The Effects of Task Selection Approaches to Emphasis Manipulation on Cognitive Load and Knowledge Transfer

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Abstract

Emphasis manipulation is a way to help learners by directing their attention to particular subcomponents of a learning task. This study investigated the effects of different approaches to emphasis manipulation on knowledge transfer and cognitive load. This was done by examining the impact of three task selection strategies: system-controlled, learner-controlled, and shared-controlled. Forty-five students (n = 45) in the first or second year of high school were randomly assigned to three groups and each group used a different type of task selection to manipulate emphasis in a complex learning context. The system-controlled group carried out learning tasks that were identified as essential by the system. The learner-controlled group selected and carried out learning tasks they needed to learn. The shared-controlled group chose and carried out learning tasks that they wanted to learn from a list of suggested learning tasks. The tasks had four learning phases: pre-test, training, mental-effort rating, and transfer test. After participants completed the training, their cognitive load was measured. One week after the training, a transfer test was conducted to measure the constituent skill acquisition. The findings revealed that the system-controlled task selection strategy was the most effective in optimizing cognitive load and enhancing knowledge transfer. In addition, learners benefited from personalized guidance on learning task selection based on their expertise. Given that the shared-controlled task selection method was more effective than the learner-controlled task selection, this study's results indicate that learners should be provided with information about how to select learning tasks when they are allowed to do so.

Keywords: cognitive load, complex learning, emphasis manipulation, task selection

Modern society requires individuals to solve real-life problems. In education, there is more and more emphasis on using complex tasks to help learners integrate the knowledge, skills, and attitudes essential for effective task performance in real-life applications (Merrill, 2002; van Meeuwen et al., 2018; Frerejean et al., 2019). Although previous studies have shown complex tasks effectively enhance learners' cognitive skills and help them achieve higher-quality solutions (Beers et al., 2005; Slof et al., 2011; Shin et al., 2018), learners can have difficulty carrying out such tasks. One reason complex tasks are difficult is they can impose a high cognitive load on learners due to the fact that they are loosely structured problems composed of diverse subcomponents (van Merriënboer & Kirschner, 2018; Jung et al., 2019).

To overcome this difficulty, researchers have suggested using whole-task sequencing strategies such as simplifying conditions, knowledge progression and emphasis manipulation (van Merriënboer & Kirschner, 2018). The simple to complex sequencing of whole tasks facilitates the learning experience by encouraging learners to coordinate and integrate the constituent skills that make up a whole task (van Merriënboer & Kirschner, 2018). One of the advantages of whole-task sequencing is that it enables learners to carry out whole tasks without segmenting the elements into individual tasks. For example, emphasis manipulation is a whole-task approach that can help learners see the "big picture", as it allows them to practice constituent skills within the context of a whole task (Gopher, 2007; van Merriënboer & Kirschner, 2018; Frerejean et al., 2021). Emphasis manipulation directs learner focus to specific subcomponents of a task, rather than having them perform the whole task all at once (Gopher et al., 1989; Frerejean et al., 2021). As a result, emphasis manipulation can help learners coordinate constituent skills and process whole tasks while focusing on learning component skills.

Although many studies have indicated emphasis manipulation is an effective way to direct learner attention within a whole-task module, some researchers have argued that it is ineffective because the whole task is repeated many times throughout the process (Gopher et al., 2007). Repetitive whole-task performance can increase cognitive load by increasing the amount of redundant information, especially as learners' expertise increases (Chen, 2008). This can cause the expert reversal effect (Sweller, 1994; Kalyuga et al., 2003), particularly for more experienced learners who are already proficient in selecting, controlling and monitoring their learning processes (Ertmer & Newby, 1996). To reduce unnecessary cognitive load and promote cognitive skill acquisition, previous researchers have recommended a *personalised* approach to emphasis manipulation based on learners' prior knowledge (Corbalan et al., 2006; Kalyuga & Sweller, 2014).

Researchers have focused on task selection strategies as an effective personalised approach (Salden et al., 2004; Salden et al., 2006). The rationale for focusing on task selection strategies is they can enable learners to learn interrelated constituent skills more efficiently. Such strategies facilitate the cognitive learning process by ensuring that the task classes match the learners' level of expertise (Corbalan et al., 2006). During task selection, learners can be provided with a personalised sequence of tasks based on their specific proficiency and current learning status. This sequence of learning tasks can be chosen by a system, an instructor or a learner (Paas et al., 2011). Ideally, more personalised learning sequences, informed by input from learners, will allow them to perform learning tasks that are most suitable for their current level of expertise. For this reason, a personalised task selection approach to emphasis manipulation is expected to prevent the expert reversal effect and promote constituent skill acquisition.

Some studies have shown that the system-controlled approach to task selection is effective at complex learning (e.g., Camp et al., 2001; Kalyuga, 2006). In contrast, others have shown that high levels of system control may negatively affect learners' motivation (e.g., Corbalan et al., 2006), suggesting that giving learners control over task selection is a more effective approach to complex learning (e.g., Salden et al., 2006). Despite the advantages of task selection, research has produced inconclusive results about the effectiveness of various task selection strategies. In addition, few studies have explored the relationships between task selection, whole-task sequencing, and emphasis manipulation.

To address these issues, the current study explored effective instructional strategies for whole-task sequencing based on personalised approaches to complex learning. Specifically, the study examined three types of task selection strategies for emphasis manipulation. These strategies were categorised according to the *agent* who selected the learning tasks: system, learner, and shared (system and learner).

This study's research questions were formulated to identify effective emphasis-manipulating task selection strategies for learners. The first question was, "What are the effects of different task selection strategies on learners' cognitive load during emphasis manipulation sequencing?" The second question was, "What are the effects of task selection strategies on knowledge transfer during emphasis manipulation sequencing?" By addressing these questions, this study was conducted to identify the most effective task selection approaches to emphasis manipulation for complex learning.

Theoretical Background

Emphasis Manipulation Sequencing

Complex learning requires learners to integrate knowledge, skills and attitudes. Researchers have proposed many methods of promoting cognitive skill acquisition during complex learning (van Merriënboer & Kirschner 2018; Jung et al., 2019). Although the methods differ, they share a focus on learning experiences based on authentic, real-life tasks (Kirschner et al., 2006; Wang et al., 2017). The cognitive tasks used in complex learning have been shown to improve learners' cognitive skill acquisition and facilitate knowledge transfer (Kester & Kirschner, 2012; van Merriënboer & Kirschner, 2018).

Studies have recommended whole-task sequencing as an effective way to help learners coordinate and integrate constituent skills and promote knowledge transfer (van Merriënboer & Kirschner, 2018). In particular, emphasis manipulation, which is a whole-task sequencing strategy that emphasises or de-emphasises constituent skills within a whole-task project, can help learners to acquire complex cognitive skills (van Merriënboer & Kirschner, 2018). In emphasis manipulation sequencing, the relative emphasis on selected subcomponents is manipulated, but the whole task remains intact (Gopher et al., 1989; van Merriënboer & Kirschner, 2018). The essence of emphasis manipulation is that learning occurs continuously as the subcomponent priorities are varied. Emphasis manipulation allows learners to work on all of the constituent skills from the beginning of the learning process while focusing learners' attention on the most significant subcomponents. It is most effective if priorities and trade-offs are established and appropriate attention-allocation learning strategies identified (Gopher, 1993).

Despite emphasis manipulation's ability to help learners focus on important subcomponents of effectively learning the target material, it can create cognitive difficulties if too much redundant information is generated. This can happen when the whole learning process is repeated from beginning to the end while emphasizing different subcomponents. As a result, instructional strategies that prevent unnecessary cognitive load and promote learning performance should be applied when using emphasis manipulation.

Task Selection Strategy

Researchers studying whole-task sequencing have proposed task selection strategies for personalised learning that can effectively provide learning content that matches the characteristics and differences of individual learners (van Merriënboer & Kirschner, 2018). Some researchers have categorised task selection strategies according to the agent who determines (controls) which learning tasks will be emphasised: system control, learner control and shared control (Corbalan et al., 2006; Corbalan et al., 2008; Paas et al., 2011). In a system-controlled condition, learning tasks are selected by an instructional agent such as the computer system or teacher (Tennyson & Buttery, 1980; Corbalan et al., 2006). The system-controlled approach is used in some electronic learning environments, providing personalised learning by selecting tasks based on learners' current stage of learning (Camp et al, 2001). However, high levels of system control may negatively affect learners' interest and task involvement in learning (Corbalan et al., 2006). To prevent this, there is a need for learner control over some aspects of the learning process.

Salden and colleagues (2006) reported that giving learners control over task selection promotes learners' motivation and helps them engage in self-regulated learning. As the aim of complex learning is to promote complex cognitive skills and self-regulation skills, learner-controlled instruction is believed to lead to learning success. Giving learners task selection opportunities assumes that they are able to identify the learning tasks that are the most suitable to their needs (van Merriënboer, 2002; Bergamin & Hirt, 2018). In turn, this may increase learner motivation and strengthen their belief that they can accomplish their learning goals, ultimately leading to successful complex learning. In addition, learner control avoids unnecessary cognitive load by eliminating non-essential learning tasks and increasing germane cognitive load by increasing learning engagement (Vandewaeter & Clarebout, 2013; Lange, 2018). However, learner-controlled task selection is not always effective. Task selection may overburden novices and learners may omit essential parts of learning tasks when selecting one learning task from a large number of learning tasks (Merrill, 2002; Schwartz, 2004).

Another task selection strategy, shared-controlled, has been developed to compensate to address the limitations of learner-controlled selection (Corbalan et al., 2006). In the shared-controlled approach, learners select tasks while referring to personalised information about the most essential learning tasks based on their expertise. Some researchers have reported that shared control is more efficient than either system control or learner control alone, as it helps learners to make the right selections and to eliminate redundant learning tasks (van Meeuwen et al., 2018).

Cognitive Load and Expert Reversal Effect

Cognitive load theory (CLT) developed by Sweller (1988) has suggested that cognitive load is a critical factor in the process of complex tasks learning (Salden et al., 2006). Cognitive load can be divided into three elements: Intrinsic cognitive load, Extraneous cognitive load, and Germane cognitive load (Sweller, 1994). Intrinsic load is determined by the complexity of learning elements that are related to performing tasks (Gerjets et al., 2006). Extraneous load is imposed learning methods, information presentation methods, and learning strategies (Corbalan et al., 2008). Intrinsic load and extraneous load do not promote learning while germane load does (Moreno & Park, 2010). Germane load is imposed as a result of the cognitive efforts required to form schemas during learning. Germane cognitive load occurs by learning methods designed to promote automation, and researchers suggest securing the space for germane load by reducing extraneous load (Jung et al., 2016). Studies exploring CLT have suggested that intrinsic load and extraneous load must be reduced and germane load promoted for successful complex learning (Sweller, 1994; Moreno & Park, 2010).

Although emphasis manipulation sequencing is effective for teaching complex cognitive skills, repeated learning processes can lead to the expert reversal effect (Sweller, 1994; Kalyuga et al., 2003). Many studies of this effect have shown that educational approaches that are successful for novice learners are often less effective for more experienced learners (Jung et al., 2016; Kalyuga & Renkl, 2010; van Merriënboer & Sweller, 2010). Repetitive cognitive processing and learning materials constitute extraneous cognitive load, which may hinder learning. Thus, appropriate learning tasks and methods that consider learners' prior knowledge are needed to prevent the expert reversal effect as learner expertise increases over the learning process (Kalyuga & Renkl, 2010; Jung et al., 2016; Choi et al., 2019).

Individualised instruction that considers learners' expertise can be an effective strategy, as it may provide learners with appropriate learning tasks and reduce unnecessary cognitive load. Individual learners' cognitive load is determined by interactions between the learners' expertise and the difficulty of the learning tasks (Paas et al., 2003); thus, redundant educational materials and support can be removed as learner proficiency in a specific learning task improves. In addition, to optimise cognitive load and promote learning efficiency, educational guides must be provided at the time they best suit learners' needs. Using a personalised learning strategy to guide emphasis manipulation is likely to be an effective approach to reducing cognitive load and achieving learning objectives because it is challenging to identify the level of learning difficulty and particular subcomponent skills that should be emphasised for each individual learner. Thus, this study examined how applying three task selection approaches (system-controlled, learner-controlled, shared-controlled) to emphasis manipulation affected the success of complex learning.

Research Methodology

Participants

Forty-five students (n = 45) in the first or second year of high school in South Korea enrolled in a career development class were participants in this study. Permission to conduct this study was initially obtained from the school, as well as the students and their parents. Thus, there were no significant ethical conflicts. The students were 17 or 18 years old and 31 students (70%) were male and 14 (30%) were female. Participants were randomly assigned to one of three groups: a system-controlled group (SC; n=15), a learner-controlled group (LC; n=15), and a shared-controlled group (SHC; n=15).

Description of Task Selection Learning Environment

The task selection learning environment developed for this study consisted of three categories of constituent skills related to some advanced features in PowerPoint: animation effects, chart and graph effects, and multimedia effects. Each category included five constituent skills (see Table 1). Each of the three groups was presented with a different set of learning tasks on the main page of a website (see Figure 1). The system-controlled instruction condition provided a list of learning tasks in which the participants were weak; the learner-controlled instruction condition provided a list of all of the learning tasks; and the shared-controlled instruction condition provided a list of suggested learning tasks. When the participants clicked on a particular learning task displayed on the main page, a short video lecture played. Brief videos (3 – 5 minutes) were provided to help participants acquire the constituent skills. None of the learning phases for constituent skill acquisition were time limited. Each group performed different learning tasks based on the type of task selection control.

Table 1
List of Constituent Skills

Animation effects	Chart and graph effects	Multimedia effects
1. Screen transitions	1. Insert a table	1. Word Art
2. Add animation effects	2. Insert a chart	2. Smart Art
3. Customise animation effects	3. Chart layout	3. Insert an audio file
4. Modify animation effects	4. Edit data in Excel	4. Insert a video file
5. Animation Pane	5. Change chart type	5. Hyperlink

Figure 1
Structure of Task Selection Learning Environment

Pre-Test

Fifteen self-rated problems were used to measure participants' prior knowledge of the target skills. A computer-based task was developed to measure the learners' level of competence in PowerPoint. The participants were asked to make PowerPoint slides so that their weakest constituent skills could be identified. Responses to pre-test items were categorized by three evaluators as either poor and awarded a score of 0 or good and awarded a score of 1. Thus, the minimum pre-test score was 0 and the maximum was 15. There was no difference between the groups' pre-test scores [$F(2, 42) = .097$, $p > .05$].

Experimental Conditions

The system-controlled (SC) instruction condition provided learners with the learning tasks that they were the weakest in, which was determined by learners input. The SC group only carried out learning tasks that were identified as essential by the system based on their pre-test results. The SC group was not given the opportunity to carry out other learning tasks (see Figure 2).

The learner-controlled (LC) instruction condition provided learners with a list of all of the learning tasks. The learners in the LC group selected the learning tasks that they needed to learn and then carried out these learning tasks. The LC group was not provided with guidance on what was essential information or feedback to help with their task selection (see Figure 3).

The shared-controlled (SHC) instruction condition provided learners with a list of suggested learning tasks based on their pre-test results. However, unlike those in the SC group, the learners in the SHC group could choose any learning task that they wanted to learn (see Figure 3).

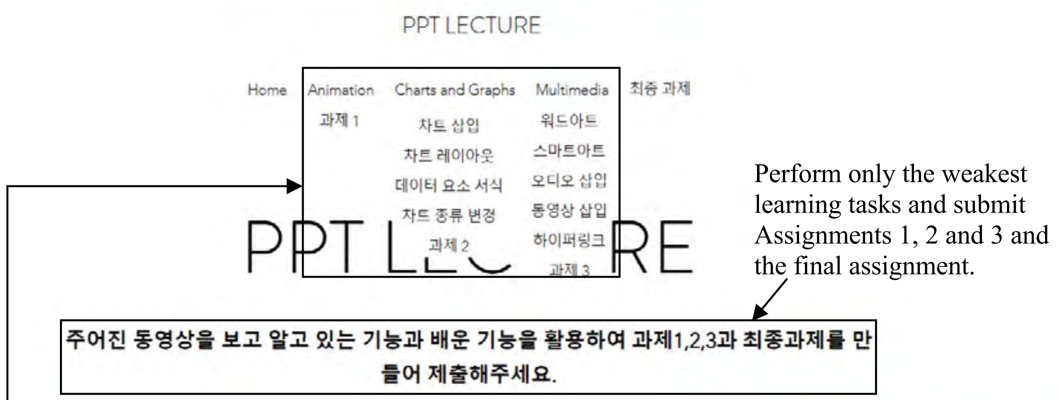
Table 2

Three Types of Selection Control and Learning Tasks

Group	Type of control	Learning tasks
SC	System	Weakest learning tasks
LC	Learner	All the learning tasks without information about which are the essential learning tasks
SHC	System and Learner	All the learning tasks with suggestions about essential learning tasks

Figure 2

Weakest Learning Tasks for the SC Group

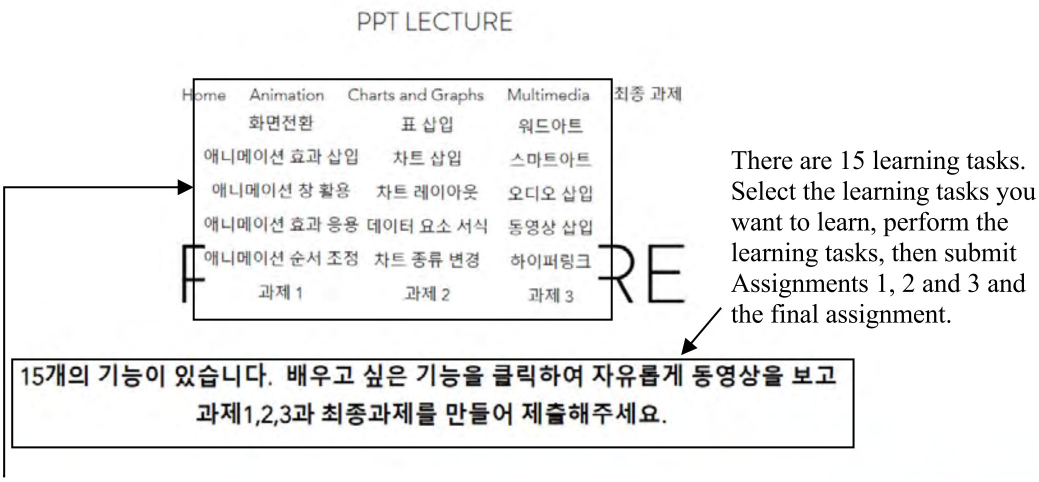


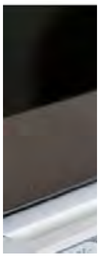
Weakest sets of learning tasks

Animation	Charts and graphs	Multimedia
Assignment 1	Insert a chart	Word Art
-	Chart layout	Smart Art
-	Edit data in Excel	Insert an audio file
-	Change chart type	Insert a video file
-	Assignment 2	Hyperlink
		Assignment 3

* *Functions to perform specific learning tasks were open to learners in the system-controlled group.*

Figure 3
All of the Learning Tasks for the LC group and the SHC Group





All of the learning tasks

Animation	Charts and graphs	Multimedia
Screen transitions	Insert a table	Word Art
Add animation	Insert a chart	Smart Art
Customise animation	Chart layout	Insert an audio file
Modify animation	Edit data in Excel	Insert a video file
Animation Pane	Change chart type	Hyperlink
Assignment 1	Assignment 2	Assignment 3

** Functions to perform whole learning tasks were open to learners in the learner-controlled group.*

Cognitive Load Measures

A 10-point Likert-scale was used to measure cognitive load (Leppink et al., 2013). Previous studies have used this instrument to measure cognitive load (e.g., Becker, Klein, Gößling, & Kuhn, 2020; Thees, Kapp, Strzys, Beil, Lukowicz, & Kuhn, 2020). The scale ranged from "*not at all the case*" (0) to "*completely the case*" (10). The measurements consisted of three intrinsic load items, three extraneous load items, and four germane load items (see Table 3). All of the participants were asked to rate their cognitive load after the training phase. The reliability analysis revealed a Cronbach's alpha value of 0.807 for the intrinsic load items, 0.895 for the extraneous load items, and 0.911 for the germane load items.

Table 3
Sample Questions to Measure Cognitive Load

Type of load	Questionnaires
Intrinsic load	The topic/topics covered in the activity was/were very complex.
Extraneous load	The instructions and/or explanations during the activity were very unclear.
Germane load	The activity really enhanced my understanding of the topic(s) covered.

Transfer Measures

Learning outcomes were measured using a transfer test. One week after the training session, the participants were asked to make PowerPoint slides related to their major and recent trends in their disciplines. The purpose was to use the constituent skills acquired during the training phase. The transfer tests were recorded in the task selection learning environment to determine whether the participants had used the constituent skills properly. Three evaluators were chosen to rate the submitted PowerPoint slides using two scale values: *poor* (0) or *good* (1). The minimum transfer test score was 0 and the maximum was 5. The measurements consisted of three items (see Table 4). Interrater reliability analysis revealed a Cohen's Kappa value of 0.765.

Table 4
Sample Indicators to Measure the Level of Knowledge Transfer

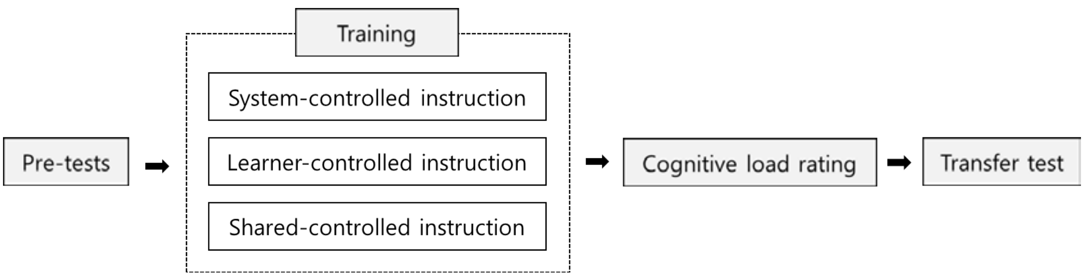
Item #	Questionnaires	Categories
1	Student made PowerPoint slides using screen transitions.	Animation effects
2	Student made PowerPoint slides using a table.	Charts and graph effects
3	Student made PowerPoint slides using a video file.	Multimedia effects

Procedure

The study was conducted over two weeks in an online learning environment. The participants were assigned to one of three groups and asked to perform tasks across four learning phases: pre-tests, training, mental-effort rating, and transfer tests (see Table 5). After the pre-tests, each group was provided with learning tasks associated with their assigned task selection condition. They then carried out the learning tasks for constituent skill acquisition. The participants were required to watch the short video lectures and then make three presentation slides that were identical to the presented samples. After the participants completed the training, their cognitive load was measured. One week after the training phase, a transfer test was administered to measure the acquisition of constituent skills.

In the transfer test, participants were asked to make PowerPoint presentation slides on a specific topic (My dream major at university). Participants were asked to use all of the functions about PowerPoint they had learned during the training phase. The PowerPoint presentation slides made in the transfer test were evaluated by one visual communication expert and two educational experts. All of the procedures and responses were recorded using a video recording program so the exact performance of the participants could be evaluated (see Figure 4).

Figure 4
Learning Processes in the Task Selection Learning Environment



Data Collection and Analysis

This study used a one-way factorial design. The independent variable was type of task selection control and the dependent variable was cognitive load, which consisted of intrinsic load, extraneous load, and germane load, as well as learning success. Analysis of variance was conducted to compare the cognitive load and learning between the three groups. The significance level was set at 0.05. The Statistical Procedures for Social Sciences version 24.0 was used to code and analyze the data.

Results

Effects of Task Selection on Learners' Cognitive Load

The SC group had the highest intrinsic cognitive load (M = 10.73; SD = 3.10), and the SHC group had the lowest intrinsic cognitive load (M = 9.40; SD = 2.26). The LC group had the greatest extraneous cognitive load (M = 10.33; SD = 2.47), and the SC group had the lowest extraneous cognitive load (M = 8.33; SD = 2.13). The SC group had the highest germane cognitive load (M = 14.13; SD = 5.09) (see Table 5).

Table 5
Descriptive Statistics for Cognitive Load and Knowledge Transfer (N=45)

Types of control	*n*	Intrinsic load		Extraneous load		Germane load		Transfer	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
System control	15	10.73	3.10	8.33	2.13	14.13	5.09	4.93	0.70
Shared control	15	9.40	2.26	9.07	3.22	9.60	4.01	4.80	0.49
Learner control	15	10.33	2.47	14.07	4.79	9.20	2.14	4.30	0.77

ANOVA for cognitive load revealed that the types of task selection control had a statistically significant effect on extraneous cognitive load [F (2, 42) = 11.59, $p < .001$, = .36] and germane cognitive load [F (2, 42) = 3.35, $p < .05$, η^2 = .26], but not intrinsic load [F (2, 42) = 1.01, $p >$ .05] (see Table 6).

A *post hoc* Tukey test showed that the differences between the extraneous cognitive loads of the SC and LC groups (p = .000) and between the SHC and LC groups (p = .001) were statistically significant. A post hoc Tukey test also showed that the differences in the germane cognitive loads of the SC and LC groups (p = .005) and SHC and LC groups (p = .011) were statistically significant. These results mean that the SC and SHC groups experienced statistically significantly less extraneous cognitive load than the LC group. However, there was no statistically significant difference in the extraneous cognitive loads experienced by the SC and SHC groups. Furthermore, the SC and SHC groups experienced statistically significantly similar germane cognitive load that was statistically significantly more than the LC group.

Table 6
ANOVA of Cognitive Load

Type of load	Sources	*SS*	*df*	*MS*	*F*	*p*	η^2
Intrinsic load	Between groups	14.04	2	7.02	1.01	.373	
	Within groups	291.87	42	6.95			
	Total	305.91	44				
Extraneous load	Between groups	292.04	2	146.02	11.59	.000*	.356
	Within groups	529.20	42	12.60			
	Total	821.24	44				
Germane load	Between groups	225.24	2	112.62	7.24	.000*	.256
	Within groups	653.73	42	15.57			
	Total	878.98	44				

$*p < .05$

Table 7
Post hoc Tukey Test Results for Cognitive Load

Cognitive Load	**Sources**	**Type of control**		
		System control	**Shared control**	**Learner control**
Intrinsic Cognitive Load	System control		1.33 (.358)	.40 (.909)
	Shared control	-1.33(.358)		-.93 (.60)
	Learner control	-.40 (.909)	.93 (.60)	
Extraneous Cognitive Load	System control		-.73 (.839)	-5.73 (.000**, -1.61)
	Shared control	.73(.839)		-5.0 (.001*, -1.41)
	Learner control	5.73 (.000**, 1.61)	5.0 (.001*, 1.41)	
Germane Cognitive Load	System control		.40 (.964)	5.13 (.005*, 1.21)
	Shared control	-.40 (.964)		4.73 (.011*, 1.11)
	Learner control	-5.13 (.005*, -1.21)	-4.73 (.011*, -1.11)	

*p<.05 **p<.001

Effects of Task Selection on Knowledge Transfer

The SC group had the highest transfer success (M = 4.93; SD = 0.70), followed in decreasing order by the SHC group (M = 4.80; SD = 0.49) and the LC group (M = 4.30; SD = 0.77) (see Table 5). The ANOVA test for transfer success showed that task selection type statistically significantly affected knowledge transfer success, F (2, 42) = 3.35, $p < .05$ (see Table 8). A *post hoc* Tukey test showed that the differences in knowledge transfer success between the SC and LC groups (p = .005) and the SHC and LC groups (p = .011) were statistically significant. Both the SC and SHC groups had statistically significantly greater knowledge transfer success than the LC group.

Table 8
ANOVA of Knowledge Transfer

Sources	*SS*	*df*	*MS*	F	*p*	η^2
Between groups	2.98	2	1.49	3.35	.045*	.138
Within groups	18.67	42	0.44			
Total	21.64	44				

*p < .05

Table 9
Post hoc Tukey Test Results for Knowledge Transfer

Sources	**Types of control** **System control**	**Shared control**	**Learner control**
System control		.20 (.950)	2.20 (.005*, 1.23)
Shared control	-.20 (.950)		2.0 (.011*, 1.12)
Learner control	-2.20 (.005*, -1.23)	-2.0(.011*, -1.12)	

Discussion

This study was conducted to investigate the effect of task selection approach type for emphasis manipulation on knowledge transfer success and cognitive load. Therefore, this study was conducted to answer the following research questions: "What are the effects of different task selection strategies on learners' cognitive load during emphasis manipulation sequencing?" and, "What are the effects of task selection strategies on knowledge transfer during emphasis manipulation sequencing?"

Effects of Task Selection on Learners' Cognitive Load

The findings indicated that there were no statistically significant differences in intrinsic cognitive load between the SC, LC and SHC groups. Intrinsic cognitive load is determined by the complexity of the content being learned, such as the number of components to be learned and how they interact (Jung, et al., 2016). This finding indicates that there was no statistically significant difference in the groups' prior knowledge or learning experiences and that task selection strategies did not have statistically significantly different effects on intrinsic cognitive load.

The results revealed that the system-controlled approach to emphasis manipulation was the most effective in reducing extraneous cognitive load and enhancing germane cognitive load. In contrast, the learner-controlled approach to emphasis manipulation produced the highest extraneous cognitive load and the lowest germane cognitive load. Because working memory capacity is limited (Sweller, 1988), reducing extraneous cognitive load is an important part of increasing germane cognitive load. Related research has shown increasing germane cognitive load can help learners secure more cognitive space for acquiring complex skills (Jung et al., 2019; Paas & Sweller, 2012; Renkl & Atkinson, 2003). The findings suggested that the system-controlled approach to emphasis manipulation effectively decreased unnecessary cognitive load by providing learners essential learning tasks based on their prior knowledge. In addition, it can be assumed that the learners in the SC group did not experience the expert reversal effect, as redundant information would have been eliminated by this approach (Sweller, 2010). However, the learner-controlled approach, which allowed learners to select learning tasks but gave them no guidance on necessary learning tasks, seemed to increase cognitive overload. These results imply that learners in the LC group experienced difficulty in accurate task selection and performed unnecessary learning tasks, potentially leading to extra cognitive work. Thus, even though learner control is typically perceived as an instructional approach that enhances learners' motivation (Corbalan et al., 2008), if learners attempt to learn all possible constituent components without any guidance about what is most essential, they may experience unnecessary cognitive load.

Although previous studies have shown that personalised task selection with shared control decreases extraneous cognitive load (Kostons et al., 2020) and increases germane cognitive load (Corbalan et al., 2006), the findings of this study were partially consistent with previous studies. The results demonstrated that the shared-controlled approach to emphasis manipulation is less effective than the system-controlled approach in optimising cognitive load, whereas it was more effective than the learner-controlled approach in diminishing extraneous cognitive load and increasing germane cognitive load. This study's results showed that *personalised* advice can help learners with task selection. This effect would likely be stronger for novice learners who are less able to accurately assess their own performance and choose learning tasks that fit their learning needs than experienced learners (Kostons, van Gog, & Paas, 2009).

In the meantime, the shared-controlled approach overcomes the difficulty of learner task selection compared to the learner-controlled approach by providing information about necessary learning tasks (Corbalan et al., 2006). The findings of this study provide evidence that a shared-control task selection strategy provides learning tasks that exclude repetitive learning tasks based on learner expertise, which may be more effective in controlling cognitive load compared to not providing such information. Therefore, this study suggests providing personalized learning information should be implemented to support accurate task selection by learners in order to support learning success.

Effects of Task Selection on Knowledge Transfer

In this study, the SC group had the best scores on the knowledge transfer test. The system-controlled approach emphasised essential learning tasks and excluded redundant learning. The findings imply that the learners in the SC group could effectively coordinate and integrate their prior knowledge and new information by focusing on learning the tasks in which they were weakest. Previous studies have shown that personalised learning based on learners' expertise leads to successful learning (Kalyuga & Sweller, 2005; Salden et al., 2004). This study provides empirical evidence that the personalised task sequencing of complex tasks leads to better knowledge transfer outcomes. A different study found that giving learners task selection opportunities increased their motivation and helped them engage in self-regulated learning (Salden et al., 2006). However, in this study, the SHC and LC groups that had control over task selection had *worse* learning outcomes than the SC group, which only had access to the learning tasks in which they were the weakest. This result indicates that learners did not have sufficient knowledge to select the learning tasks that were the most suitable to their needs.

The findings suggest that a task selection strategy that only provides essential learning tasks in consideration of learners' prior knowledge can effectively lead to success in learning by allowing learners to learn only the learning tasks in which they were weakest. Previous researchers have recommended using shared-controlled instruction to overcome the limitations of learner-controlled instruction (Corbalan et al., 2006). As shown by the SHC group's higher scores on the knowledge transfer test, providing learners with a list of suggested learning tasks based on their expertise appears to eliminate repetitive and redundant learning tasks and thereby promote knowledge transfer. This result is partially consistent with the empirical evidence that shared control is more efficient than either system control or learner control alone (van Meeuwen et al., 2018). Although the findings of this study indicated that the SC group had higher scores than the SHC group, given that the SHC group had better transfer scores than the LC group, it can be assumed that the task selection strategy of providing learners with a list of suggested learning tasks is more effective than not providing any learning information. Thus, the findings of this study provide empirical evidence that providing information about essential learning tasks can help learners select necessary learning tasks and improves knowledge transfer acquisition in contexts that use emphasis manipulation.

Conclusion and Limitations

This study investigated the effects of task selection strategies for emphasis manipulation on cognitive load and knowledge transfer. Three task selection strategies for emphasis manipulation were tested: system control, learner control and shared control. The system-controlled task selection approach to emphasis manipulation was found to be the most effective in optimising cognitive load and enhancing knowledge transfer. The results were consistent with previous studies of how personalised task sequencing focusing on learners' weaknesses can improve learning (e.g. Camp et al., 2001; van Merriënboer et al., 2002). In addition, the findings demonstrated that the system-controlled task selection strategy which provided necessary learning tasks based on learners' prior knowledge was effective in eliminating redundant information and preventing the expert reversal effect. The shared-controlled task selection strategy for emphasis manipulation was also found to be more effective than the learner-controlled task selection strategy. These findings revealed that providing learners with individualised information about essential learning tasks can help them select necessary learning tasks and achieve their learning goals (Corbalan et al., 2006).

In this study, it was hypothesized that allowing learners to select their own learning tasks would increase their motivation and improve learning outcomes as a result. However, the LC group had the most control over their task selection strategy, but learners did not have sufficient expertise to accurately select the most suitable tasks and, as a result, had the worst learning outcomes. Taken together, the results indicate that learners should be provided with information about how to select learning tasks when they are allowed to do so. Learners should be allowed to select learning tasks according to their prior knowledge level. In addition, learners should be presented essential information regarding how to select meaningful learning tasks.

This study has some limitations. First, the study focused on task selection strategies for emphasis manipulation in complex learning contexts. However, there is a need for more research on investigating task selection strategies suitable for novice and more experienced learners. Second, in this study, we investigated the effects of task selection on cognitive load and knowledge transfer. Future research should diversify the dependent variables to include motivation, engagement and self-efficacy. Third, this study only had 45 participants in total. More data is needed to examine the effects of task selection strategies in emphasis manipulation with various domains of expertise.

References

Beers, P. J., Boshuizen, H. P. E., Kirschner, P. A., & Gijselaers, W. H. (2005). Computer support for knowledge construction in collaborative learning environments. *Computers in Human Behavior, 21*(4), 623–643. https://doi.org/10.1016/j.chb.2004.10.036

Becker, S., Klein, P., Gößling, A., & Kuhn, J. (2020). Using mobile devices to enhance inquiry-based learning processes. *Learning and Instruction*, *69*, 101350. https://doi.org/10.1016/j.learninstruc.2020.101350

Bergamin, P., & Hirt, F. S. (2018). Who's in Charge?—Dealing with the Self-regulation Dilemma in Digital Learning Environments. In K. North, R. Maier, & O. Haas (Eds.), Knowledge Management in Digital Change (pp. 227–245). Springer. https://doi.org/10.1007/978-3-319-73546-7_14

Camp, G., Paas, F., Rikers, R., & van Merriënboer, J. J. (2001). Dynamic problem selection in air traffic control training: A comparison between performance, mental effort and mental efficiency. *Computers in Human Behavior, 17*(5-6), 575–595. https://doi.org/10.1016/S0747-5632(01)00028-0

Chen, C. M. (2008). Intelligent web-based learning system with personalized learning path guidance. *Computers & Education, 51*(2), 787–814. https://doi.org/10.1016/j.compedu.2007.08.004

Choi, S., Kim, N., Choi, S., & Kim, D. (2019). Emphasis manipulation effect in terms of the least-abled sets on cognitive load, transfer, and instructional efficiency. *Problems of Education in the 21st Century, 77*(2), 228–243. https://doi.org/10.33225/pec/19.77.228

Corbalan, G., Kester, L., & van Merriënboer, J. J. (2006). Towards a personalized task selection model with shared instructional control. *Instructional Science, 34*(5), 399–422. https://doi.org/10.1007/s11251-005-5774-2

Corbalan, G., Kester, L., & van Merriënboer, J. J. (2008). Selecting learning tasks: Effects of adaptation and shared control on learning efficiency and task involvement. *Contemporary Educational Psychology, 33*(4), 733–756. https://doi.org/10.1016/j.cedpsych.2008.02.003

Ertmer, P. A., & Newby, T. J. (1996). The expert learner: Strategic, self-regulated, and reflective. *Instructional Science, 24*(1), 1–24. https://doi.org/10.1007/BF00156001

Frerejean, J., van Merriënboer, J. J., Kirschner, P. A., Roex, A., Aertgeerts, B., & Marcellis, M. (2019). Designing instruction for complex learning: 4C/ID in higher education. *European Journal of Education, 54*(4), 513–524. https://doi.org/10.1111/ejed.12363

Frerejean, J., van Geel, M., Keuning, T., Dolmans, D., van Merriënboer, J. J., & Visscher, A. J. (2021). Ten steps to 4C/ID: training differentiation skills in a professional development program for teachers. *Instructional Science*, 1–24. https://doi.org/10.1007/s11251-021-09540-x

Gerjets, P., Scheiter, K., & Catrambone, R. (2006). Can learning from molar and modular worked examples be enhanced by providing instructional explanations and prompting self-explanations? *Learning and Instruction, 16*(2), 104–121. https://doi.org/10.1016/j.learninstruc.2006.02.007

Gopher, D. (1993). The skill of attention control: Acquisition and execution of attention strategies. In D. E. Meyer & S. Kornblum (Eds.), *Attention and Performance XIV: Synergies in Experimental Psychology, Artificial Intelligence, and Cognitive Neuroscience* (pp. 299–322). Cambridge, MA: MIT Press.

Gopher, D. (2007). Emphasis change as a training protocol for high-demand tasks. In A. F. Kramer, D. A. Wiegmann, & A. Kirlik (Eds.), *Attention: From theory to practice* (pp. 209–224). New York: Oxford University Press.

Gopher, D., Weil, M., & Siegel, D. (1989). Practice under changing priorities: An approach to the training of complex skills. *Acta Psychologica, 71*(1-3), 147–177. https://doi.org/10.1016/0001-6918(89)90007-3

Jung, J., Kim, D., & Na, C. (2016). Effects of WOE Presentation Types Used in Pre-training on the Cognitive Load and Comprehension of Content in Animation-Based Learning Environments. *Educational Technology & Society, 19*(4), 75–86. https://www.jstor.org/stable/10.2307/jeductechsoci.19.4.75

Jung, J., Shin, Y., & Zumbach, J. (2019). The effects of pre-training types on cognitive load, collaborative knowledge construction and deep learning in a computer-supported collaborative learning environment. *Interactive Learning Environmen*ts, 1–13. https://doi.org/10.1080/10494820.2019.1619592

Kalyuga, S. (2006). Assessment of learners' organised knowledge structures in adaptive learning environments. *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition, 20*(3), 333–342. https://doi.org/10.1002/acp.1249

Kalyuga, S., Ayres, P., Chandler, P., & Sweller, J. (2003). The expertise reversal effect. *Educational Psychologist, 38*(1), 23–31. https://doi.org/10.1207/S15326985EP3801_4

Kalyuga, S., & Renkl, A. (2010). Expertise reversal effect and its instructional implications: Introduction to the special issue. *Instructional Science, 38*(3), 209–215. https://doi.org/10.1007/s11251-009-9102-0

Kalyuga, S., & Sweller, J. (2005). Rapid dynamic assessment of expertise to improve the efficiency of adaptive e-learning. *Educational Technology Research and Development, 53*(3), 83–93. https://doi.org/10.1007/BF02504800

Kalyuga, S., & Sweller, J. (2014). The redundancy principle in multimedia learning. In R. E. Mayer (Ed.), *Cambridge handbook of multimedia learning* (2nd revised ed.). New York: Cambridge University Press.

Kester, L., & Kirschner, P. A. (2012). Cognitive tasks and learning. In N. Seel (Ed.), *Encyclopedia of the Sciences of Learning* (pp. 619–622). New York: Springer

Kirschner, P. A., Sweller, J., & Clark, R. E. (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching. *Educational Psychologist, 41*(2), 75–86. https://doi.org/10.1207/s15326985ep4102_1

Kostons, D., Van Gog, T., & Paas, F. (2012). Training self-assessment and task-selection skills: A cognitive approach to improving self-regulated learning. *Learning and Instruction, 22*(2), 121-132. https://doi.org/10.1016/j.learninstruc.2011.08.004

Lange, C. (2018). The relationship between system-provided learner control and maintained situational interest within e-learning courses. *Interactive Technology and Smart Education, 15*(3), 205–219. https://doi.org/10.1108/ITSE-12- 2017-0062

Leppink, J., Paas, F., van der Vleuten, C. P., van Gog, T., & van Merriënboer, J. J. (2013). Development of an instrument for measuring different types of cognitive load. *Behavior Research Methods, 45*(4), 1058–1072. https://doi.org/10.3758/s13428-013-0334-1

Merrill, M. D. (2002). First principles of instruction. *Educational Technology Research and Development, 50*(3), 43–59. https://doi.org/10.1007/BF02505024

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

Paas, F., & Sweller, J. (2012). An evolutionary upgrade of cognitive load theory: Using the human motor system and collaboration to support the learning of complex cognitive tasks. *Educational Psychology Review, 24*(1), 27–45. https://doi.org/10.1007/s10648-011-9179-2.

Paas, F., van Merriënboer, J. J. G., & van Gog, T. (2011). Designing instruction for the contemporary learning landscape. In K. Harris, S. Graham, & T. Urdan (Eds.), *APA educational psychology handbook: Vol. 3. Application to learning and teaching* (pp. 335–357). Washington: American Psychological Association.

Renkl, A., & Atkinson, R. K. (2003). Structuring the transition from example study to problem solving in cognitive skill acquisition: A cognitive load perspective. *Educational Psychologist, 38*(1), 15–22. https://doi.org/10.1207/S15326985EP3801_3

Salden, R. J., Paas, F., Broers, N. J., & van Merriënboer, J. J. G. (2004). Mental effort and performance as determinants for the dynamic selection of learning tasks in air traffic control training. *Instructional Science, 32*(1-2), 153–172. https://doi.org/10.1023/B:TRUC.0000021814.03996.ff

Salden, R. J. C. M., Paas, F., & van Merriënboer, J. J. G. (2006). A comparison of approaches to learning task selection in the training of complex cognitive skills. *Computers in Human Behavior, 22*(3), 321–333. https://doi.org/10.1016/j.chb.2004.06.003

Schwartz, B. (2004). *The paradox of choice: Why more is less.* New York, NY: HarperCollins.

Shin, Y., Kim, D., & Jung, J. (2018). The effects of representation tool (Visible-annotation) types to support knowledge building in computer-supported collaborative learning. *Journal of Educational Technology & Society, 21*(2), 98–110. https://www.jstor.org/stable/26388383

Slof, B., Erkens, G., & Kirschner, P. A. (2011). Constructing part-task congruent representations to support coordination of collaborative problem-solving tasks. In *Proceedings of the International Conference on CSCL 2011* (pp. 264–271).

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257–285.

Sweller, J. (1994). Cognitive load theory, learning difficulty, and instructional design. *Learning and Instruction, 4*(4), 295–312. https://doi.org/10.1016/0959-4752(94)90003-5

Sweller, J. (2010). Cognitive load theory: Recent theoretical advances. In J. L. Plass, R. Moreno, & R. Brünken (Eds.), *Cognitive load theory* (pp. 29–47). New York, NY: Cambridge University Press. https://doi.org/10.1017/CBO9780511844744.004

Tennyson, R. D., & Buttery, T. (1980). Advisement and management strategies as design variables in computer-assisted instruction. *Educational Communication and Technology Journal, 28*(3), 169–176. https://doi.org/10.1007/BF02765363

Thees, M., Kapp, S., Strzys, M. P., Beil, F., Lukowicz, P., & Kuhn, J. (2020). Effects of augmented reality on learning and cognitive load in university physics laboratory courses. *Computers in Human Behavior, 108*, 106316. https://doi.org/10.1016/j. chb.2020.106316.

Vandewaetere, M., & Clarebout, G. (2013). Cognitive load of learner control: Extraneous or germane load? *Education Research International, 2013*(1), 1–11. https://doi.org/10.1155/2013/902809

van Meeuwen, L. W., Brand-Gruwel, S., Kirschner, P. A., de Bock, J. J., & van Merriënboer, J. J. (2018). Fostering self-regulation in training complex cognitive tasks. *Educational Technology Research and Development, 66*(1), 53–73. https://doi.org/10.1007/s11423-017-9539-9

van Merriënboer, J. J. G., Schuurman, J. G., De Croock, M. B. M., & Paas, F. (2002). Redirecting learners' attention during training: Effects on cognitive load, transfer test performance and training efficiency. *Learning and Instruction, 12*(1), 11–37. https://doi.org/10.1016/S0959-4752(01)00020-2

van Merriënboer, J. J. G., & Sweller, J. (2010). Cognitive load theory in health professional education: design principles and strategies. *Medical Education, 44*(1), 85–93. https://doi.org/10.1111/j.1365-2923.2009.03498.x

van Merriënboer, J. J. G., & Kirschner, P. A. (2018). *Ten steps to complex learning: a systematic approach to four-component instructional design*. New York: Routledge.

Wang, M., Derry, S., & Ge, X. (2017). Guest editorial: Fostering deep learning in problem-solving contexts with the support of technology. *Journal of Educational Technology & Society, 20*(4), 162–165. http://www.jstor.org/stable/26229214

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