Based on Balanced Cognitive Load: The Impact of Students' Self-Regulated Learning Competence on Information Display of Digital Teaching Interfaces

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Abstract: From the perspective of balanced cognitive load, this study investigates how linear and networked digital teaching interfaces, together with undergraduates' self-regulated learning (SRL) competence, affect their learning outcomes and cognitive load composition. A mixed experimental design of linear, networked (interface type)×continuous variable (self-regulated ability) was used. 148 art-design undergraduate students were recruited as subjects. Data were collected via self-regulated learning questionnaires, three-dimensional cognitive load scales and learning outcome tests. The experiment shows a significant interaction effect between teaching interface type and self-regulated ability on learning outcomes. High-self-regulated learners have better learning outcomes in networked interfaces than in linear ones, while low-self-regulated learners show no significant difference. Subsequent analyses demonstrate that learners with high SRL capacity present lower extraneous cognitive load and higher germane cognitive load in networked interfaces, thereby accomplishing the redistribution of cognitive resources; this mechanism is mediated by learning strategies such as structural construction and inhibitory control. The study indicates that the positive effect of self-regulated ability depends on teaching interface adaptability. High-self-regulated learners can achieve "balanced cognitive load" through networked interfaces, while low-self-regulated learners are more suitable for linear interfaces.

Keywords: Digital Teaching Interface; Self-Regulated Learning Ability; Cognitive Load; Linear Instructional Interface; Network Instructional Interface

1. Introduction

"Digital teaching", as an educational practice model covering various forms such as online course platforms, intelligent tutoring systems, and hypermedia textbooks, has evolved from merely serving as an information transmission channel in the early days to a core environmental variable influencing learners' cognitive processing. During this process, digital teaching interfaces, with their specific information presentation methods, not only convey subject content but also continuously guide learners' attention resource allocation, mental schema construction, and metacognitive monitoring. However, compared with traditional teaching interfaces, the design logic of digital teaching interfaces is generally assumed that the same information presentation method is equally suitable for all learners. This assumed logic ignores individual differences in self-regulated learning (SRL) ability, which may cause some learners to bear a high extraneous cognitive load in interfaces with a more complex information structure, thereby suppressing their learning performance and leading to a passive state of cognitive input [1,2]. In a digital teaching context, if learners lack active self-regulated learning ability, the probability of overload in the cognitive processing will also increase. Cognitive load theory suggests that the key to effective learning is not to minimize the total amount of cognitive load absolutely, but to release limited cognitive resources from inefficiently consumed redundant information and strategically re - allocate them to deep semantic processing and the associative construction of knowledge networks. This theoretical perspective of "balanced cognitive load" provides a new analytical entry point for evaluating the effectiveness of digital teaching interfaces, and SRL ability plays the functions of executive control and resource allocation therein. According to Zimmerman's cyclical model, SRL includes three phases: forethought planning, task implementation, and self-evaluation. In digital teaching interfaces, learners with a higher SRL level often show stronger cognitive adaptability. They can actively identify and avoid certain cognitive consumption points in the teaching interface and employ compensatory strategies, thus redirecting some of the resources that would otherwise be consumed on extraneous cognitive load to associative processing. In contrast, learners with a lower SRL level may get lost in navigation due to the excessive freedom given by the interface and passively bear additional cognitive load. Existing research has widely examined the influences of digital teaching interface design characteristics on cognitive load, as well as the predictive association between SRL competence and learning performance. Nevertheless, the potential interactive effect of these two factors has not undergone systematic empirical validation. [3,4]. Consequently, this research aims to investigate the distinctions in three types of cognitive load and learning achievements among learners having diverse SRL ability levels while they are confronted with linear and network - oriented digital teaching interfaces. Additionally, it will examine the mediating function of learning strategies.

2. Literature Review

Cognitive load refers to the overall volume of information imposed on the cognitive system as individuals complete a task within a specified period [3]. Depending on its source, cognitive load can be divided into three types: intrinsic cognitive load (ICL), extraneous cognitive load (ECL), and germane cognitive load (GCL) [4-7]. ICL is constrained by the complexity of the learning material and the learner's prior understanding, and it is generally difficult to reduce simply by modifying instructional design. ECL, by contrast, can be managed through the way information is presented, thereby lowering overall cognitive load and supporting more efficient learning. In conventional teaching settings, when learners are confronted with an excess of information in a short period or struggle to discern the hierarchical structure of that information, information redundancy tends to arise-a common indicator of excessive cognitive load. A large portion of current research adopts an individual-differences lens, examining how prior knowledge, self-regulated behavior, and cognitive load jointly relate to working memory capacity [8]. Findings indicate that learners who lack prior knowledge tend to spend more time processing information, carry a heavier working memory load, and exhibit a decline in cognitive performance. Conversely, delivering information via the integration of textual and visual elements has been found to accelerate the construction of mental models, highlighting the function of display formats in modulating extraneous cognitive load [9]. Unpacking the interplay between individual differences and cognitive load, and leveraging balanced cognitive load to improve learning outcomes, thus emerges as a central concern. Progress toward this goal is contingent upon learners' SRL ability. SRL refers to the process in which learners actively monitor, control, and maintain their cognition, motivation, and behaviors to achieve learning goals [10]. However, without systematic training, learners often struggle to calibrate their learning behaviors with precision, thereby diluting the benefits of SRL. Evidence further suggests that richer prior knowledge and experience tend to be associated with stronger self-regulation skills, and substantial individual differences in SRL emerge across varying levels of expertise [11] pointing to knowledge structures as a probable foundation of SRL ability. Engaging in SRL itself, however, draws on cognitive resources; self-regulation demands considerable mental effort, and under certain conditions, it can even detract from learning. Given these mechanisms, the way information is laid out on a teaching interface directly shapes learners' extraneous load, while self-regulated learning ability continually modulates how cognitive resources are allocated and utilized. This raises a pressing question: how can interfaces be designed to adapt to learners' SRL so as to optimize the distribution of cognitive load? Answering this question calls for careful investigation. In summary, current research on cognitive load mostly focuses on reducing the total amount of load, paying less attention to "re-investing" extraneous load into germane load to achieve balanced cognitive load. Research on self-regulated learning ability mainly examines its main effects, lacking the test of interaction effects with digital teaching interface types. The impact of the information presentation method of teaching interfaces on cognitive load has been preliminarily explored, but the core question of which interface is suitable for learners at what self-regulated learning level has not been answered empirically. Based on this, the following three hypotheses are proposed:

Hypothesis 1 (H1): Digital teaching interface types and self-regulated learning ability exert a significant interactive influence on learning outcomes.

Hypothesis 2 (H2): SRL ability helps learners achieve a resource allocation state of "balanced cognitive load" in network-based digital teaching interfaces.

Hypothesis 3 (H3): The application of learning strategies mediates the link between the interactive effect of digital teaching interface types and self-regulated learning ability and learning outcomes.

3. Research Methods

3.1 Experimental Design

This study adopted a 2 (interface type: linear interface vs. Networ-based interface, between-subjects) ×2 (learning period: pre- test vs. Post-test, within-subjects) mixed design. Among them, the interface type was the independent variable, and SRL ability was used as a continuous moderator variable (without extreme grouping treatment). The dependent variables included: (a) learning outcomes (scores of comprehension questions and transfer questions); (b) three-dimensional cognitive load (intrinsic, extraneous, and germane); (c) self-evaluation of the use of learning strategies (used as a process measurement index). In all statistical analyses, learners' prior knowledge was controlled as a covariate to exclude its potential confounding effects on the dependent variables.

3.2 Research Subjects

This study employed GPower 3.1 software to conduct a priori power analysis. Following the effect size guidelines established by Cohen (1988), the interaction effect test was assigned a medium effect size of f*=0.25, with a significance level set at α=0.05 and statistical power (1-β) fixed at 0.80. The calculation results showed that the minimum sample size required to test this interaction effect was 128 people. Considering possible data loss or invalid responses, 150 people were actually recruited in this study, meeting the above-mentioned power requirements. The 150 selected subjects were all undergraduate students majoring in art and design, and they had all taken the same art-design-related course. Their visual acuity or corrected visual acuity was normal. After the experiment, subjects who did not complete the entire process or whose responses showed an obvious random pattern were excluded. Finally, 148 valid samples were obtained (72 males and 76 females; age range 18-24 years old, with an average age of 20.4 years old, SD = 1.4. The basic characteristic information of the valid samples is shown in Table 1.

Table 1. Basic Characteristic Information Table of Research Subjects

Characteristics of Research Subjects	Gender		Grade			Major			
	Male	Female	Sophomore	Junior	Senior	VCD	DMA	E. Design	P. Design
Quantity	72	76	68	50	30	40	38	35	35
Proportion	48.6%	51.4%	45.9%	33.8%	20.2%	27.1%	25.7%	23.6%	23.6%

3.3 Research Tools

The main tools used in this study include the Online SRL Questionnaire (OSLQ), the test questions before and after the course study, and the cognitive load assessment scale. Among them, the OSLQ is the questionnaire developed by Barnard-Brak et al. A 5-point Likert-type scale is utilized (1 = totally disagree, 5 = totally agree). In the present study, the overall Cronbach's α coefficient of the scale is 0.89, and the α values for each dimension vary between 0.76 and 0.88. The average total score of each subject is used as a continuous moderator variable without high-low grouping treatment. The prior knowledge test aims to assess the subjects' prior understanding of the cognitive load theory. Before the experiment, all subjects completed a 10-question multiple-choice and true-false test, covering the basic concepts of the learning materials. The questions were independently compiled by two doctoral students in educational psychology and reviewed by a full professor, with a content validity index (CVI) of 0.92. The learning outcome test is used for an immediate post-test after the learning is completed. The test is divided into two types: "comprehension questions" and "transfer questions". "Comprehension questions" examine the memory of basic facts and concepts, such as "Which of the following is a source of extraneous cognitive load?" There are 6 questions, 1 point for each question, with a full score of 6 points. "Transfer questions" examine the ability to apply principles in new situations, such as "Please design an interface improvement plan to reduce the extraneous load in multimedia courseware and explain the reasons." A 0-4 point grading scale is used, and two raters grade independently and blindly, with an inter-rater reliability ICC of 0.85. There are 4 questions, with a maximum score of 16 points. The total learning outcome score is the sum of the comprehension score and the transfer score, with a full score of 22 points. The cognitive load instrument adopted in this study was the tripartite cognitive load scale developed by Leppink et al., which comprises 10 items in total, including 3 items assessing intrinsic load, 4 items measuring extraneous load, and 3 items evaluating germane load. A 7-point Likert-type format was employed for all items (1 = totally disagree, 7 = totally agree). In the current investigation, the Cronbach's α coefficients for the three dimensions were 0.82, 0.87, and 0.79, respectively.

3.4 Experimental Procedure

This research experiment is divided into three stages: self-regulated learning ability assessment, learning ability grouping and preliminary cognitive load detection, and formal cognitive load measurement. For the SRL ability assessment, before the experiment, subjects need to learn and master the basic methods of SRL. The experimenter uniformly explains the experimental instructions and precautions to ensure that all subjects fully understand the task requirements. Subsequently, participants completed online learning of the assigned course modules using laboratory-provided computer devices. No time restrictions were imposed to replicate an authentic SRL environment. After the self-study stage, subjects immediately take the online SRL ability scale (OSLQ) assessment to quantify the baseline level of their SRL ability. For the learning ability grouping and preliminary cognitive load detection, the learning ability of subjects is preliminarily detected through the test questions after the course study. Subjects need to answer the pre - test questions (i.e., learning outcome test) designed according to the course knowledge points. The assessment items cover single-choice and open-ended questions, with a total score of 100 points. Researchers perform descriptive statistical analyses on the obtained scores, and classify participants into high and low academic competence groups based on the overall average score for further inter-group difference analysis. Based on the test results obtained from the SRL ability assessment, the formal measurement of cognitive load is carried out on the high-and low-learning-ability groups. According to the distribution of knowledge points in the online learning, key measurement points are set after learning four sub-topics, after completing all the content, and at the end of the review stage. At each measurement point, subjects need to fill in the cognitive load self-assessment scale compiled by Pass to evaluate their current subjective cognitive load feelings. Finally, the average value of the six measurement data is used as a statistical indicator to evaluate the overall cognitive load level of the subjects.

4. Results Analysis

4.1 Descriptive Statistics and Correlation Analysis among Variables

First, descriptive statistics and Pearson product-moment correlation analysis were conducted on the scores of 148 valid subjects on each main variable, and the results are shown in Table 2. The table clearly reveals that SRL ability is significantly positively correlated with learning outcomes ($r=0.37$, $p<0.01$), significantly negatively correlated with extraneous cognitive load ($r=-0.29$, $p<0.01$), and significantly positively correlated with germane cognitive load ($r=0.41$, $p< 0.01$). The correlation between interface type (0 = linear, 1 = network-based) and learning outcomes did not reach a significant level ($r=0.08$, $p=0.32$), but it is positively correlated with extraneous cognitive load ($r=0.22$, $p<0.05$) and negatively correlated with germane cognitive load ($r=0.18$, $p<0.05$). The correlation coefficient between prior knowledge and learning outcomes is 0.31 ($p<0.01$), indicating the necessity of including it as a covariate in subsequent analyses. There is no strong correlation among the variables, and the risk of multicollinearity is low.

4.2 Interaction Effect of Teaching Interface Type and SRL Ability on Learning Outcomes

To test whether there is a significant interaction effect between digital teaching interfaces and self-regulated learning ability on learning outcomes, the study took learning outcomes as the dependent variable, interface type and SRL ability as independent variables, and prior knowledge as a covariate, and conducted a two-way analysis of covariance (ANCOVA). The results are shown in Table 3.

Table 2. Means, Standard Deviations, and Correlation Coefficient Matrix of Main Variables (N = 148)

	M	SD	Self-regulated Learning Ability	Interface Type (0/1)	Prior Knowledge	Learning Outcomes	Extraneous Cognitive Load	Intrinsic Cognitive Load
Self-regulated Learning Ability	3.42	0.68	1					
Interface Type(0/1)	—	—	0.04	1				
Prior Knowledge	7.25	1.84	0.27**	-0.02	1			
Learning Outcomes	16.38	3.91	0.37**	0.08	0.31**	1		
Extraneous Cognitive Load	3.27	1.16	-0.29**	0.22*	-0.19*	-0.44**	1	
Intrinsic Cognitive Load	4.53	1.01	0.41**	-0.18*	0.15	0.53**	-0.38**	1

Note: $p < 0.05$, $^{**}p < 0.01$; The interface type is a dummy variable (0 = linear, 1 = network - based); The learning outcome is the total score of comprehension questions and transfer questions (full score is 22 points); The cognitive load is measured on a 7 - point scale.

Table 3. ANCOVA Results of Learning Outcomes (N=148)

	SS	df	MS	F	p	η_p^2
Prior knowledge (covariate)	46.28	1	46.28	6.12	0.015	0.04
Interface Type	12.05	1	12.05	1.59	0.209	0.01
Sel -regulated Ability	68.37	1	68.37	9.04	0.003	0.06
Interface Type × Sel - regulated Ability	41.92	1	41.92	5.55	0.020	0.04
Error	1077.46	143	7.53			

The study shows that the main effect of interface type did not reach a significant level ($F=1.59$, $p=0.209$, $\eta_p^2=0.01$), indicating that after controlling for prior knowledge, there is no statistically significant difference in the average learning outcomes under the two interface conditions. The primary effect exerted by SRL ability reaches a significant level ($F=9.04$, $p=0.003$, $\eta_p^2=0.06$), thwhich indicates that learners with stronger self-regulated learning competence achieve better learning performance. Moreover, the interaction effect between interface type and SRL ability is significant ($F=5.55$,$p=0.020$,$\eta_p^2=0.04$),verifying that digital teaching interface types and SRL ability exert a significant interactive influence on learning outcomes.

4.3 The Balancing Effect of SRL Ability on the Cognitive Load Structure

To verify whether self-regulated learning competence enables learners to reach the rational resource distribution status of balanced cognitive load within online digital teaching interfaces, this research took extraneous and germane cognitive load as outcome variables separately. Twoway analysis of covariance (ANCOVA) was adopted to examine the main effects of interface category, SRL level as well as their interactive influence. The results are shown in Table 4.

Table 4. ANCOVA Results of Extraneous Cognitive Load and Germane Cognitive Load

	Effect	F	p	η_p^2
Extraneous cognitive load	Interface Type	4.21	0.042	0.03
	Sel-regulated Ability	10.86	0.001	0.07
	Interface Type × Sel-regulated Ability	6.73	0.010	0.05
Germane cognitive load	Interface Type	3.98	0.048	0.03
	Sel-regulated Ability	21.42	0.001	0.13
	Interface Type × Sel-regulated Ability	7.15	0.008	0.05

The study shows that in the balanced effect of SRL ability on the cognitive load structure, the interaction effect of extraneous cognitive load is significant ($F = 6.73$, $p= 0.010$). Through simple slope analysis, it can be seen that in the high self - regulated learning ability group, the extraneous load of the network-based teaching interface($M=2.75$,$SE=0.14$)is significantly lower than that of the linear teaching interface($M=3.41$, $SE=0.13$),$b=-0.66$, $t=-3.72$, $p<0.001$; while in the low self-regulated learning ability group, the extraneous load of the network-based teaching interface($M=3.98$, $SE=0.15$)is significantly higher than that of the linear teaching interface($M=3.24$, $SE=0.14$),$b=0.74$,$t=4.16$,$p<0.001$. This indicates that learners with high self-regulated learning ability can effectively avoid the extraneous load brought by navigation decisions in the network-based teaching interface, while learners with low self-regulated learning ability bear a higher extraneous load due to the increased freedom of the interface. For germane cognitive load, the interaction effect is also significant (F (1,143) =7.15, p=0.008). In the high SRL ability group, the germane load of learners in the networ-based teaching interface (M=5.36, SE=0.11) is significantly higher than that in the linear teaching interface (M=4.52, SE=0.10), b=0.84, t=5.25, p < 0.001; while in the low self-regulated learning ability group, there is no significant difference in germane load under the two teaching interface conditions. Based on the above results, learners with high SRL ability show the characteristics of "low extraneous cognitive load + high germane cognitive load" in the network-based teaching interface, that is, they achieve the reallocation of cognitive resources from extraneous load to germane load; while learners with low SRL present a structure of "high extraneous cognitive load + medium germane cognitive load" in the network-based teaching interface and fail to reach a balanced state. Therefore, it can be proved that SRL ability helps learners achieve a resource allocation state of "balanced cognitive load" in network-based digital teaching interfaces.

4.4 Test of the Mediating Effect of Learning Strategies

To test whether the use of learning strategies plays a mediating role in the impact of the interaction between interface type and SRL ability on learning outcomes, the study will use PROCESS v4.1 for testing. In the experiment, the interface type is the independent variable (X), self-regulated learning ability is the moderator variable (W), the use of learning strategies is the mediating variable (M), learning outcomes are the dependent variable (Y), and prior knowledge is the covariate. Bootstrap sampling is conducted 5000 times to calculate the moderated indirect effect (index of moderated mediation). The results are shown in Table 5.

Regarding the structural construction strategy as a mediating variable, the moderated mediation index is 0.38, and the 95% CI is [0.11, 0.69], which is significant. Under high self-regulated learning ability, compared with the linear teaching interface, the indirect effect of the network-based teaching interface on learning outcomes through enhancing the use of structural construction strategies is 0.26, and the 95% CI is [0.09, 0.47]; under low SRL self-regulated learning ability, this indirect effect is not significant (-0.12, with 0 in the CI). This indicates that learners with high self-regulated learning ability use the structural construction strategy more frequently in the network-based interface, thus achieving higher learning outcomes. For the inhibitory control strategy, the moderated mediation index is 0.31, and the 95% CI is [0.07, 0.58], which is also significant. Under high SRL ability, the indirect effect of the network-based teaching interface through promoting the use of inhibitory control strategies is 0.23, and the 95% CI is [0.08, 0.41]; under low SRL ability, this effect is not significant. Therefore, the application of learning strategies mediates the link between the interactive effect of digital teaching interface types and SRL ability and learning outcomes.

Table 5. Test Results of the Moderated Mediation Model

Mediating Variable	Level of Moderator Variable	Indirect Effect	BootSE	95% CI	Index of Moderated Mediation	BootSE	95% CI
Structural Construction Strategy	Low SRL(-1 SD)	-0.12	0.11	[-0.34, 0.09]	0.38	0.15	[0.11, 0.69]
	Hight SRL(+1 SD)	0.26	0.09	[0.09, 0.47]			
Inhibitory Control Strategy	Low SRL(-1 SD)	-0.08	0.09	[-0.27, 0.08]	0.31	0.13	[0.07, 0.58]
	Hight SRL(+1 SD)	0.23	0.08	[0.08, 0.41]			

Note: CI represents the bias - corrected Bootstrap confidence interval. A value that does not contain 0 indicates significance.

5. Conclusion

Integrating questionnaire surveys with experimental methods, this study examined how SRL ability shapes cognitive load and learning outcomes among college students using digital teaching interfaces. Grounded in cognitive load theory and self-regulated learning models, we proposed three hypotheses: interface type and self-regulated learning ability interact in influencing learning outcomes; within network-based interfaces, self-regulated learning ability may help learners achieve a “balanced cognitive load” in resource allocation; learning strategies mediate this interaction. Results indicated that SRL ability shaped how learners processed the information presented in digital teaching interfaces. In network-based interfaces, higher SRL ability tended to reduce extraneous load, increase germane load, and improve learning outcomes. At the same time, the direct effect of SRL ability on cognitive load was not pronounced in the data; instead, an interaction between self-regulated learning ability and interface type emerged. This interaction operated through mediating pathways that involved structural construction and inhibitory control strategies, aligning with the study's core hypotheses. Crucially, the beneficial role of SRL ability does not emerge automatically but hinges on the interface environment and learners' own ability levels. These results suggest that, in instructional design, merely strengthening SRL may not be enough; more decisive is dynamically adapting the information presentation of teaching interfaces to learners' ability profiles. For instance, learners with high SRL ability could be offered network-based interfaces to foster strategic exploration, whereas those with low self-regulated learning ability might be better served by linear interfaces that curb excessive extraneous load. Such adaptive arrangements can deliver the personalized support implied by "catering to different abilities."

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