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The Relationship of Learning Engagement and Cognitive Load of Online Learners: The Moderator Effect of Computer Self-efficacy

Yansen Zhang

Lanzhou Vocational Technical College, Lanzhou, China
zhangr68are@sina.com

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Abstract: The study examined the effects of learning engagement and computer self-efficacy on cognitive load of online learners. The participants who recruited on the WeChat public platform completed the Utrecht Work Engagement Scale (UWES), the General Self-Efficacy Scale (GSES), and the Workload Profile Index Ratings (WP) on computers. The results of correlation analyses showed (The results of multi-level analyses showed) that both learning engagement and computer self-efficacy were significantly related to cognitive load; learning engagement was positively correlated with computer self-efficacy; Moreover, the hierarchical regression analyses showed that computer self-efficacy has a moderator role between learning engagement and cognitive load; and low computer self-efficacy could strengthen the positive effect of learning engagement on cognitive load.

1. Introduction

Innovative curriculum integrated with multimedia and technology involvement has changed the ways of teachers teaching and students learning. As users of mobile technologies become dramatically widespread worldwide, it is more likely that they would become ubiquitous in the lives of learners (Looi et al., 2010). The increasing and ubiquitous use of Web 2.0 activities, such as WeChat which is the most widely used social networking service in China and has become an important social media platform for computer-mediated communication (Gao & Zhang, 2013), provides a viable and innovative avenue for online learning proactively (Gan & Li, 2018; Wang, Wang, Fang, & Lin, 2010). Pedagogically, engaging learners in online learning involved sharing their ideas, hold-to-talk voice messaging, one-to many messaging(Lien & Cao, 2014), and working cooperatively and helpfully to complete group projects. It is one of the major pathways to scaffold learning development (Chen & Bryer, 2012; Effandi & Zanaton, 2007) as learning is a social activity. However, when tasks are presented to learners at computers, their motivation to join and keep working on tasks can fade quite rapidly and their working memory may overload (Martens, Gulikers, & Bastiaens, 2004). Cognitive load may be a key factor which affected online learners' information processing in the web-based learning.

Cognitive Load Theory (CLT), which is a theory in psychology (Moreno & Park, 2010), defines cognitive load as processed information in active memory (Hsiao, 2010), and explains learning according to three important aspects: the types of memory (working and long-term memory), the learning process and the forms of cognitive load that affect our learning (Marco, Sissel, & Christoph, 2018). The basic domain of CLT is individual's cognitive structure and it claims that there is a limitation to the long term memory (Clark, Nguyen, & Sweller, 2011; Leppink, Paas, Van der Vleuten, Van Gog, & Van Merriënboer, 2013; Paas, Renkl, & Sweller, 2004; Reiser & Dempsey, 2007; Sweller, 1988; 2005; 2010). In addition, the theory emphasizes that the importance of information, which is stored in the long term memory, guiding cognitive processes and it also highlights the importance of preventing overloading in active memory (Kalyuga, 2009). Each learner has an individual maximum cognitive load, and the germane cognitive load span is specific to everyone. It is important to adapt the difficulty of a task to the level and engagement of the learner [1].

Learning online is a self-regulated process in which learners can freely select the course materials and control their learning pace and path (Li & Tsai, 2017), the aim of which is to support the students to learn professional activities that are characterized by the convenient and efficient integration of multiple sets of knowledge and skills. All types of online learning activities provide ubiquitous capabilities for learners to receive specific instruction, guidance and content when they need them (Kukulska-Hulme, 2009; Luckin, 2010). Learning online can also bridge learners and their environment for supporting more augmented experiences (De Jong et al., 2008; Fahraeus, 2004; Wilde et al., 2003). These properties requires learners to be agents of their own learning in a way that they control their behavior and cognition (Wong et al., 2015). Therefore, the key issue is that if learners are to learn effectively in any given learning environment, their cognitive system, the related influencing factors, and interactions among them must be understood, accommodated and aligned (Femke, Liesbeth, & Gemma, 2011). In online learning, when learners need to process multiple types of information (such as visual information, auditory information, etc.) at the same time, the integrated preprocessing of multi-sensory channel information needs more mental efforts, psychological resources, and take more time[2]. According to CLT, Cognitive load refers to the mental burden that performing a task imposes on the learner (Sweller, 1988). Three types of cognitive load have been identified in the literature (Sweller, van Merriënboer, & Paas, 1998). Of these, intrinsic load is imposed by the inherent complexity of the content, which relates to the extent to which various information elements interact. When information interactivity is low, content can be understood and learned one element at a time. Conversely, highly interactive information in online learning environment that is more difficult to learn may cause inappropriately high levels of cognitive load, which may also reduce learning efficiency (Antonenko & Niederhauser, 2010). If learners are more engaged with a specific task, they may improve their information processing effect and thereby improve their learning efficiency when it comes to highly interactive information and complex content ((Burrows, 2010)). Thus, learning effectiveness and efficiency online which can be managed will rely on learners' engagement and motivation (Mancinetti, Guttormsen, & Berendonk, 2018) [3].

Engagement is considered as a positive psychological state in students studying, which is also the most commonly used indicator to measure learning outcomes in online learning (Jung & Lee, 2018). Engagement concentrates on the cognitive and affective motivation of involvement with work tasks over long periods (Wefald & Downey, 2009). It is the ongoing effort that a learner spends on the learning process to achieve learning goals (Coates, 2006). The frequent criteria for learning engagement online were motivation, cognition, emotion and the behavioral aspect (Hew, 2016; Milligan et al., 2013). Cognitive engagement is regarded as learners' cognitive efforts to acquire complex content or skills in the online learning process (Jung & Lee, 2018). And remarkable, cognitive load associated with the effort and engagement that is required for the acquisition and automation of cognitive schemas (Femke, Liesbeth, & Gemma, 2011). They were both established when students exert an amount of mental effort to engage with the learning material (Richardson & Newby, 2006; Walker, Greene & Mansell, 2006). These findings suggest that cognitive engagement may positively influence cognitive load [4].

The previous literature has shown that self-efficacy was another important factor which influenced cognitive load (Vasilea, Marhana, Singera, & Stoicescua, 2011). Self-efficacy is defined as individuals' beliefs about their ability to successfully achieve goals and manage environments that affect their lives (Bandura, 1989) and is a crucial determinant of behavior (Bandura, 1986, 1989, 1997). Hence, computer self-efficacy refers to individuals' beliefs about their ability to successfully solve tasks and manage situations online (Compeau & Higgins, 1995; Marakas, Yi, & Johnson, 1998). Bandura (1978) considered that students whose sense of efficacy was raised set higher aspirations for themselves, achieved higher intellectual performances, and were more accurate in evaluating the quality of their performances than were students of equal cognitive ability who were led to believe they lacked such capabilities. Researchers agree on the idea that individuals who perceive themselves capable on a given task will probably engage more than when they do not feel themselves competent enough (Ching, 2002; Jackson, 2002; Margolis & McCabe, 2003; Pajares, 1996). Therefore, a high self-efficacy drives the investment of mental effort (Feldon, Franco, Jie, Peugh, & Maahs-Fladung, 2018), and leads to a strong sense of competence, which helps cognitive processes and performance in areas such as academic achievement, while a low self-efficacy is associated with low self-esteem and negative thoughts about the individual's cognitive ability, and low results in learning [5].

The diversity of information in online learning may lead to the increase of students' cognitive load. The current research showed that the increase of learning engagement, as well as the high self-efficacy of learners, may reduce learners' cognitive load and thus improve learning efficiency (Feldon, Franco, Jie, Peugh, & Maahs-Fladung, 2018). We expect that computer self-efficacy serves as a moderator between learning engagement and cognitive load for the following reasons. First, the insight from the job demands-resources (JD-R) model (Rich et al., 2010) may explain why self-efficacy improves individuals' level of engagement at work. This extended model is adopted to articulate the notion how these resources psychologically impact their engagement level at work (Chen, 2017) [6]. According to the conservation of resources (COR) theory (Hobfoll, 1989, 2002), individuals are motivated to maintain, acquire, and protect their resources, and resources refers to "……those entities that either are centrally valued in their own right, or act as means to obtain centrally valued ends" (Hobfoll, 2002). Tims et al. (2014) claim that when individuals have high levels of personal resources (i.e., self-efficacy), they are intrinsically motivated to cultivate their work environment so that they can easily obtain job-related resources (e.g., social support and opportunities to learn new knowledge; Bakker & Demerouti, 2014) that can help them to better manage the challenges of the job. This suggests that positive self-efficacy may affect people's engagement in their jobs or tasks [7].

A number of previous studies suggested that self-efficacy contributes to positively predicted and improved work engagement (Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2009a, 2009b). In a study in which 17 supervisors evaluated 364 nurses' extra-role performance, Salanova, Lorente, Chambel, and Martínez (2011) also revealed that nurses' self-efficacy improves their work engagement. In turn, there are studies reveal that students with low computer self-efficacy engage in their work may not experience positive feelings, which also influences their learning performance (Chen, 2017). Therefore, this study hypothesizes that learning engagement will reduce the cognitive load of online learners, which is moderated by learners' self-efficacy. In other words, computer self-efficacy serves as a moderator between learning engagement and cognitive load for the following reasons. Our hypotheses were as follows: Learning engagement is beneficial to cognitive load (H1); and computer self-efficacy plays a moderator role between learning engagement and cognitive load (H2).

2. Methods

2.1. Participants and procedures

A total of 312 participants (84 men and 228 women) were recruited on the WeChat public platform, through the simple random sampling method. The ages of 312 users ranged from 17 to 50 years (Mean=25.79, S.D=6.80). Among them, 135 (43.3%) were psychology majors and 177(56.7%) were non-psychology majors; 64 (20.5%) possessed a senior high graduation certificate, 145 (46.5%) possessed a bachelor's degree and 103 (33.0%) possessed a master's degree. Following the completion of informed consent forms, participants filled in a series of questionnaires including the Utrecht Work Engagement Scale (UWES), the General Self-Efficacy Scale (GSES), and the Workload Profile Index Ratings (WP) on computers. After completing the questionnaires, each of the participants was thanked and given a gift [8].

2.2. Study measures

2.2.1. Learning engagement

Learning engagement has been evaluated by using the Utrecht Work Engagement Scale (UWES), which was developed in 2002 (Schaufeli & Bakker, 2004). The UWES is a self-report questionnaire and containing three subscales vigor (VI, 6 items), dedication (DE, 6 items), and absorption (AB, 5 items) (Schaufeli, Salanova, González-Roma, & Bakker, 2002; Schaufeli & Bakker, 2006).The questionnaire works with a 7-point Likert scale ranging from 0 (strongly disagree) to 6 (strongly agree), with higher scores indicating higher levels of engagement. The UWES consists of 17 items in total. Sample items were "At my job, I feel strong and vigorous" or "Today, I felt bursting with energy at work" and "Today, I felt strong and vigorous at work"(Stefanie, Karin, & David, 2015).Validity and reliability were proved and verified ((Schaufeli, Salanova, González-Roma, & Bakker, 2002). Reliabilities of the UWES was .93 for the total score, and ranged from .79 to .89 for the three subscales (Schaufeli & Bakker, 2004) [9].

2.2.2. Self-efficacy

General self-efficacy was used to assess an overall sense of perceived self-efficacy (Schwarzer & Jerusalem, 1995) and was measured using the validated Chinese version of the General Self-Efficacy Scale developed by Schwarzer, Bäßler, Kwiatek, Schröder, and Zhang (1997). The instrument contains 10 items (e.g., I can always manage to solve difficult problems). All items were scored on a 5-point Likert scale ranging from 1 (Very untrue of me) to 5 (Very true of me). The general self-efficacy measure displays high reliability (α=0.81) and acceptable construct validity (χ^2/df =19.812; GFI=0.91; AGFI=0.90; RMR=0.05; SRMR=0.03; RMSEA=0.06; NFI=0.92; CFI=0.93).

We note that the scale was not originally designed to assess computer self-efficacy and that scales that specifically measure computer self-efficacy exist, such as the scale proposed by Murphy, Coover, and Owen (1989). We argue that existing computer self-efficacy scales may be overly technical (e.g., whether one feels confident that he or she can use a computer to write email or copy discs) for use in our study [10]. In this research, we aim to investigate whether individuals feel as though they are capable of using a computer or network to manage challenging learning tasks in general rather than to perform particular computer operations (e.g., writing email/ copying discs). In light of the above concerns, we used the General Self-Efficacy Scale to align the items with the purpose of this study.

2.2.3. Cognitive Load

Cognitive load of the learners online was measured by the Workload Profile Index Ratings. WP (the Workload Profile Index Ratings) is a new subjective evaluation load scale developed by Tsang and Velazquez (1996) based on the multiple resources model of Workload. Mental load multiple resource model was proposed by Wickens (1987).The model believes that the learner completes the learning task into four stages (dimensions), each of which occupies two different psychological resources: 1) information processing stage, occupation center Processing resources and response resources; 2) encoding processing stage, occupying spatial coding resources and language resources; 3) input stage (channel dimension), occupying visual receiving stage and auditory receiving stage; 4) output stage (reaction dimension), occupying operation output Resources and language output resources.

Using the WP, the participants are required to give a number between 0 and 1 according to their subjective feeling after completing the learning task. ”0” means that the resource is not occupied at all, “1” means that the resource is fully occupied. Finally, the 8 numbers are added together to get the overall psychological load index [11].

2.3. Statistical analyses

To test the relationships among learning engagement, cognitive load of online learners and computer self-efficacy, the Pearson correlations were computed. Hierarchical regression analyses were used to analyze the effects of learning engagement and computer self-efficacy on the cognitive load, especially the moderating role of computer self-efficacy between learning engagement and cognitive load. Data analyses were carried out using SPSS 21.0.

3. Results

3.1. Descriptive statistics and correlation matrix

The means, standard deviations, and correlations between learning engagement, computer self-efficacy and cognitive load are presented in Table 1.

Table 1: All variables' means, standard deviations, and correlation matrix.

	M	SD	Learning engagement	Computer self-efficacy
learning engagement	48.35	9.47	-	
computer self-efficacy	2.70	0.55	.55**	-
cognitive load	6.55	1.58	.31**	.19**

** $p < .01$.

Learning engagement was positively correlated with cognitive load; computer self-efficacy was positively correlated with cognitive load; and learning engagement was positively correlated with computer self-efficacy.

3.2. The influence of learning engagement and computer self-efficacy on cognitive load

A hierarchical multiple linear regression was conducted to examine whether computer self-efficacy moderated the relations between learning engagement and cognitive load. Before the regression analysis, the independent variables (learning engagement and computer self-efficacy) were centered, and the interactions between learning engagement and computer self-efficacy were then calculated. The regression involved two steps: all of the independent variables were introduced into the regression equation to test the main effects (step 1), and the interaction terms were introduced into the regression equation to test the moderating effects (step 2).

First, as shown in Table 2, the main effects of learning engagement were positively significant for cognitive load (β=0.297, t=4.582, p<0.001). However, the main effects of computer self-efficacy were not significant for cognitive load (β=0.026, t=0.396, p>0.05). In addition, in every model, the β of learning engagement was higher than the β of computer self-efficacy. Second, the interactions between learning engagement and computer self-efficacy were significant for cognitive load (β= -0.168, t= -3.108, p<0.01). Simple slope analyses were conducted to further examine the two-way interactions on cognitive load [12].

Table 2: Results of the hierarchical regression analyses for predicting cognitive load (n = 312).

			Model 1				Model 2			
			B	β	t	p	B	β	t	p
cognitive load	Step1	learning engagement	0.049	0.297	4.582	0.000	0.051	0.306	4.794	0.000
		computer self-efficacy	0.074	0.026	0.396	0.692	0.126	0.044	0.680	0.497
	Step2	learning engagement × computer self-efficacy					-0.040	-0.168	-3.108	0.002
	Adjust R2		0.091				0.116			
	F		16.587***				14.587***			

*** p<0.001

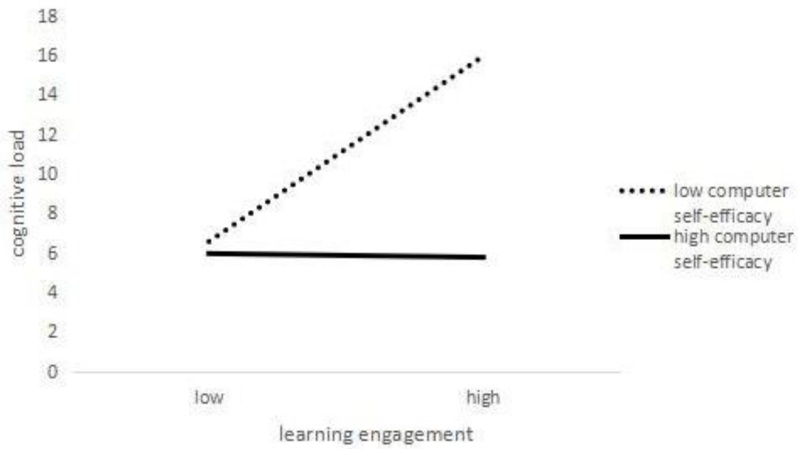

Figure 1: The moderating function of computer self-efficacy on the relationship between learning engagement and cognitive load

As shown in Fig. 1, among low computer self-efficacy participants (lower than−1 SD), learning engagement positively predicted cognitive load (β=0.426, t=4.609, p<0.001). However, among high computer self-efficacy participants (higher than +1 SD), learning engagement showed no significant prediction for cognitive load (β=0.100, t=1.012, p>0.05). Thus, low computer self-efficacy could strengthen the positive prediction of learning engagement on cognitive load. In other words, for participants with low computer self-efficacy, the higher their learning engagement, the higher cognitive load [13].

In general, the results of the hierarchical regressions showed that learning engagement positively predicted cognitive load. Thus, H1 was supported. More importantly, computer self-efficacy played a moderating role between learning engagement and cognitive load. Specifically, low computer self-efficacy strengthened the positive prediction of learning engagement on cognitive load. Therefore, H2 was also supported.

4. Discussion

This study aims to investigate computer self-efficacy as a moderator of the relationship between learning engagement and cognitive load. Hypotheses were developed based on the data and theories about learners' goals, preferences, and motivations, different levels of engagement and behavior patterns in online learning. We administered a series of survey to 312 participants recruited on the WeChat public platform for the purpose of better understanding the learning characteristics of online learners. The analytic results showed that learning engagement positively predicted cognitive load. Additionally, we found that computer self-efficacy played a moderating role between learning engagement and cognitive load. Specifically, low computer self-efficacy strengthened the positive prediction of learning engagement on cognitive load [14].

4.1. The relationship between learning engagement and cognitive load

The present study supports that learning engagement is beneficial to cognitive load. This result is consistent with previous research (Femke, Liesbeth, & Gemma, 2011; Strauser et al., 2012; Salmela-Aro & Upadyaya, 2014; Bakker et al., 2015). The positive effect of learning engagement on cognitive load could be explained as follows: The cognitive load learners experience when working on a learning task can be caused by the intrinsic nature of the task or by the manner in which the information within the task is presented to them. 'Intrinsic' load is imposed by the number of interactive information elements in a task. The more elements there are within a learning task and the more interaction there is between them, the higher the experienced intrinsic cognitive load will be (Femke, Liesbeth, & Gemma, 2011).In online learning, the information is diversified and the difficulty of learning task is different. Learners introspected on their cognitive processes in assigning numerical values to the perceived task difficulty or invested mental effort (Paas, Tuovinen, Tabbers, & Van Gerven, 2003) without formal instruction. This requires the learners' multi-sensory channel processing, which leads to cognitive load [15].

The manner in which the online learning information is presented to learners can either impose an 'extraneous' or 'germane' load. Extraneous information needs more learning engagement that directly contribute to cognitive load. One way to manage intrinsic load is by applying a so called part-whole approach, in which the number of information elements and interactions between elements is initially reduced by simplifying the tasks and reducing the engagement, after which more and more elements and interactions are added (e.g., Van Merriënboer, Kester & Paas, 2006). In addition, a complex task has more constituent skills that must be coordinated and thus is likely to yield a higher intrinsic load than a simple task (Femke, Liesbeth, & Gemma, 2011). That means learning engagement positively predicted cognitive load.

4.2. The moderator role of computer self-efficacy between learning engagement and cognitive load

The present study reveals the moderator role of computer self-efficacy between learning engagement and cognitive load. Specifically, low computer self-efficacy strengthened the positive prediction of learning engagement on cognitive load. In other words, individuals with low computer self-efficacy, learning engagement has a beneficial effect on cognitive load. Considering the previous literature supporting the positive correlation between computer self-efficacy between learning engagement (Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2009), this finding is somewhat surprising. However, we argue that it is understandable and illuminating. Since the positive relationship between learning engagement and cognitive load among participants with low computer self-efficacy may rest on the point that when students' self-evaluation level is not high, they will work harder and put more energy into learning, which will increase their cognitive load. Learners play an active role in their own learning process, they can be stimulated to invest this important effort, and consequently improve their learning (Paas, 2003). When facing stressful events or complex and difficult tasks, low motivation could protect against the negative effect of negative feedback and it is easy to maintain personal interest and vigilance in work, while reducing the adverse impact of anxiety on work ((Linnenbrink & Pintrich, 2002; Eccles & Roeser, 2009). Thus, it is understandable that that low computer self-efficacy individuals' learning engagement would not be reduced, or would even be promoted, because they have more balanced mental resources to resist the stress from the environment. In contrast, people with high computer self-efficacy who not only have the skills and knowledge to execute a task successfully, but also have a certain level of expectation for success (Bandura, 1997)), may spent less effort on the task (Diseth, 2011) [16].

4.3. Implications

The present study investigated the relationship between learning engagement and cognitive load in combination with computer self-efficacy. The result of the positive relationship between learning engagement and cognitive load among low computer self-efficacy individuals extends prior work about the relationship between learning engagement and cognitive load. It is of great significance to intervene and improve the learning efficiency of online learners. Moreover, our study has some practical implications for online learning in learners' behavior. In online learning, those who with low self-efficacy should adapt to the environment of online learning, cultivate the cognitive ability and learning strategy of online course information, improve the ability to process and judge information, and actively engage in interactive learning, so as to stimulate learners' learning motivation and develop their interest and thirst for knowledge in learning . In particular, it is important to focus on computer self-efficacy and cognitive load, not only because of the positive main effect of learning engagement on cognitive load but also because of the moderating role of computer self-efficacy between learning engagement and cognitive load[17].

Some limitations and future directions must be considered. Firstly, this study only examined the cognitive load and did not directly examine learning performance. In future studies, learning performance or learning evaluation can be added as dependent variables. Secondly, this study only investigated the online learners in specific areas, future studies can explore the reliability of these findings with a more general sample. Thirdly, online learning platforms are diverse and have different functions. This study only investigated learners on WeChat public platform, and the conclusions may be affected. Finally, conclusion about the moderating role of computer self-efficacy between learning engagement and cognitive load should be treated with caution because the findings are based on correlational data, and not on experimental data.

5. Conclusions

The current study found that learning engagement and computer self-efficacy are beneficial to cognitive load; learning engagement was positively correlated with computer self-efficacy; and, moreover, computer self-efficacy has a moderator role between learning engagement and cognitive load and low computer self-efficacy can strengthen the positive impact of learning engagement on cognitive load.

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