis revealed no significant difference in intrinsic motivation in the first period, with the group used heterogeneous instructional scoring 3.2 points higher (M=40.57, SD=4.88) than the group used homogeneous instructional (M=37.37, SD=6.75, t[28]=1.49, p=.148). However, from the second to the fourth period, significant differences were observed. In the second session, the heterogeneous group's motivation was higher by 3.4 points (M=43.03, SD=3.33), with statistical significance (t[28]=2.2, p=.036) and an effect size of .8. The third session continued this pattern with the heterogeneous group scoring 2.63 points higher (M=40.1, SD=3.05) than the homogeneous group (M=42.73, SD=2.76), which was significant (t[28]=2.48, p=.02) and had an effect size of .9. In the fourth session, the heterogeneous group's score was 1.6 points higher (M=42.63, SD=.93), with a significant t-value: (t[28]=4.5, p=.000) and a substantial effect size of 1.65.

Results of Learning Transfer Between Groups on Sequencing Types

Addressing **RQ3**, the study assessed the impact of different sequencing types on learning transfer, as depicted in **Table 6**. Prior to performing the independent samples, Levene's test was conducted to verify homoscedasticity test, and it satisfied the conditions for the independent samples t-test. The difference in learning transfer between groups based on the sequencing types was significant. The learning transfer score was .9 points higher in the individual who learned with the heterogeneous instructional sequencing (M=7.4, SD=1.63) than individual who learned with the homogeneous instructional sequencing (M=6.5, SD=1.59) and was statistically significant: t(58)=2.2=.035. Magnitude of effect is .56, which confirmed its actual significance.

Table 6. Results of learning transfer on sequencing types

S	Sequencing types	n	Levene's		t	Learning transfer			
			F	p		M	SD	p	ES (d)
	Homogeneous sequencing	15	.279	.60	2.16	6.50	1.59	.035*	.56
	Heterogeneous sequencing	15				7.40	1.63		
	Total/mean	30				6.95	1.61		

Note. S: Session; n: Number of groups; M: Mean; & SD: Standard deviation

CONCLUSIONS

This study examines the effects of heterogeneous instructional sequencings on extraneous collective cognitive load, intrinsic motivation, and learning transfer within CSCL context. The task under study involved the creation of a digital healthcare proposal. The cohort of which the members collaborated after acquiring heterogeneous knowledge through heterogeneous instructional sequencings showed noteworthy positive results among extraneous collective cognitive load, intrinsic motivation, and learning transfer.

Impact of Heterogeneous Instructional Sequencings on Extraneous Collective Cognitive Load

In CSCL setting focused on complex-task solving, it was examined that the extraneous collective cognitive load was more efficiently managed by the groups learning through heterogenous instructional sequencings compared to that with homogeneous instructional sequencings, particularly in the 2nd, 3rd, and 4th sessions, except for the 1st.

The inefficiency of the initial session is attributed to the supportive information provided in the first task class, which inhibits the level of interdependence among the collaborators. The overall task, designed for CL, was supposed to integrate instructions from both types of instructional sequencings and, at the same time, be challenging for an individual to perform alone. However, influenced by the simplifying conditions approach, the instruction of the initial collaborative task class was explicit, limiting the learner's performance area (van Merriënboer & Kirschner, 2017). As a result, collaborative work might have been perceived as unnecessary. A learner acquiring knowledge through an emphasis manipulation would not have been able to notice a significant difference between what the opponent learned through the simplifying conditions approach and the supportive information given in the collaborative task class. This aligns with the research conducted by Schenider et al. (2020), which observed that low performance in collaborative work often stems from a lack of perceived usefulness of the other participants' knowledge, where it benefits only individual members and not the group as a whole.

In contrast, from the second to the fourth session, as the task instructions became less clear and the problem space gets broader, it led to a rise in interdependent transactional activities among collaborators. As Janssen and Kirschner (2020) suggested, individuals, when they encounter a task that is difficult for them to solve themselves, start noticing a difference in the knowledge represented that collaborators bring, resulting in increased *means interdependence*.

Impact of Heterogeneous Instructional Sequencings on Intrinsic Motivation

In CSCL environment, it was observed that in the groups engaged with heterogeneous instructional sequencing, intrinsic motivation increased in sessions 2, 3, and 4, with the exception of the first session. This pattern, similar to extraneous collective cognitive load, suggests that group members developed a stronger trust relationship for collaboration as the level of interdependence rose. This finding agrees with previous work finding that trust relationships are likely to form when individuals perceive that their resources can be preserved or expanded within an interdependent relationship (Janssen & Kirschner, 2020), thereby enhancing intrinsic motivation (Halbesleben et al., 2014). The absence of trust in the first session can be attributed to the similarity in information presented by individuals using digital concept map and the supportive information provided in the collaborative task classes. Consequently, as indicated by Dillenbourg et al. (2009), transactional activities between collaborators may not have been as active in the initial sessions, where CL was perceived as unnecessary. However, for the second to the last session, the problem space increased as the supportive information was phased out. This caused the total cognitive resources required to exceed the sum of what the individuals members could provide (Kirschner et al., 2011), leading to a more active interdependent relationship. This finding also aligns with the research conducted by Fransen et al. (2011), which highlighted that the information shared before CL helps understand the extent of shared knowledge, and as interdependency on diverse knowledge resource rises, so does intrinsic motivation.

Impact of Heterogeneous Instructional Sequencings on Learning Transfer

In a CSCL setting involving complex task solving, it was found that individuals who acquired knowledge through a heterogeneous instructional sequencings exhibited a higher level of learning transfer compared to those who learned via homogeneous instructional sequencings. Janssen and Kirschner (2020) have highlighted the importance of considering task complexity when inducing means interdependence in collaborative setting. Contrary to their concerns, this study revealed that the complementary knowledge acquired through heterogeneous instructional sequencings effectively enhances means interdependence, even when the task complexity is high. This finding implies that this approach equips groups to better solve practical problems through collaborative exchange of explanations and complementary teamwork (Herrington & Oliver, 2000), which induces lower extraneous collective cognitive load and higher intrinsic motivation, and increased learning transfer.

IMPLICATIONS & LIMITATIONS

Theoretical Implications

The theoretical implications of this study are as follows: First, configuring the domains of complex tasks differently through heterogeneous instructional sequencing in CSCL situations can facilitate relatively extensive complex learning and promote positive interactions among learners. Complex tasks, requiring the integration and coordination of knowledge, skills, and attitudes, involve high cognitive load as it necessitates connecting procedures in task performance. When constructing a complete task from interconnected procedures, performing it as a single whole-task becomes challenging. While van Merriënboer and Kirschner (2017) propose dividing the whole task into sub-tasks as a solution to the difficulty of complex tasks, they do not restrict it to the sole remedy. In CSCL situations, where knowledge can be represented, as demonstrated in this study, adjusting individual domains of complex task performance can lead to positive interactions for problem-solving. Prior studies (Fischer et al., 2007; Yang, 2023) have suggested the use of scripts as a method for coordination in CSCL, but adjusting sequencing at IL phase can also contribute to enhancing interactions in collaborative problem-solving.

Second, encouraging the exploration of heterogeneous knowledge among individuals using cognitive representation tools can enhance trust for collaborative problem-solving and elevate intrinsic motivation. Providing situations conducive to collaboration alone does not guarantee effective collaboration; there must be an interdependent relationship among the collaborating members. Within such relationships, individuals aim to invest and expand their knowledge resources. Engaging in learning by phases within these interdependent relationships can promote proactive motivation for CL by establishing a strong transactive memory system. Consequently, encouraging awareness of shared knowledge in complex collaborative task performance involves bringing others' knowledge into the problem space and contributing one's own knowledge. This process facilitates complementary knowledge building through the integration of two complementary sets of expertise.

Third, structurally inducing interdependence in CSCL situations based on heterogeneous knowledge allows for the occurrence of complex CL, encouraging high mental effort, and fostering positive interactions. The integration and coordination of heterogeneous knowledge enables more effective exploration and adjustment of the problem space compared to homogeneous knowledge. This aligns with the concept of the collective working memory effect, as suggested by Sweller et al. (2019), where the individual working memory spaces of members are shifted to a collective working memory space. This promotes gradual adjustment and effective elaboration through shared processing.

Practical Implications

First, to facilitate efficient transaction activities in performing complex tasks in CSCL settings, teams should be composed of members possessing heterogeneous knowledge. Performing ill-structured tasks like complex problem-solving requires generating diverse solutions and exploring the problem space in various ways (Jonassen, 2000). Members with heterogeneous knowledge can engage in a range of interactions and utilize the problem space more productively (Yang, 2023). According to Zhang et al. (2016), teams composed of members with homogeneous knowledge may not require coordination activities for communication or could have detrimental effects on learning. Therefore, when constructing teams for CL, instructors should form teams that interdependently rely on differences in domains rather than differences in knowledge levels to ensure more effective collaboration.

Second, instructors should also consider the design of IL to develop a CL environment, where positive interactions can take place. CL aims for maximizing the learning of each member by collectively solving problems (Johnson & Johnson, 1999). Such a collaborative approach to performing complex learning tasks should enable efficient problem-solving for the whole task (Kirschner et al., 2018). Vogel et al. (2016) suggests using scripts as a method to provide positive interactions. However, from a design perspective, this is not necessary as adjusting the domain of individual knowledge acquisition differently and ensuring differences in prior knowledge can lead to efficient knowledge acquisition through shared integration and coordination during CL phase.

Third, CSCL is not a learning method intended to replace face-to-face situations but requires consideration of how technology can supplement aspects that are challenging to achieve in face-to-face scenarios (Dillenbourg et al., 2009). In situations where CL is conducted face-to-face, it is essential to devise methods for effectively sharing heterogeneous knowledge. One approach, such as in this study, is to use cognitive representation tools to make partners aware of each other’s knowledge. This fosters the perception that partners can contribute equally to problem-solving by possessing knowledge different from each member of the group. Consequently, this encourages individuals to willingly engage in interactions, potentially enhancing individual roles and responsibilities (Wang, 2009).

Limitations & Future Research

The limitations of this study are as follows: First, this study conducted a quantitative analysis using questionnaires. We analyzed the questionnaires collected for each session of the learning process. The questionnaires were analyzed to examine extraneous collective cognitive load and intrinsic motivation. However, to clearly identify the reasons behind the high or low scores, in-depth interviews should be conducted alongside the quantitative analysis. Second, it is crucial to investigate the interaction of effective differences occurring within the groups. This study divided the groups into heterogeneous and homogeneous groups to examine inter-group differences, aligning with the design paradigm in CSCL paradigm proposed by Yang (2023). However, since paradigms are continuously interconnected and have mutual influences, it is necessary to identify which interactions might have had an impact. Future research should include within-group analysis, similar to the analysis by Schneider et al. (2020) of interactions within high-performance and low-performance groups, to enable a more comprehensive analysis. Third, the approach of performing CSCL in groups with heterogeneous compositions should be validated in practical settings. This study conducted experiments with enrolled learners, excluding considerations for partnerships. In practical situations, members may form a certain level of partnerships, leading to a higher basic level of interaction. In such cases, learners might perceive collaboration facilitated by tools as unnecessary interaction. Therefore, promoting face-to-face collaboration to exchange heterogeneous knowledge can foster more positive interactions and achieve a higher level of elaboration.

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