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The Impact of Self-Regulated Learning Behaviors on Cognitive Load and Academic Performance in Online Learning Environments

Abstract: - The purpose of this study is to investigate the impact of college students' self-regulation abilities on cognitive load and learning proficiency within online learning environments. A sample of 160 undergraduate students was selected for this research, with their self-regulatory capacities in online learning being surveyed and analyzed descriptively and for correlation. The analysis revealed significant differences between self-regulatory abilities and learning outcomes. Furthermore, a descriptive analysis of the rating data was conducted, dividing the participants into high self-regulatory and low self-regulatory groups. Subsequent to this, two-factor variance analysis and simple effects tests were employed to further examine the data. The results indicated that factors affecting cognitive load and academic performance did not significantly differ. However, a significant interaction was observed between self-regulatory abilities and learning proficiency from the perspective of two-factor variance analysis. Simple effects tests further disclosed that under conditions of low learning proficiency, the cognitive load for the high self-regulatory group was greater than that for the low self-regulatory group; conversely, with higher learning proficiency, the cognitive load for the high self-regulatory group was lower. According to cognitive load theory, these findings suggest that learners who appropriately utilize their self-regulatory abilities can effectively alleviate cognitive load, thereby enhancing academic performance.

Keywords: Online Learning, Self-Regulated Learning Ability, Cognitive Load

1.Introduction

“Online learning models” have emerged as a pivotal approach to talent cultivation under the current backdrop of educational informatization, evolving from early solitary localized systems to the present-day expansive multimedia, multimodal, and visual learning methods. This model leverages internet technology to offer learners a variety of educational scenarios, including online communication, resource sharing, and knowledge visualization, which have significantly enhanced the efficiency of knowledge acquisition. Nevertheless, compared to traditional offline learning, online learning is constrained by individual habits and conditions of learners, facing challenges in instructional design and the utilization of teaching resources. Concurrently, as human-computer interaction systems become more complex and the number of online learning resources rapidly increases, the cognitive information load that learners must process is also on the rise, potentially leading to either excessive or insufficient cognitive load during online learning. Such conditions may result in suboptimal self-directed learning outcomes, such as slowed “cognitive input–processing–storage” processes or delayed

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responses, leaving learners in a perpetual state of aimless learning [1-2].

Hence, while utilizing online learning resources, learners need to engage in effective “Self-Regulated” learning strategies to avert cognitive overload. “Self-Regulated” learning refers to a series of cyclical cognitive activities undertaken by learners throughout the learning process, encompassing anticipation of learning outcomes, volitional control over behavioral performance or cognitive processes, and reflection on cognitive processes[3]. Existing research indicates that self-regulatory abilities can be enhanced through appropriate training, and higher levels of self-regulation significantly improve learning outcomes. It is evident that self-regulatory abilities, by enabling learners to control their own behaviors and plan their learning schedules, facilitate comprehension of knowledge, thereby balancing cognitive load in online learning and achieving superior learning outcomes[4]. This study aims to analyze the impact of self-regulatory abilities on the cognitive load experienced by learners in online learning, to explore the interrelationships between learners’ self-regulatory abilities, cognitive load, and learning proficiency, and to provide new insights for personalized development in online learning.

2.Literature Review

2.1. Research on Cognitive Load in Online Learning

"Cognitive load" refers to the total amount of activity imposed on an individual's cognitive system during the completion of a task within a specific time frame[5]. This concept was initially introduced by Australian psychologist John Sweller in 1988, who posited that as the quantity of information individuals receive, process, and elaborate on increases, so does cognitive load. In traditional teaching processes, cognitive load can arise due to factors such as the overwhelming amount of information received by learners in a short period or the inability to discern the priority of information, leading to informational redundancy in the brain. Based on the varying sources of cognitive load, John Sweller and colleagues categorized cognitive load into three types: intrinsic cognitive load, extrinsic cognitive load, and associative cognitive load[6]. "Intrinsic Cognitive Load" arises from the inherent characteristics of the learning material and burdens the working memory when the material's structure is complex or the associations between the learner's existing knowledge and experience are unclear. "Extrinsic Cognitive Load" is caused by factors such as the presentation of learning materials and teaching methods, and it is related to the ways in which learners receive and process information. "Associative Cognitive Load" occurs when learners allocate their remaining cognitive resources to tasks related but not essential to the learning task at hand[7-9]. In teaching, it is challenging to reduce intrinsic load solely through instructional design due to the influence of learning materials and learners' comprehension abilities. Consequently, reducing extrinsic cognitive load is often the approach taken to decrease the overall cognitive load on learners, thereby enhancing learning efficiency[10-11].

With the rapid advancement of internet technology, the sharing of online teaching resources has significantly improved. However, this advancement has also brought about a series of issues, particularly regarding the quality of instruction in online learning, which has become a key research topic in academia. Research into cognitive load in online learning environments has accordingly gained focus in recent years. Researchers have started to investigate the connection between individual differences among learners and cognitive load theory.

They have explored how factors such as learners' prior knowledge, cognitive styles, and self-regulatory behaviors affect the capacity of their working memory[12-13]. Typically, learners' prior knowledge and experience are crucial factors influencing learning outcomes in online learning environments. If learners lack sufficient prior knowledge, they will require more time to process and elaborate on information to understand and complete tasks, which inevitably increases the burden on their working memory and affects their cognitive performance[14]. According to cognitive load theory, presenting information through a combination of text and graphics can help learners build mental models more quickly and facilitate deeper understanding[15].This implies that the manner in which information is presented significantly impacts learners' extrinsic cognitive load and is related to their cognitive styles. For instance, learners who rely on visual perception tend to use materials such as images, dynamic graphics, and videos to receive and process information. This approach not only reduces intrinsic cognitive load but also allows them to allocate their remaining cognitive resources to other information processing, thereby enhancing learning outcomes[16]. Balancing cognitive load is often necessary to improve learning outcomes through the utilization of different cognitive methods. As such, one of the primary focuses of current online learning research is to explore the relationship between individual differences and cognitive load among learners and to optimize learning outcomes by balancing cognitive load. However, this also places higher demands on learners' self-regulatory abilities.

2.2. Self-Regulated Learning in Online Education

The concept of "Self-Regulated Learning" was first formally introduced by Zimmerman at the 1986 annual meeting of the American Educational Research Association. He posited that self-regulated learning is the ability of learners to adjust and sustain their psychological activities to achieve learning goals[17]. Among the various models of self-regulated learning, the most influential include Zimmerman's self-regulatory cycle model[18], Pintrich's conceptual framework model[19], Boekaerts' dual-process model[20], and Winne's information processing model[21]. While these models agree that self-regulated learning is a cyclical process, they differ in their specific applications and foci. Zimmerman and Pintrich's models focus more on describing the process of self-regulated learning, Boekaerts emphasizes the importance of emotions, and Winne approaches the topic from a metacognitive perspective. Zimmerman's self-regulatory cycle model, in particular, has had a profound impact. It divides self-regulated learning into three cyclical stages: pre-planning, task execution, and self-reflection, explaining the process of learners' self-regulation through these stages. This process is iterative, mutually reflective, and mutually reinforcing[22]. However, the academic community has not yet formed a unified theoretical framework for research on self-regulatory abilities. There are two main perspectives on the definition of self-regulatory abilities: one views it as a learning process, and the other as a capability. Despite the varying research angles on the definition, a commonality among scholars' findings is that learners engaging in self-regulation need to adjust their psychological and physiological behaviors to achieve their intended goals.

Existing research indicates that learners without professional training struggle to control their learning behaviors precisely, especially in online learning environments. Behaviors related to task execution, reflection, and evaluation all affect the effectiveness of self-regulated learning. Most researchers believe that the richer the learner's prior knowledge and experience, the stronger their self-regulatory abilities. There are differences in self-regulatory abilities among learners with varying levels of knowledge and experience[23]. This suggests that self-regulatory abilities are closely related to learners' prior knowledge and experience, indicating that the knowledge structure learners possess is linked to their self-regulatory abilities[24]. Additionally, self-regulatory abilities are associated with extrinsic cognitive load. Learners often need to invest significant psychological and cognitive resources in self-regulatory activities, which may negatively impact their learning to some extent. Currently, in online learning environments, the use of new technologies or assistive tools can help learners set goals, make plans, self-monitor, self-regulate, and reflect, thereby enhancing their self-regulatory abilities and influencing learning outcomes. The better learners perform in the planning and execution stages of self-directed learning, the more significant the learning outcomes, further highlighting the importance of self-regulated learning.

2.3.Methods for Measuring Self-Regulated Learning in Online Education

Research has indicated that different perspectives require various methods for measuring self-regulated learning. For instance, quantitative studies can be conducted using self-regulated learning scales to understand the current state and differences in online self-regulated learning among college student[25]. Additionally, qualitative comparative analysis methods, such as interviews and questionnaires, can delve into the impact of cognitive materials on self-regulated learning behaviors and how these influences lead to varying academic achievements[26]. Some researchers have also employed data analysis techniques to quantify the online learning process and transform it into visual data for validation[27]. These research cases illustrate that the methods for measuring self-regulated learning are typically designed for specific contexts. Currently, the most commonly used methods for measuring self-regulated learning in online education are non-real-time methods, such as surveys and questionnaires. These methods primarily focus on non-real-time measurements of self-regulatory abilities displayed by research subjects during different learning tasks in the online learning process[28]. Among the widely used measurement tools are Zimmerman's "Self-Regulated Learning Interview Schedule," the "Online Self-Regulated Learning Questionnaire" proposed by Barnard-Brak and others, and the Motivated Strategies for Learning Questionnaire developed by Pintrich and colleagues[29]. In addition to these non-real-time measurement methods, real-time methods such as eye-tracking experiments, systematic observation, and learning trace analysis are also extensively used in measuring self-regulated learning in online education. These methods typically require the use of experimental equipment or software to record learners' behaviors in real-time and to monitor their completion of self-regulated learning experiments.

3. Research Method

3.1.Research Subjects and Research Questions

This study selected 160 undergraduate students from a university, comprising 60 males and 100 females, all aged between 18 and 23 years. The majority of the students were in their second and third years of undergraduate studies, and all were majoring in design fields, including Visual Communication Design, Digital Media Art, Environmental Design, and Product Design. All participants had completed the same online course in art and design. The characteristics of the research subjects are presented in Table 1.

Table 1. Basic Characteristics of Research Subjects

Characteristics of Research Subjects	Gender		Grade			Major			
	Male	Female	Sophomore	Junior	Senior	Visual Communication Design	Digital Media Art	Environmental Design	Product Design
Number	60	100	80	65	15	50	40	35	35
Percentage	37.5%	62.5%	50%	40.6%	9.4%	31.2%	25%	21.9%	21.9%

After a comprehensive review and precise analysis of existing research findings, we have discovered that there is a divergence of opinions within the academic community regarding the impact of learners' self-regulatory abilities on their cognitive load. Moreover, the interaction mechanisms between self-regulatory abilities and various types of cognitive load are not yet clearly defined and require further clarification. Consequently, this study has chosen undergraduate students majoring in art and design as the research sample, aiming to explore the specific influence of learners' self-regulatory abilities on cognitive load and learning ability within the online learning environment. The study will proceed based on the following two hypotheses: (1) The various behavioral manifestations of self-regulatory abilities will lead to differences in learning outcomes. (2) When learners appropriately utilize their self-regulatory abilities, they can effectively alleviate cognitive load and enhance their academic performance.

3.2.Research Tools

The primary tools employed in this study include the Online Self-Regulated Learning Questionnaire (OSLQ), pre- and post-course learning test items, and a cognitive load assessment scale. To cater to the specific needs of the research theme, the OSLQ was locally adjusted to form a measurement questionnaire with 24 items, and a 5-point Likert scale was used to assess learners' self-regulatory abilities during online learning, encompassing six main dimensions: goal setting, environment construction, task strategies, time management, seeking help, and self-evaluation. Through reliability analysis, the Cronbach'sαcoefficients for each dimension exceeded 0.70, indicating a high level of reliability for the questionnaire. The post-course learning test items were designed by the researcher, ensuring consistency in terms of quantity, type, and knowledge points of the items, while appropriate variations were made to the test items. The internal consistency of the test items was tested using Cronbach'sαcoefficient, with the results showing reliability coefficients of 0.80 for the test items. Additionally, the assessment of cognitive load utilized Pass's Mental Effort Self-Assessment Scale, which also employs a 5-point Likert scale and aims to quantify the level of cognitive load experienced by learners during the learning process.

3.3.Experimental Procedure

The study's experiment is conducted in three stages. The first stage is the assessment of self-regulated learning abilities. Initially, the participants are required to learn and master the methods of self-regulated learning, fully grasping the experimental instructions and basic precautions. Subsequently, participants are instructed to use the computer equipment provided by the experiment to study the selected course chapters online without time constraints. Once the self-study phase is completed, the participants will undergo an assessment of their online self-regulatory abilities using the self-regulatory ability scale.

The second stage involves a preliminary assessment of cognitive load through post-course learning test items. In this stage, the participants must answer pre-test questions designed by the experimenter based on the knowledge points of the course. Through descriptive statistical analysis of the test results, the participants are categorized into high-learning ability and low-learning ability groups, and subsequent cognitive load tests are conducted for these two groups.

The third stage is the measurement of cognitive load. Based on the test results of the online self-regulatory ability scale, the cognitive load of the two groups of participants is measured. This measurement process is set at six key measurement points according to the knowledge points of online learning, with the average score of these six measurements used as the numerical value to assess the cognitive load of the participants.

4. Result Analysis

4.1.Impact of Self-Regulated Learning Abilities on Online Learning

After testing the participants' self-regulated learning abilities, a descriptive statistical analysis was conducted on the collected data to assess college students' online self-regulated learning abilities. The analysis results for each dimension are detailed in Table 2. It is evident from the table that the coefficient of variation (CV) for all experimental variables did not exceed 0.15, indicating that there were no outliers in the data, which laid a reliable foundation for the subsequent experimental research. Through the analysis of the mean values of each dimension, we found that the overall self-regulated learning abilities displayed by the participants in the online learning environment were not outstanding. The mean values for the "Environment Structure," "Time Management," and "Seeking Help" dimension were significantly lower than those of other dimensions, a finding that warrants further attention and discussion.

Table 2. Descriptive Analysis of Undergraduate Students' Online Self-Regulated Learning Abilities

Variable Name	N	Mean	Standard Deviation	Median	Variance	Coefficient of Variation（CV）
Goal Setting	160	3.375	1.354	4	1.832	0.101
Environment Structure	160	2.688	1.298	3	1.686	0.083
Task Strategy	160	3.362	1.305	4	1.702	0.088
Time Management	160	2.875	1.391	3	1.934	0.084
Seeking Help	160	2.987	1.307	3	1.709	0.038
Self-Assessment	160	3.385	1.315	4	1.731	0.121

In exploring the correlation between different dimensions of self-regulated learning ability and learning proficiency, we employed the Pearson correlation analysis method to conduct a detailed analysis on the six key dimensions: goal setting, environment structure, task strategy, time management, seeking help, and self-assessment. The results of the correlation analysis are presented in Table 3. The analysis revealed significant correlations among the dimensions, and all variables showed a positive correlation with online self-regulated learning ability. This finding preliminarily supports the basic hypothesis of this study: that different behaviors of self-regulated learning ability will produce different learning effects. This insight provides valuable understanding of the role of self-regulated learning ability in online learning environments and points to further research directions.

Table 3. Correlation Analysis of Undergraduate Students'Online Learning Self-Regulated Learning Abilities

	Mean	Standard Deviation	Goal Setting	Environment Structure	Task Strategy	Time Managemen	Seeking Help	Self-Assessment
Goal Setting	3.075	0.883	1					
Environment Structure	3.375	0.848	0.334**	1				
Task Strategy	3.263	0.807	0.396**	0.335**	1			
Time Management	3.375	0.998	0.354**	0.266*	0.206*	1		
Seeking Help	3.038	1.119	0.310**	0.338**	0.249*	0.301**	1	
Self-Assessment	3.650	0.638	0.371**	0.258*	0.233*	0.310**	0.302**	1

* p<0.05 ** p<0.01

Due to the normal distribution characteristics of the collected related behavioral data, this study utilized one-way ANOVA to analyze the relationship between self-regulated learning abilities and online academic performance. In this analysis, various dimensions of self-regulated learning ability were treated as independent variables, while the gender, age, and major of the participants were treated as dependent variables. The significance P-value results are detailed in Table 4. The analysis revealed that in terms of grade, the P-value for online self-regulated ability and its dimensions was greater than 0.05, indicating that students of different grades did not exhibit significant differences in online self-regulated ability. However, in terms of major, significant differences were observed in the goal setting ($P=0.024<0.05$) and task strategy ($P=0.044<0.05$) dimensions, while other dimensions did not show significant differences. Furthermore, in terms of gender, significant differences were found in the goal setting ($P=0.011<0.05$) and seeking help ($P=0.048<0.05$) dimensions, while no significant differences were observed in other dimensions. These results indicate that online self-regulated ability varies among different student groups, providing an important reference for subsequent experiments.

Table 4. Analysis of Variance for Different Variables in Undergraduate Students' Online Learning Self-Regulated Learning Abilities

Variable	Gender Differences	Major Differences	Grade Differences

	F	P	F	P	F	P
Goal Setting	6.773	0.011**	3.33	0.024**	2.156	0.128
Environment Structure	0.553	0.459	0.502	0.682	1.162	0.318
Task Strategy	1.368	0.259	4.183	0.044**	1.152	0.321
Time Management	0.013	0.908	1.429	0.241	1.579	0.213
Seeking Help	2.734	0.048**	0.252	0.617	0.934	0.397
Self-Assessment	2.133	0.148	0.712	0.548	0.413	0.663

***, **, * represent significance levels of 1%, 5%, and 10% respectively

4.2.Impact of Self-Regulated Learning Abilities on Cognitive Load

To ensure the effectiveness and accuracy of the study, a descriptive statistical analysis was conducted on the test scores of the participants. Based on these results, the participants were grouped, with the specific results detailed in Table5. The analysis revealed no outliers (CV>0.15) in the current test results, indicating a high data quality suitable for grouping using the mean. Given that the average total score was 79.86, participants scoring above this threshold were classified into the high learning ability group (n= 86), while those scoring below were classified into the low learning ability group (n=74). This grouping method aids in better understanding the distribution characteristics of learning outcomes and their relationship with self-regulated learning abilities.

Table 5. Descriptive Analysis of Group Evaluation

Variable	N	Mean	Standard Deviation	Median	Variance	Coefficient of Variation（CV）
Single Choice Questions	160	26.315	2.059	26.735	4.24	0.078
Fill-in-the-Blanks	160	12.649	1.477	13.1	2.183	0.117
Short Answer Questions	160	40.896	3.755	40.75	14.101	0.092
Total Score	160	79.86	5.639	79.655	31.794	0.071

Subsequently, the experiment treated self-regulated learning ability as the independent variable and common factors influencing cognitive load as the dependent variable, and conducted a descriptive statistical analysis. The specific results are presented in Table 6. The analysis revealed that the main effect of self-regulated learning ability was not significant (P > 0.05). Furthermore, except for difficulty level, the main effect of learning ability did not exhibit significance in other dimensions (P > 0.05).

Table 6. Descriptive Analysis of Factors Affecting Cognitive Load and Academic Performance

Variable	High Score Group（n=86）	Low Score Group（n=74）
Interest	3.05±0.84	3.84±0.51

Table 6. Descriptive Analysis of Factors Affecting Cognitive Load and Academic Performance

Variable	High Score Group（n=86）	Low Score Group（n=74）
Curiosity	3.25±0.82	3.93±0.50
Confidence	4.12±0.43	3.68±0.57
Practicality	3.60±0.79	3.47±0.53
Difficulty	2.36±0.89	2.67±0.76
Comprehension Ability	2.97±1.01	2.59±0.93

Using the cognitive load measurement scale, with cognitive load as the dependent variable and self-regulated learning ability and learning skill level as the independent variables, a two-factor ANOVA was conducted. The detailed results are presented in Table 7. The analysis revealed that the level of learning ability showed significance (F=9.673, P<0.01), indicating a significant impact on cognitive load and a main effect. Specifically, the cognitive load experienced by participants with lower learning ability levels was significantly higher compared to those with higher learning ability levels. However, the main effect of the independent variable, self-regulated learning ability, did not show significance (P>0.05). Furthermore, the interaction effect between the two variables was significant (P<0.01), suggesting that self-regulated learning ability plays a certain regulatory role in the impact of learning ability level on cognitive load.

Table 7. Two-Factor ANOVA Analysis of Cognitive Load

Variable	SS	df	MS	F	P
Learning Ability Level	19.40	1	19.40	9.67	0.000***
Self-Regulated Learning Ability	2.59	1	2.59	1.94	0.151
Intercept	663.63	1	663.63	992.88	0.000***
Error	49.46	74	0.67		

***, **, * represent significance levels of 1%, 5%, and 10% respectively

To further analyze the results of cognitive load measurement, the experiment conducted simple effect tests, with the specific results presented in Table 8. The tests revealed that there were significant differences between the two groups in terms of self-regulated learning ability (P > 0.05). Specifically, when the learning ability was lower, the cognitive load experienced by the group with better academic performance was significantly higher than that of the group with poorer academic performance. Conversely, when the learning ability was higher, the cognitive load experienced by the group with better academic performance was significantly lower than that of the group with poorer academic performance. This finding suggests that there is a dynamic relationship between self-regulated learning ability and learning skill level, and this relationship has a significant impact on cognitive load.

Table 8: Simple Effect Test of Cognitive Load on Learning Self-Regulated Ability at Different Levels of Learning Ability

学习能力水平		SS	df	MS	F	P
Low Academic Performance Group	Between Groups	2.68	1	2.68	8.34	0.000***
	Within Groups	9.74	37	0.26		
	Total	12.42	38			
High Academic Performance Group	Between Groups	1.67	1	1.78	7.01	0.012**
	Within Groups	6.30	37	0.17		
	Total	7.97	38			

***, **, * represent significance levels of 1%, 5%, and 10% respectively

5.Result Analysis

The study found that college students' self-regulated learning abilities in online learning environments are generally average. Particularly, in the dimensions of environmental structure, time management, and seeking help, their performance is not ideal. However, when analyzing the correlation between these variables and online self-regulated learning abilities, we discovered significant correlations among them and a positive correlation with online self-regulated learning abilities. This result preliminarily verifies the different learning effects among the behavioral variables in self-regulated learning abilities[31]. When analyzing the self-regulated learning abilities of students from different grades, ages, and majors, we found that there were no significant differences between students of different grades in any of the dimensions. However, in terms of major and gender, there were significant differences in certain dimensions. In the major dimension, there were significant differences in goal setting ($P=0.024 < 0.05$) and task strategy ($P=0.044 < 0.05$). Through interviews with the participants, we found that some participants from the majors of Digital Media Art and Product Design were non-artistic students (all non-artistic students were science students), which led them to be more inclined to rational thinking in the execution of goal setting and task strategy. In the gender dimension, there was a significant difference in seeking help ($P=0.048 < 0.05$). The interview results showed that female participants sought help more frequently than male participants, and the proportion of art students was higher. Overall, the analysis shows that non-artistic students outperformed art students in all dimensions.

In analyzing the impact of self-regulated learning abilities on cognitive load, we first conducted tests on participants after course learning and performed descriptive statistical analysis based on the test results. The results showed that all test data did not contain any outliers ($CV > 0.15$). Therefore, it was decided to use the mean to group the participants, categorizing them into high and low learning ability groups. Subsequent tests revealed that the cognitive load and academic performance of the two groups of participants were not influenced by independent variables such as interest and curiosity. However, from the perspective of cognitive load testing, the impact of self-regulated learning abilities on cognitive load was not significant ($P = 0.151 > 0.05$). This does not imply that self-regulated learning abilities have no effect on cognitive load, as there may be interaction effects between them, leading to the effects of related independent variables being masked. From the results of the two-factor ANOVA, a significant interaction effect was found between self-regulated learning abilities and learning abilities[32]. Therefore, we continued with simple effect tests, and the results showed that there were significant differences between the two groups ($P > 0.05$). According to the theories of cognitive psychology, when the learning ability level of the participants is low, the higher the self-regulated learning ability, the more it can enhance the cognitive load of the participants. This cognitive load is related to time management, task strategy, and learning control in the learning process, which is an effective cognitive load that is beneficial to learning. Therefore, the above test results indicate that learners who can correctly utilize their self-regulated learning abilities can reduce cognitive load and thereby improve their academic performance.

6.Summary

This study, through methods of questionnaire surveys and data analysis, explored the impact of self-regulated learning abilities on college students' cognitive load and learning ability within the online learning environment. It proposed two hypotheses: the first being that "different behaviors of self-regulated learning abilities will produce different learning effects," and the second being that "learners can reduce cognitive load and improve academic performance by appropriately utilizing self-regulated learning abilities." The study's conclusions indicate that self-regulated learning abilities have a significant impact on learning outcomes. However, in the online learning environment, college students generally exhibit low levels of self-regulated learning abilities, particularly in the dimensions of "environment structure," "time management," and "seeking help." Additionally, there are differences in these abilities based on the dimensions of major and gender, with particularly significant differences observed in the major dimension.

While correctly utilizing self-regulated learning abilities can reduce cognitive load and enhance academic performance, the test results suggest that the main effects of self-regulated learning abilities and cognitive load are not significant. However, there is a significant interaction between self-regulated learning abilities and learning ability levels, which supports our hypotheses. It is important to note that the impact of self-regulated learning abilities is closely related to the individual learning ability level of the learner. These findings underscore the significance of enhancing self-regulated learning abilities in the online learning environment and demonstrate how the optimization of learning skills through improved self-regulated learning abilities can enhance learning efficiency and academic performance.

References

[1] Pintrich P R. The role of goal orientation in self -regulated learning [M]//Boekaerts M, Pintrich P R, Zeidner M. Handbook of self-regulation. California: Academic Press,2000:451-502.

[2] Kim D,Yoon M, Joi. Learning analytics to support self-regulated learning in asynchronous online courses: a case study at a women's university in South Korea [J]. Computers & education，2018,127;233-251.

[3] Zimmerman,B.J.Development self-fulfilling cycles of academic regulations: An analysis of expemplary instructional models. In D.H. Schunk & B.J. Zimmerman, self -regulated learning：From teaching to self –regulated practice

[M].New York : Guilford,1998:1-19.

[4] Azevedo,R.,& de Groot, E.V.Motivaltional and self-regulated learning facilitate students' learning with hypermedia [J].Journal of Educational Psychology,20014,96(3):523-535.

[5] Sweller, J. Cognitive load during problem solving, effects on learning [J]. Cognitive Science,1988,12(2):257-285.

[6] Sweller, J.,Van Merrienboer, J.J.G.,& Paas, F.Cognitive architecture and instructional design [J]. Educational Psychology Review,1998,10(3):251-296.

[7] Paas, F.,Renkl,A.,&Sweller,J. Cognitive load theory and instructional design: Recent Developments [J]. Educational Psychologist,2003,38(1):1-4.

[8] Geary,D.C. An evolutionarily informed education science [J]. Educational Psychologist, 2008,43:179-195.

[9] Sweller, J. Cognitive load theory, learning diffculty, and instructional design [J].Learning and Instruction,1994,4(3):295-312.

[10] Xia Fengqin, Jiang Shumei, Sun Chongyong. Educational Psychology [M] Higher Education Press, 2010: 140-141.

[11] Pang Weiguo. Cognitive Load Theory and Its Teaching Significance [J]. Contemporary Education Science, 2011, 25 (12): 23-28.

[12] Wang Xizhe, Tu Yaxin, Zhang Linjie, et al. A study on the efficiency enhancement mechanism of online collaborative learning from the perspective of cognitive load [J]. Research on Electronic Education, 2022, 43 (09): 45-52+72.

[13] Macaluso JA, Beuford RR, Fraundorf SH. Familiar Strategies Feel Fluent: The Role of Study Strategy Familiarity in the Misinterpreted-Effort Model of Self-Regulated Learning. Journal of Intelligence. 2022; 10(4):83.

[14] Kalyuga. S., Ayres, P., & Sweller, J. The Expertise reversal effect [J]. Educational Psychologist,2011, 38(1):23-31.

[15] Liu Rude, Zhao Yan, Chai Songzhen, Xu Juan. Cognitive mechanisms of multimedia learning. Journal of Beijing Normal University (Social Sciences Edition), 2007, 52 (5): 22-27.

[16] DeLeeuw, K.E.. & Mayer, R.E. A comparison of three measures of cognitive load, evidence for separable measures of intrinsic, extraneous, and germane load [J]. Journal of Educational Psychology, 2008, 100(1):223-234.

[17] Zimmerman B J .Attaining selfregulation: Asialcognitive perspective [M] Handbook of selfrelfregulation. Academicpress, 2000:13-39.

[18] Zimmerman B J, Schunk D H. Handbook of self-regulation of learning and performance [M]. Routledge/Taylor & Francis Group, 2011.

[19] Pintrich P R. The role of goal orientation in self-regulated learning [A]. Boekaerts M, Pintrich P R, Zeidner M. Handbook of self-regulation [C]. Salt Lake City: Academic Press，2000 :451-502.

[20] Boekaerts M. Self - regulated lerning: where we are today[J].International Joumal of Educational Research,1999(6) :445-457.

[21] Winne P H. Inherent details in self-regulated learning[J]. Educational Pswchologist. 1995(4):173- 187.

[22] Azovedo, R., & Cromly, J.G. Does training on self-regulated learning faxilitate students' learning with hypermedia [J]. Joumal of Educational Psychology, 2004, 96(3):523-535.

[23] Leutner, D., Leopold, C., & den Elzen-Rump, V. Self-regulated learning with a text-highlighting strategy: A training experiment [J]. Zeitschrift fur Psychologie/Journal of Psychology, 2007, 25(3): 174-182.

[24] Shi Wei. Analysis of Issues in Cognitive Load Teaching Design Theory [J]. Journal of Southwest Normal University (Natural Science Edition), 2011, 36 (3): 287-291.

[25] Xue Yisheng, Song Chunhui, Chen Huandong. University Students' Self-Regulation Ability in Online Learning and

Intervention Suggestions [J]. Computer Knowledge and Technology, 2023, 19(32): 177-180.

[26] Li Wenhao, Ren Xiaotong, Zhu Xiya, et al. A Study on the Mechanism of Self-Regulated Learning Behavior Under Cognitive Flexibility Design Affecting Academic Performance [J]. Research in Electricity-Assisted Education, 2022, 43(02): 64-71.

[27] Wang Xizhe, Tu Yaxin, Zhang Linjie, et al. A Study on the Efficiency Mechanism of Online Collaborative Learning From the Perspective of Cognitive Load [J]. Research in Electricity-Assisted Education, 2022, 43(09): 45-52+72.

[28] Laer S V, Elen J. The effect of cues for calibration on learners' self-regulated learning through changes in learners' learning behaviour and outcomes[J]. Computers & education, 2019,135(7):30-48.

[29] Broadbent J, Panadero E, Lodge J, Barba P. Technologies to enhance self-regulated learning in online and computermediated learning environments [M].Switzerland:Spring Nature AG, 2020:37-52.

[30] Janssen J, Kirschner P A. Applying collaborative cognitive load theory to computer-supported collaborative learning:towards a research agenda[J]. Educational technology research and development,2020,68(2):783-805.

[31] Deng Guomin, Han Xibin, Yang Juan. The impact of self-regulated learning behavior based on OERs on learning outcomes [J]. Research on Electronic Education, 2016, 37 (3): 42-49,58.

[32] Bannert M, Reimann P, Sonnenberg C. Process mining techniques for analysing patterns and strategies in students' selfregulated learning[J]. Metacognition and learning, 2014,9(2):161-185.

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