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COGNITIVE LOAD CHANGE IN CHEMICAL CONCEPT LEARNING: INSIGHTS FROM EVENT-RELATED POTENTIALS

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Abstract. *This study explored the impact of oxidation-reduction reaction problem difficulty on university students' cognitive load using event-related potentials (ERPs). Forty-eight balanced low and high difficulty problems were designed. Fifteen undergraduate students majoring in chemistry (8 females and 7 males) participated in the study. Results demonstrated significantly increased reaction time, significantly decreased accuracy, and highly significantly elevated subjective effort as task difficulty intensified. ERP analysis revealed significant differences in N200, P300, and N400 amplitudes between easy and difficult problems, indicating increased demands on control, working memory, and in-depth processing under high load. The study provided physiological evidence supporting cognitive load theory and offered implications for optimizing oxidation-reduction reaction teaching. The findings bridged the gap between cognition and education, suggesting potential avenues for improving chemistry education through cognitive load management.*

Keywords: *oxidation-reduction reactions, chemistry learning, cognitive load, event-related potentials*

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Introduction

Cognitive load theory is an important theoretical framework for studying the relationship between instructional design and human cognitive architecture (Sweller, 1993). The theory posits that a learner's working memory capacity is limited, and learning tasks themselves consume some cognitive resources. If the cognitive load of a task is too high, it will exceed the processing capacity of working memory, resulting in decreased learning effects. Therefore, the core of instructional design is to control an appropriate level of cognitive load (intrinsic load, extraneous load and germane load), allowing learners to fully utilize limited cognitive resources to effectively acquire and integrate knowledge (Sweller et al., 1998). Cognitive load theory believes that increasing task difficulty will lead to increased cognitive load, thereby affecting the allocation of cognitive resources and information processing (Van Merriënboer & Sweller, 2005). In educational practice, appropriately increasing task difficulty can promote students' cognitive development, but excessive cognitive load will also have negative impacts on learning (Sweller et al., 1998). Therefore, accurately measuring the cognitive load levels caused by tasks of different difficulties is very important for guiding instructional design and improving learning outcomes.

Solving chemistry problems requires the integrated application of chemical knowledge, mathematical models and reasoning and calculation abilities, involving multiple cognitive processes. As the difficulty of chemistry problems increases, the complexity of interactions between elements in the problem increases, requiring processing and integrating a larger amount of information, thus demanding higher working memory and control functions (intrinsic load increases); the chemical concepts required to solve problems are also more abstract, requiring deeper levels of information processing and integration (germane load increases), all leading to increased cognitive load (Schnotz & Kürschner, 2007; Sweller et al., 1998). Johnstone and Al-Naeme (1991), and Pollock et al. (2002) found that as the conceptual abstraction of chemistry problems increases, students' error rates also increase. This suggests that more abstract chemistry concepts may impose higher cognitive demands on students when solving problems. The study by Gabel and Bunce (1994) showed that the cognitive load of solving stoichiometric problems (problems that directly provide chemical equations for students to balance) is greater than

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conceptual chemical equation problems (problems described in text requiring students to first convert to chemical equations and then balance). Ngu and Yeung (2012) used the dual-task paradigm to assess the occupation of cognitive resources by chemistry calculation problems of different difficulties, finding that more difficult chemistry problems consume more working memory resources.

Methods of measuring cognitive load include subjective rating methods, dual-task methods, and physiological indicators (Paas et al., 2003). Among the physiological indicators, event-related potentials (ERPs) as a brain electrophysiological recording technique have the advantages of high time resolution without interfering with task execution, providing an effective physiological indicator for evaluating cognitive load (Alday & Kretzschmar, 2019). N200, P300, and N400 are distinct components of ERP (Event-Related Potential), each generating a specific waveform at a particular time interval: N200 appears as a negative wave approximately 200 milliseconds after the stimulus, related to attention and conflict detection; P300 emerges as a positive wave around 300 milliseconds post-stimulus, reflecting the brain's attention and cognitive evaluation process; N400 manifests as a negative wave about 400 milliseconds after the stimulus, primarily involving language processing and semantic understanding. Previous studies have used ERP techniques to compare the impact of working memory tasks (Walshe et al., 2015) and arithmetic tasks (Grabner & De Smedt, 2011) of different difficulties on cognitive load. Cognitive load studies have shown that changes in amplitude of P300, N400 waves and other components can reflect increases in task difficulty (Alday & Kretzschmar, 2019); increased N200 amplitude is also often seen as a sign of increased demand for cognitive control. In addition to changes in ERP components, changes in brain electrophysiological power in different frequency bands can also assess cognitive load. For example, increased frontal theta power (4–8 Hz) and reduced parietal alpha power (8–13 Hz) often indicate increased working memory load (Antonenko et al., 2010). However, ERP research on science education or chemistry education is still lacking. Apart from the ERP technique, other physiological measures have also been widely employed in recent years to assess cognitive load. Eye-tracking is a non-invasive bio-sensing technology that can capture the allocation of visual attention in real-time, thereby indirectly reflecting the degree of cognitive processing investment. Pienta et al. utilized eye movement data to evaluate changes in cognitive load during chemical concept learning tasks (Pienta, 2003). Heart rate variability is another commonly used indicator, reflecting the autonomic nervous system's response to cognitive stress. Grove et al. found that participants' heart rate variability decreased when solving more difficult chemistry calculation problems (Grove et al., 2012). Functional near-infrared spectroscopy (fNIRS) is an emerging neuroimaging technique that can measure changes in blood oxygenation levels in the cerebral cortex. Shi et al. (2023) discovered through fNIRS that learners' prefrontal cortex activation levels significantly increased as the difficulty of chemistry concepts increased. Skin conductance response (SCR), which measures minute changes in skin conductance reflecting an individual's physiological arousal state, has been applied to evaluate cognitive load during mathematics learning (Cai et al., 2022). Moreover, functional magnetic resonance imaging (fMRI) and other techniques are gradually being incorporated into the field of cognitive load research. The development and integration of various physiological measurement methods will undoubtedly provide more technical support for the application of cognitive load theory in chemistry education.

Oxidation-reduction reactions are an important component of chemical education but are also one of the subject matters that many students find difficult (Zheng, 2016). Mastering the basic concepts of oxidation-reduction reactions is very important for students' further learning of electrochemistry, inorganic chemistry and other professional knowledge (Lu et al., 2014). However, due to the relatively abstract and complex concepts of oxidation number changes and electron transfers in oxidation-reduction reactions, determining oxidizing agents and reducing agents also has a certain degree of difficulty, which has long been a difficulty in chemical education (Brandriet & Bretz, 2014). In response to this phenomenon, researchers have carried out a series of chemical education studies to improve students' understanding of oxidation-reduction reactions. For example, Lu et al. (2014) designed oxidation-reduction teaching experiments to improve students' conceptual understanding and found that students' average scores on oxidation-reduction tests increased significantly. Cole et al. (2019) used concept mapping teaching to improve students' understanding of oxidation-reduction reactions. However, most of the above studies used test scores or subjective evaluations without being able to deeply reveal students' internal cognitive processing.

Research Aim and Research Hypothesis

This study intended to use ERP technology to explore the impact of oxidation-reduction reaction problems of different difficulties on students' cognitive load, and the results could provide more physiological index support for the teaching of oxidation-reduction reactions, and gave targeted recommendations for optimizing cognitive load, thereby improving the teaching effectiveness of this part of knowledge. Overall, this study enriched the research

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methods on the teaching of oxidation-reduction reactions and provided a new perspective for the optimization of chemical education.

Literature Review

Redox Reactions Instruction in Chinese High Schools

The participants in this study were from China, where they received systematic chemistry education in high school. As reported, the high school chemistry curriculum in China provides comprehensive coverage of oxidation-reduction reactions, encompassing both theoretical knowledge and experimental operations (Lu et al., 2014). Through intensive classroom instruction and hands-on experiments, students can solidify their understanding of fundamental concepts in this domain and develop relevant experimental skills. Specifically, prior to entering university, the participants had already gained extensive learning experiences in oxidation-reduction chemistry. They were well-versed in the core concepts, such as the nature of these reactions, changes in ionic charges, and electron transfer processes. They had also become proficient in various quantitative methods pertaining to redox reactions, such as formulating balanced chemical equations and performing stoichiometric calculations, through developing problem-solving skills in authentic contexts. Moreover, students had directly observed and conducted a variety of typical oxidation-reduction reactions during laboratory sessions, fostering an intuitive understanding of the phenomena. This systematic and comprehensive knowledge base, combined with practical skills, laid a solid foundation for their further in-depth study of related concepts and analysis of complex problems.

ERP Measurement Principles and Theoretical Basis

Event-related potentials (ERPs) are a non-invasive neuroimaging technique that can precisely measure the time course of brain neural activity associated with cognitive processing and behavior (Luck, 2014). When individuals perform cognitive tasks, different levels of cognitive load may influence the activation patterns of relevant neural clusters, thereby causing characteristic changes in the ERP waveforms. Different components of the ERP waveform reflect the sensitivity of different cognitive processes to cognitive load. The N200 is a negative peak (around 200 ms), commonly regarded as related to conflict detection and cognitive control (Folstein & Van Petten, 2008). Some studies have found that under high cognitive load conditions, due to the limited working memory and attentional resources, the ability to detect and resolve conflicting information may be impaired, leading to a delay or increase in the N200 amplitude (Scharinger et al., 2008). However, other research has suggested that this effect may be influenced by task characteristics and specific experimental conditions (Kopp et al., 1996). The P300 is a positive peak (300–600 ms), associated with processes such as attention resource allocation and working memory updating (Polich, 2007). Numerous studies have consistently found that a higher cognitive load reduces P300 amplitude and prolongs its latency (Ullsperger et al., 2001). The N400 is a signature component of semantic violation effects, sensitively reflecting semantic integration processing (Kutas & Federmeier, 2011). Most research has shown that under high cognitive load conditions, due to limited resources, semantic integration efficiency decreases, resulting in an increase in N400 amplitude (Fuhrmeister et al., 2022). However, some studies have found that under specific conditions, high cognitive load may decrease N400 amplitude (Smith & Kutas, 2015). The N200, P300, and N400 ERP components, to some extent, reflect the impact of cognitive load on different cognitive stages such as attention allocation, conflict monitoring, and semantic processing (Yeung et al., 2022). However, this impact may be modulated by various factors, including task type, stimulus materials, and experimental conditions. Analyzing the patterns of change in these indices under different cognitive load conditions can help to gain a deeper understanding of the mechanisms underlying cognitive load, providing guidance for optimizing cognitive task design and alleviating cognitive overload.

As a cognitive neuroscience technique, ERPs offer several notable advantages. First, it has an excellent temporal resolution and can track real-time changes down to the millisecond range during cognitive processing. Second, the technique is non-invasive, simply requiring sensors attached to the scalp (Luck, 2014). Finally, the cost of ERP equipment tends to be more affordable than other neuroimaging techniques like fMRI, and it is also highly portable, suitable for research across different environments (Singh et al., 2021). However, ERP also has its limitations. The technique is primarily sensitive to activity in cortical structures, rather than subcortical regions (Cohen, 2017). Additionally, the ERP signal amplitude is relatively small and susceptible to physiological and environmental noise interference, requiring averaging across multiple trials to extract reliable ERP components, resulting in relatively long experiment times (Luck, 2014; Woodman, 2010).

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Rationale for Electrode Site Selection

The present study selected the frontal (Fz), central (Cz), and parietal (Pz) electrode sites for ERP data analysis, based on the following theoretical grounds: First, according to the classic 10–20 electrode position system (Klem et al., 1999), the frontal region is primarily responsible for higher-order cognitive control processes, such as working memory, attention allocation, and conflict monitoring; the central region is involved in motor control and spatial attention; while the parietal region is associated with perceptual processing, visuospatial representations, and visual working memory (Bledowski, 2009). Second, these three regions correspond to the cognitive stage pool, visual channel pool, and response channel pool, respectively, in Wickens' multiple resource theory (Wickens, 2008). Furthermore, they align with Braver's dual-process theory (Braver et al., 2007), which distinguishes between two levels of cognitive processing: automatic inner processes and controlled outer processes. Automatic inner processes, such as initial sensory processing and long-term memory activation, are relatively automatic and require fewer cognitive resources, mainly subserved by posterior regions like the parietal cortex. In contrast, controlled outer processes, such as operational working memory, attention control, conflict detection, and inhibition, are higher-order cognitive functions that demand more cognitive resources and are primarily mediated by anterior regions like the frontal cortex. Finally, the aforementioned regional layout is consistent with the distribution patterns of classic ERP components, such as N2 and P3 (Luck, 2014). Therefore, the selection of the Fz, Cz, and Pz electrode sites has a reasonable theoretical basis, which will aid in comprehensively measuring the effects of cognitive load on different cognitive stages and brain regions, thereby providing insights into the underlying cognitive neuroscience mechanisms.

Based on the literature review presented, this study addresses the problem of how the complexity of oxidation-reduction reaction problems affects the cognitive load experienced by students during the problem-solving process. The hypothesis posited is that as problem complexity increases, cognitive load is expected to rise accordingly. This rise in cognitive load is predicted to lead to specific changes in the amplitudes of students' ERPs, namely a decrease in the peak amplitude of the P300 component and an increase in the peak amplitudes of the N200 and N400 components. The aim of this study is to investigate this hypothesis and gain a deeper understanding of the relationship between problem difficulty, cognitive load, and ERP amplitudes. Specifically, this research seeks to answer the following questions: How does problem complexity influence cognitive load during problem-solving? And how do these changes in cognitive load manifest in the ERP amplitudes of the P300, N200, and N400 components? By addressing these questions, this study aims to contribute to the field's understanding of cognitive processes in solving complex chemical problems.

Research Methodology

Background

Conducted within a controlled laboratory environment during the autumn semester of 2023, the research was grounded in cognitive load theory as its theoretical framework. To empirically examine this relationship, a methodology was devised that utilized ERPs as a physiological indicator of cognitive load. The sample consisted of 15 university students who had previously completed high school chemistry courses, and thus possessing a foundational understanding of the subject matter. By presenting a series of problems with varying levels of difficulty and recording the corresponding ERP data, as well as reaction times, accuracy rates, and subjective assessments of effort, the study sought to elucidate the interaction between problem complexity, cognitive load, and neural activity. The findings of this study contribute to a deeper understanding of cognitive processes in science education and have implications for the development of more effective teaching strategies that account for the cognitive demands placed on students.

Participants

Fifteen healthy undergraduates (8 women, 7 men) between 20–24 years old, pursuing engineering or science majors at university and having finished the high school chemistry course, took part in this study. All participants were right-handed, with normal or corrected normal vision, no history of mental illness or neurological diseases, and did not consume caffeine or any medication regularly or on the day of testing that could potentially affect cognitive performance. Participants also reported their previous chemistry courses, including inorganic chemistry, physical chemistry, etc., and the time elapsed since their last study of the experiment-related chemistry content, ranging from 3 to 6 months. Before the experiment, the subjects read and voluntarily signed the experimental protocol.

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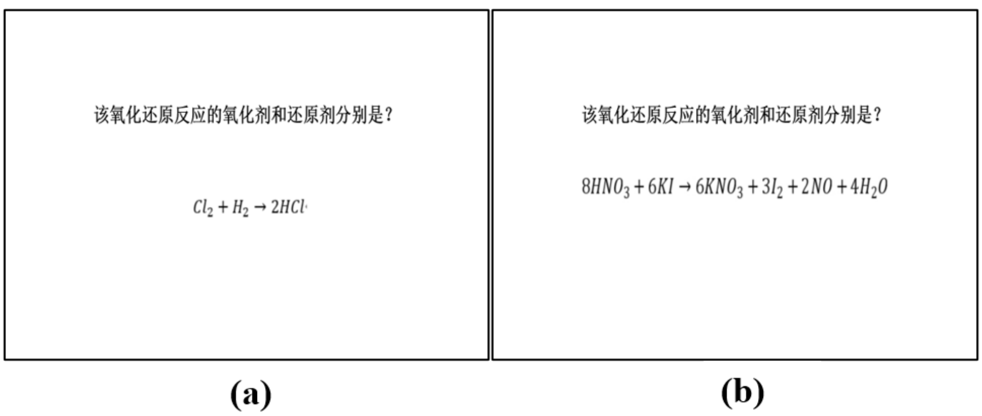
Upon completion of the experiment, a brief semi-structured interview was conducted with each participant to gather subjective feedback regarding their experience. All participants received monetary compensation for their involvement in the study.

Chemistry Questions

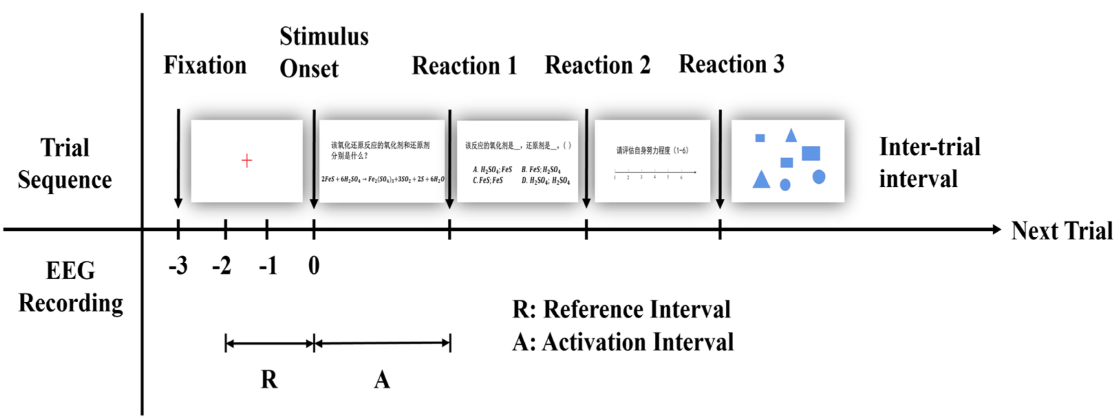
The chemistry problems used in our study were tasks of determining oxidizing agents and reducing agents in various oxidation-reduction reactions. Determining oxidizing agents and reducing agents plays an important role in chemical learning and is a basic step in solving many chemistry problems. However, determining oxidizing agents and reducing agents generally has a certain degree of difficulty for students, especially in analyzing oxidizing agents and complex oxidation-reduction reactions. To solve these problems, students need to retrieve concepts about oxidation-reduction reactions and make judgments based on the presented information.

Figure 1
Examples of Chemical Problems Presented in the Task.



Note. ((a) Low difficulty level questions. (b) High difficulty level questions). What are the Oxidant and Reducing Agent of this REDOX Reaction?

Figure 2
Schematic Diagram of a Single Test



Note: The time period from the start of the chemical problem to reaction 1 is used as the activation interval, and the time period 1-3 s after the start of the fixation crossing is used as the reference interval.

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The entire task consisted of 48 chemistry problems, which were divided into two levels of complexity. For low-complexity problems, the involved oxidizing and reducing agents were simple substances or compounds, with oxidizing agents such as oxygen and chlorine, and reducing agents such as common metals. For high-complexity problems, more complex compounds and more difficult oxidation-reduction reactions were involved. Typical examples of chemistry problems under low and high complexity conditions are shown in Figure 1. In the experiment, participants were asked to answer the question, "Which substances are the oxidizing and reducing agent for this reaction?" based on the redox reaction equation presented. The 48 chemistry problems were selected from the question bank of oxidation-reduction reactions in high school. The questions in the question bank were carefully selected from exercises involving basic redox reactions in standardized high school chemistry textbooks, as well as from questions related to redox reactions in past official chemistry examination papers. These questions were designed to assess students' fundamental understanding of electron transfer processes and the principles underlying redox reaction. The evaluation of complexity was carried out by a committee consisting of 3 experienced chemistry teachers and 2 university chemistry professors to ensure the validity of complexity classification. To ensure the validity of complexity classification, the committee followed a rigorous process: They first independently evaluated and categorized each problem as low or high complexity based on their expertise and teaching experience. For problems where there were disagreements initially, the committee discussed and reached a consensus through careful examination of the problem characteristics, like the abstractness of concepts involved, the amount of information processing required, and the level of reasoning and integration needed to solve the problem. Inter-rater reliability was calculated using Cohen's kappa, which showed a high level of agreement (K = 0.92) among the raters after the consensus discussions. This rigorous evaluation process by the expert committee ensured that the complexity levels assigned to the chemistry problems were valid and reliable for the purposes of this study. In the experiment, students were required to determine the oxidizing agents and reducing agents in the oxidation-reduction reaction equations. We assumed that high-complexity problems require higher levels and higher cognitive loads. We also predicted that the different real-time cognitive load levels during problem solving would be reflected in brain electrical signals. Control tasks were also developed in this study, in which students only needed to count the number of a specific shape of objects.

Procedures

A total of 96 stimuli were included, including 48 chemistry problems and 48 control tasks, designed and generated using the E-prime 2.0 software. The stimuli were presented according to the event-related design as shown in Figure 2. At the beginning of each trial, a fixation cross was presented at the center of the screen for 3000 ms, followed by the presentation of stimulative materials. Subjects needed to determine the oxidizing agents and reducing agents in the stimulative materials and the problems remained on the screen until participants obtained the answers and requested the answer options by keypress (reaction 1). During each chemistry problem, participants were not allowed to write down the problem-solving process on scratch paper. This setting of prohibiting writing helped minimize the influence of motion and visual processing associated with writing on the EEG data. Then, the chemistry problems disappeared from the screen, and the answer options were presented. Participants selected the answers from four options by pressing the corresponding option buttons (reaction 2). Finally, a subjective rating scale was provided to evaluate the effort invested in solving the problem, and participants indicated their actual situation by pressing the corresponding buttons (reaction 3). After the subjective rating scale, a control task would be displayed. The control tasks were intended to reset the subjects' mental activity to normal levels and eliminate the effects of previous problems. The inter-stimulus interval was 3000ms as the resting period before the next trial.

The experiment took place in a dimly lit, quiet EEG laboratory, where participants were comfortably seated approximately 75 cm away from the computer screen. Participants were instructed to keep still while focusing on completing the experiment. A total of 48 chemistry problems were designed, evenly split between low and high difficulty levels. During the formal experiment, each participant was presented with all 48 problems in a random order, comprising an equal number of low- and high-difficulty items, and completed the entire set. Prior to the formal experiment, all participants went through the same practice session, which included both low-difficulty and high-difficulty example problems, to familiarize themselves with the experimental procedure. Brain electrical signals of participants during tasks were recorded simultaneously. Upon completion of the experiment, each participant immediately underwent a semi-structured interview lasting approximately 5–10 min, aiming to comprehensively collect their subjective experiences and feedback throughout the experimental process. The interviews commenced with pre-determined open-ended questions, primarily focusing on the following aspects: a) participants' subjective evaluation of the task difficulty and

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identification of relatively more challenging components; b) psychological experiences, emotional fluctuations, and attentional states across different experimental stages; c) the influence of the experimental environment (e.g., room setup, facilities) and equipment (e.g., computers, displays) on their overall experience; d) any additional comments or suggestions pertaining to the experiment. During the interviews, the researchers did not merely follow a rigid sequence of questions but flexibly guided in-depth discussions on specific topics based on participants' responses, probing with further exploratory or explanatory follow-up questions as needed. All interview content was recorded and transcribed for subsequent qualitative data analysis. Through this semi-structured interviewing approach, the researchers not only gathered participants' subjective feedback but also gained deeper insights into the underlying reasons and details, providing valuable supporting evidence for interpreting the experimental results.

Behavioral Data Analysis

Response time, response accuracy, and subjective effort (from 1 to 7) assessment behavior data were recorded using the E-prime 2.0 software. In our study, response time was defined as the time interval between the appearance of the chemistry problem and the keypress of reaction 1. Response accuracy for each problem was determined based on their keypress of the answer option for reaction 2. Subjective effort level evaluation was obtained based on their keypress of reaction 3. First, the behavioral data of each student were averaged according to low-difficulty and high-difficulty problems. Then, the average value and standard deviation of each behavioral data under each problem condition were calculated.

EEG Recording and Data Analysis

Brain electrical signals were recorded using a 32-channel electrode cap based on the international 10–20 system, including 30 scalp electrodes and two earlobe reference electrodes A1 and A2. Eye movements were recorded simultaneously using electrooculography (EOG) to monitor their impact on EEG. The signals were amplified and digitalized using a Neuracle EEG system with a sampling rate of 500 Hz and a band-pass filter of 0.05–60 Hz. After EOG noise removal on each trial's raw EEG data, segments were extracted from 1 s before and 2 s after stimulus presentation to constitute ERP data segments. Data analysis selected the Fz, Cz and Pz electrodes. Within the preset time windows, the mean potential values for the N200 (162–182 ms), P300 (272–332 ms), and N400 (370–420 ms) ERP components were extracted across all participants. Repeated measures analysis of variance was performed using SPSS 27 software to examine the interaction between problem difficulty (two levels) and brain area (three levels), with Greenhouse–Geisser correction and Bonferroni multiple comparisons correction, with a statistical threshold of 0.05.

Research Results

Behavioral Results

According to the data of this study, the study obtained behavioral results under tasks of different difficulties. The average response time, response accuracy and subjective effort evaluation for low and high difficulty questions are shown in Table 1. Under low-difficulty tasks, participants responded quickly, with an average time of 3.39 seconds and high accuracy of around 85%. They also reported low subjective effort. In contrast, under high-difficulty tasks, response times significantly increased to an average of 16.83 seconds, accuracy dropped to around 71%, and subjective effort levels rose. These findings are summarized in the table provided. Through the Wilcoxon signed rank test, this study found that problem complexity significantly affected response time ($p < .001$), accuracy ($p < .001$) and subjective effort assessment ($p < .001$). This shows that students need longer reaction times to solve high-difficulty tasks, while accuracy will also decrease. In addition, students answered in interviews that these high-complexity problems required more effort. All behavioral results support that the design and difficulty classification of chemistry problems in this study are reliable. The experiment successfully engaged students in solving chemistry problems with different difficulties.

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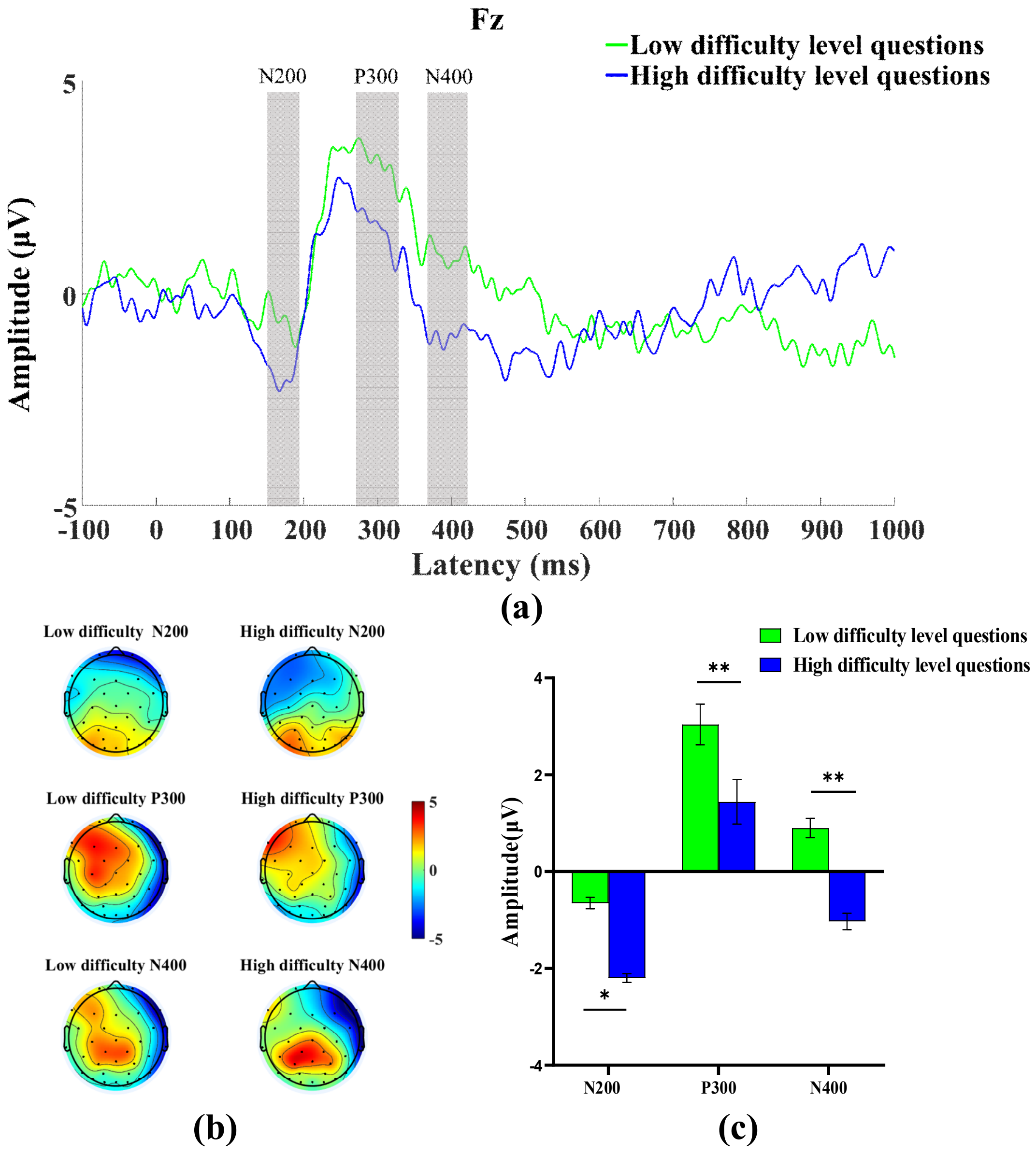
Table 1
Mean Reaction Time, Response Accuracy, and Subjective Effort

Problem difficulty	Reaction time (s)	Response accuracy (%)	Subjective effort evaluation
	M (SD)	*M (SD)*	*M (SD)*
Low	3.39(1.28)	85.12(35.61)	1.17(0.494)
High	16.83(8.52)	71.07(45.43)	2.84(1.16)

Figure 3
ERP on Fz Electrodes While Solving Low and High Difficulty Chemical Problems



((a) ERP image on Fz electrodes under two difficulty conditions. (b) Topographic maps of N200, P300 and N400 under two difficulty conditions. The scale ranges from -5 to 5, representing the potential values in microvolts (µV). (c) Significance analysis of N200, P300 and N400 on Fz electrode.)

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This study's ERP research analyzed the N200, P300 and N400 components at the Fz, Pz and Cz electrodes and measured them within specific time windows. The ERP discrepancy on the Fz electrode when solving low-difficulty and high-difficulty problems is presented in Figure 3.

On the Fz electrode, in the 162–182 ms time window for the N200 component, the potential difference between high difficulty and low difficulty tasks reached significance ($p < .05$). Specifically, the average potential of the N200 under low difficulty task conditions was -0.65 μV, while the average potential under high difficulty task conditions was -2.17 μV. This significant difference reflects the increased demand for cognitive control under high difficulty tasks.

For the P300 component, in the 272–332 ms time window, the potential difference between high difficulty and low difficulty tasks also reached significance ($p < .01$). The average potential of P300 under low difficulty task conditions was 3.04 μV, while the average potential under high difficulty task conditions was 1.44 μV. This result reveals the increased working memory load under high difficulty tasks.

Similarly, in the 370–420 ms time window for the N400 component on the Fz electrode, a significant potential difference was observed between high difficulty and low difficulty tasks ($p < .01$). The average potential of N400 under low difficulty conditions was 0.90 μV, while the average potential under high difficulty task conditions was −1.02 μV. This result further confirms the increased cognitive load caused by high difficulty tasks.

On the Pz electrode, a significant potential difference was observed between low difficulty and high difficulty tasks in the 342–382 ms time window ($p < .01$). The average potential under low difficulty conditions was 2.36 μV, while the average potential under high difficulty task conditions was 3.78 μV. This result shows that high difficulty tasks cause potential increases in this time range, possibly reflecting higher demands for deeper information processing.

Meanwhile, in the 120–150 ms time window, the study also found a significant potential difference between low difficulty and high difficulty tasks ($p < .05$). The average potential under low difficulty task conditions was 0.37 μV, while the average potential under high difficulty task conditions was −1.11 μV. This result may imply higher demands for cognitive resource investment in the early processing stage under high difficulty tasks.

However, on the Cz electrode, no ERP component showed significant potential differences between high difficulty and low difficulty tasks within the measurement scope of this study. This may indicate that the cognitive load of the brain area represented by the Cz electrode did not differ significantly in processing the two types of tasks, or these differences could not be effectively captured within the measurement range of this study. This result reminds us that different brain areas may have different activity patterns when processing the same cognitive tasks, which needs to be fully considered in the design and interpretation of results in this study.

Discussion

This study employed ERP techniques to investigate how the difficulty of oxidation-reduction reaction problems influences students' cognitive load. The findings revealed that as the problem difficulty increased, both behavioral data and brain electrical data demonstrated a significant elevation in students' cognitive load.

The behavioral data results further support the viewpoint of cognitive load theory. As the difficulty of the oxidation-reduction reaction problems increased, participants' reaction time in solving the problems significantly prolonged, while their accuracy rate markedly declined, and the subjective rating of cognitive effort correspondingly elevated. This finding is consistent with previous studies, reflecting that more difficult problems impose greater demands on learners' cognitive resources, such as working memory, thereby inducing a higher cognitive load. Ngu and Yeung's research (2012) found that more difficult chemistry calculation problems consumed more working memory resources, with students taking longer time and achieving lower accuracy in problem-solving. When studying geometric problems, Ayres (2006) also observed that as problem difficulty increased, students' reaction time prolonged, error rate rose, and subjectively rated cognitive load intensified. Investigating the spacing effect, Chen and Yan (2016) revealed that difficult problems led to longer reaction times and lower accuracy rates. The behavioral data results of the present study provide direct empirical support for cognitive load theory, indicating that increased task difficulty aggravates learners' cognitive load, manifested as greater consumption of cognitive resources and declined learning efficiency.

A notable finding in the present study is that, unlike the frontal and parietal regions, no effects of task difficulty on ERP data were observed at the Cz electrode site. A primary reason might be that the brain areas reflected by the Cz electrode are largely involved in basic cognitive processes, such as attention concentration and working memory operations (Chen & Yan, 2016), rather than being closely associated with the higher-order cognitive processing demands (e.g., conceptual understanding, logical reasoning) triggered by varying task difficulty levels. The redox

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reaction problems employed in this study mainly assessed students' in-depth understanding and application of chemical reaction principles, representing more complex cognitive activities. Previous research has revealed that the prefrontal cortex is sensitive to such higher-order processing (Cazalis et al., 2003); however, the areas reflected by the Cz electrode may have limited involvement, thus failing to manifest the neural activation differences induced by task difficulty variations. This study found significant changes in the N200, P300 and N400 components of subjects' brain electrical signals with the increasing difficulty of oxidation-reduction reaction problems.

When determining the oxidizing and reducing agents in redox reaction equations of varying difficulty, students encounter several challenges and misconceptions that impact their problem-solving processes. Firstly, students often mistakenly believe that "the higher the oxidation state, the stronger the oxidizing power" or "the lower the oxidation state, the stronger the reducing power." This misconception hinders their ability to accurately determine the oxidation states of reactants and products (Garnett & Treagust, 1992). In addressing such problems, students first need to identify the oxidation states of each element. However, due to insufficient understanding of the nature of oxidation state changes, they may wrongly assume that substances with high oxidation states are always oxidizing agents and those with low oxidation states are always reducing agents. This misconception leads to confusion when identifying oxidizing and reducing agents, increasing cognitive load. The N200 component, primarily associated with conflict detection and cognitive control, showed significant amplitude increases in high-difficulty tasks, indicating that students require more cognitive control and conflict monitoring when determining oxidation states. Secondly, when distinguishing between oxidizing and reducing agents, students often rely on simple memorized rules rather than deeply analyzing the electron transfer processes, making it difficult for them to accurately identify these agents in complex reactions. Students frequently misunderstand that "an oxidizing agent undergoes oxidation, and its product is the oxidizing agent," leading to errors in complex reactions (Sanger & Greenbowe, 1997). This reliance on simple rules causes mistakes in complex scenarios, thereby increasing the working memory load. The P300 component, related to attention resource allocation and working memory updating (Kong et al., 2013), showed a significant decrease in amplitude during high-difficulty tasks, reflecting the increased working memory load and reduced attentional resources when students attempt to distinguish oxidizing and reducing agents. Lastly, students have an unclear understanding and improper application of redox reaction principles, such as the relative strength of oxidizing and reducing agents (the comparative ability of substances to act as oxidizing or reducing agents), the order of electron transfer (the sequence in which electrons are transferred between substances), and the rules for assigning oxidation states (systematic guidelines to determine the oxidation state of each element) (Garnett & Hackling, 1995). The N400 component, typically associated with semantic integration and deep information processing (Walshe et al., 2015), showed significant amplitude increases in high-difficulty tasks, indicating that students require more semantic integration and information processing when applying redox reaction principles. It can be seen that when solving difficult redox reaction problems, students need to mobilize many cognitive functions, such as selective attention, working memory, semantic knowledge activation, etc., in order to fully understand the nature of the response, and flexibly apply the learned response rules to new problem situations. The changes in the N200, P300 and N400 components consistently indicate that high-difficulty oxidation-reduction reaction problems impose greater demands on cognitive resources and impose a higher cognitive load. These ERP changes are consistent with previous studies using brain electrical signal techniques to evaluate the increased cognitive load caused by increasing task difficulties in arithmetic tasks and working memory tasks (Walshe et al., 2015). These cognitive load-related ERP changes support common classroom observations relatively simple oxidation-reduction reaction concepts and judgments can be gradually mastered by students, while complex oxidation-reduction reactions and judgments still have a certain degree of difficulty for most students (Brandriet & Bretz, 2014), which may be related to the complexity of concepts and the difficulty of judgment (Lu et al., 2014). ERP technology, which can dynamically and continuously evaluate students' cognitive states in solving science problems of different difficulties, has been used to evaluate changes in cognitive load in flight simulation tasks and provides a theoretical basis for optimizing problem design and guiding instruction.

While this study yielded valuable findings, there were still some limitations in the research design and methodology. Firstly, the sample size was relatively small, comprising only university students, which limits the representativeness of the results. Secondly, the experimental materials were solely restricted to oxidation-reduction reaction problems, presenting a limited range of problem types. Moreover, although this study employed a multidimensional approach by combining behavioral data and ERP techniques, the analysis focused exclusively on ERP, lacking direct examination of the functional connectivity patterns among brain regions. Another limitation is the absence of significant ERP results in the Cz region, possibly due to a mismatch between the cognitive functions associated with this area and the nature of the tasks.

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Conclusions and Implications

This study used ERP techniques to explore how oxidation-reduction reaction problem difficulty affects students' cognitive load. Behavioral data showed that as problem difficulty increased, participants experienced longer reaction times, lower accuracy, and higher mental effort ratings, indicating greater cognitive resource usage, which supports cognitive load theory. ERP data revealed amplitude changes in the N200, P300, and N400 components under high difficulty, reflecting increased demands on attention, working memory, and deeper processing. These findings suggest high-difficulty tasks heighten cognitive load. Brain region analysis showed significant ERP activity in the frontal (Fz) and parietal (Pz) areas, but there were no differences in the central (Cz) region, indicating varying brain region activity during the same task. These findings provide neuroscientific support for cognitive load theory and highlight cognitive overload in learning redox reactions, offering insights for improving chemistry education.

This study provided new neuroimaging evidence supporting cognitive load theory, deepening our understanding of its physiological mechanisms and extending its application to chemistry and STEM education. The introduction of ERP techniques into chemistry education research also promotes interdisciplinary integration of neuroscience and education. Practically, the study identifies cognitive overload in learning redox reactions, offering guidance on adjusting instructional strategies and difficulty levels to align with students' cognitive capacities, thereby enhancing teaching efficiency and knowledge retention. Despite limitations in sample size and experimental control, future research can address these issues by expanding the sample, conducting classroom interventions, and integrating multimodal data (e.g., fMRI, eye-tracking). Further exploration in other disciplines and the use of AI and big data for personalized learning interventions will optimize teaching strategies and contribute to improving educational quality.

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Declaration of Interest

The authors declare no competing interest.

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