electronics

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Analysis of Differences in Self-Regulated Learning Behavior Patterns of Online Learners

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Abstract: Self-regulated learning is one of the important skills to achieve learning goals and is also the key factor to ensure the quality of online learning. With the rapid development of intelligent education and information technology, online learning behavior has become a new trend in the development of education modernization. Behavior data of online learning platforms are an important carrier to reflect the learners' initiative to plan, monitor, and regulate their learning process. Self-regulated learning (SRL) is one of the important skills to achieve learning goals and is an essential means to ensure the quality of online learning. However, there are still great challenges in studying the types and sequential patterns of learners' self-regulated learning behaviors in online environments. In addition, for higher education, the defects of the traditional education mode are increasingly prominent, and self-regulated learning (SRL) has become an inevitable trend. Based on Zimmerman's self-regulation theory model, this paper first classifies learning groups using the hierarchical clustering method. Then, lag sequence analysis is used to explore the most significant differences in SRL behavior and its sequence patterns among different learning groups. Finally, the differences in academic achievement among different groups are discussed. The results are as follows: (1) The group with more average behavior frequency tends to solve online tasks actively, presenting a "cognitive oriented" sequential pattern, and this group has the best performance; (2) the group with more active behavior frequency tends to improve in the process of trial and error, showing a "reflective oriented" sequence pattern, and this group has better performance; (3) the group with the lowest behavior frequency tends to passively complete the learning task, showing a "negative regulated" sequence pattern, and this group has poor performance. From the aspects of stage and outcome of self-regulated learning, the behavior sequence and learning performance of online learning behavior mode are compared, and the learning path and learning performance of different learning modes are fully analyzed, which can provide reference for the improvement of online learning platform and teachers' teaching intervention.

Keywords: self-regulated learning; intelligent education; machine learning; hierarchical clustering; behavior sequence

Citation: Ye, Z.; Jiang, L.; Li, Y.; Wang, Z.; Zhang, G.; Chen, H. Analysis of Differences in Self-Regulated Learning Behavior Patterns of Online Learners. *Electronics* **2022**, *11*, 4013. https://doi.org/10.3390/electronics11234013

Academic Editor: Juan M. Corchado

Received: 10 November 2022
Accepted: 1 December 2022
Published: 3 December 2022

1. Introduction

Self-regulated learning (SRL) refers to the process of students' activation and maintenance of cognition, emotion, and behavior to achieve personal goals [1]. SRL has become an important topic in education and psychology in the past three decades [2,3], with the cross-application of more machine learning algorithms [4,5]. Studies have pointed out that one of the main objectives of education should be to cultivate students' SRL skills so that they can independently obtain and interpret information inside and outside the classroom [6,7]. From the perspective of self-regulated learning, learners actively monitor their learning process, independently complete meaning construction, determine learning rhythm, make relevant decisions, and evaluate learning results [8] and are more likely to achieve personal goals than learners lacking sufficient self-regulation skills [9]. This technology, especially for high-level education (such as physics, mathematics, ideological and political education, and other disciplines), can help teachers adjust students' learning behavior and improve the quality and effect of precision online education.

A large number of studies has proven the impact of self-regulated learning on students' learning performance [10–13], mainly using variable-centered statistical methods, focusing on the relationship between self-regulated learning variables and learning outcomes measured by students' self-report. Studies have shown that learners with higher SRL skills are more likely to use their ability and learning environment to control their learning to achieve good learning results. Based on this, recent studies have explored SRL behavior in the learning process. More and more studies regard SRL as a real-time process event in learning and problem solving [14]. This is partly due to the progress of the digital learning environment, which can record learners' behavior at the fine-grained level. Up to now, SRL behavior process pattern mining has attracted more and more attention and has become the mainstream of current research. A series of methods for detecting, tracking, collecting, and analyzing online learning process data are being gradually introduced into SRL research.

Although some progress has been made in the process research of SRL, most studies are usually focused on the relative contributions of different types of SRL behaviors and their interactions and regulatory effects [15–18]. Although these emerging studies demonstrate the potential of learning analytics in SRL research, few studies specifically explain how learners' SRL develops over time in online learning environments [19], for example, over time, students' learning behavior, cognition, and metacognition in learning and whether some learning modes are superior to other learning modes. The study on the dynamic process of SRL can objectively describe a series of events or actions (learning traces) performed by learners in learning rather than the subjective views of those actions or mental states generated by these actions [20].

This study uses the lag sequence analysis method to track and identify learners' learning patterns through the SRL behavior sequence at different stages. This method not only captures the sequential pattern of SRL behavior but also reveals the degree of interaction between SRL behaviors. By focusing on the interaction between students' self-regulated learning behavior, the lag sequence analysis method naturally grasps the objective fact of the dynamic change of SRL behavior in online learning. At the same time, this study can also help teachers understand the learner's learning mode, formulate intelligent guidance or intervention mechanisms, and provide the basis for developing and improving the online self-regulated learning platform.

In this study, we use clustering and lag sequence analysis based on the SRL social cognitive model of Zimmerman [21] to study the time series of SRL when learners complete relevant learning tasks in the network environment and explore the learning behavior path of SRL in different learning stages over time and how these behavioral sequence patterns lead to performance differences. The self-regulated learning behavior sequence model represents how learners guide their learning process. Different learners have different SRL behavior strategies and ultimately show different performance levels. Therefore, exploring the differences in learners' self-regulated learning behaviors and behavior patterns helps elucidate the implicit thinking modes such as information processing and prompt calibration of different learners. This study focuses on the following three issues through the collation, induction, and pattern analysis of online learning platform self-regulation behavior:

(1) How should we divide different SRL groups according to learners' SRL behaviors in an online learning environment?
(2) What are the differences in behavior sequence patterns among different SRL groups?
(3) Does learning performance (performance) differ among different SRL groups?

The rest of this paper is organized as follows: Section 2 focuses on related research to describe the development of self-regulated learning, research directions of self-regulated learning, SRL behavior pattern mining, and this study. Section 3 introduces the design of the study of the behavior coding, data sources, and tools and methods. Section 4 analyzes the experimental results and introduces the behavior sequence characteristics and the difference of learning achievement of different learning pattern groups. Section 5 concludes the paper with discussion, conclusions, limitations, and suggestions for future research.

2. Literature Review

2.1. The Development of Self-Regulated Learning

SRL originated from Albert Bandura's social cognitive theory involving self-monitoring and self-correction of behavior [22]. Since then, SRL has become a broad research paradigm for educational research [23,24]. Researchers found that self-regulation is the basis for students to adjust and improve their learning process and learners can update their psychological ability to academic skills [25]. Winne [26] explained that SRL is an effective learning method. Students can use metacognitive knowledge and application strategies to monitor and regulate task performance 7. Lung-Guang [27] believed SRL is an active learning strategy. Cognitive methods can help individuals understand their abilities and environments to control their learning. Self-regulated learners are characterized by their ability to initiate metacognitive, cognitive, emotional, motivational, and behavioral processes to take action to achieve their learning objectives and persist until they succeed [8]. Specifically, studies have shown that strong SRL skills can also predict high self-efficiency and satisfaction, which can bring better learning achievement [28]. Due to potential psychological, cognitive, or sensory problems, self-regulated learning (SRL) has also been proved to improve individual participation in daily activities [29]. Research shows that students with strong SRL skills are more likely to succeed in the classroom [30] or online learning environment [12,31,32].

2.2. Research Directions of Self-Regulated Learning

Subjective reporting measures learners' use of self-regulated learning strategies. The primary measurement contents include cognition, metacognition, resource management strategies, and regulation [12]. They have proven the relationship between self-regulated learning strategies and academic performance. However, it mainly focuses on the relationship between learners' psychological characteristics, ability attributes, and final academic performance [17]. It cannot explain how these strategies are externalized into self-regulated learning behaviors and how they work. There is growing interest in shifting research focus from variable-centered relational research to student-centered behavioral process research [33,34]. Learners' descriptions allow us to identify and classify learners with different learning behavior patterns. The analysis method also enables researchers to fully understand holistically the complex interrelationship between different SRL behaviors. From the analysis perspective, students' self-regulation recognition includes a series of SRL behaviors rather than just trying or using specific strategies.

To further clarify the conceptual structure and connotation of self-regulated learning, some scholars have modeled learners' SRL from different theoretical perspectives and further analyzed the elements and relationships of self-regulated learning, which provides the basis for subsequent research, such as the SRL information processing model [6], SRL overall framework model [8], and SRL social cognitive model [21]. Winne and Hadwin [6] proposed a four-stage model from the information processing perspective: task definition, goal setting, planning, enactment, and adaptation. Winne's four-stage model focuses on implicit rather than explicit processes. When analyzing the impact of motivation on whether a learner will use a particular learning strategy, the model does not focus on societies or communities that may influence metacognition and academic achievement factor. Pintrich [8] proposed a self-regulated learning model focusing on different types of SRL strategies and identified three types of learning strategies that students should apply to regulate their learning: cognitive strategies, metacognitive strategies, and resource management strategies. Zimmerman [21] developed a process model of self-regulated learning. This model is based on the social cognitive theory proposed by Bandura [22]. Zimmerman's three-stage cycle model holds that self-regulated learning is a dynamic and cyclic series of events. He divided the process of self-regulated learning into three interrelated stages: forethought, performance, and self-reflection. The model emphasizes the relationship between individual, environment, and behavior. These three processes are divided by the occurrence of learners' learning behaviors and focus on the relationship between learners' learning strategies, cognitive beliefs, and physical and social environments.

2.3. SRL Behavior Pattern Mining

In recent years, the emergence of large-scale and fine-grained datasets has led to cross-study of SRL and learning analysis. SRL behavior pattern mining complements and potentially replaces traditional self-report measures, providing a new perspective on SRL in online learning environments [20,35]. It not only supplements the traditional methods and technologies but may also change the contemporary concept of SRL [36]. For example, Qiu et al. [37] proposed an e-learning performance prediction framework based on behavior classification. The framework selects the characteristics of online learning behaviors, fuses the behavior data according to the behavior classification model, and obtains the category eigenvalues of each type of behavior. Finally, a machine-based model is constructed. Siadaty et al. [38] studied how to support workplace SRL through scaffolding intervention in recommender systems and found information differences between self-reporting and actual behavior. Chen et al. [39] divided English learners into three models by using latent profile analysis (LPA), namely metacognitive model, cognitive model, and memory model, and compared the differences in English proficiency test performance among the three groups. Qiu et al. [40] proposed a new E-learning behavior classification model (E-learning Behavior Classification model—EBC model) to form a new learning behavior classification and further explore the optimal E-learning behavior feature space through entropy method, method filtering, and data visualization.

Behavior pattern mining can improve the objectivity of testing self-regulated learning theory, but there are still some limitations in current research. First, online learning is massive and unstructured. The screening, evaluation, and quantification of process data on the online platform are relatively abstract and lack theoretical support, and the interpretability of related algorithms is poor. Second, SRL has periodicity and concealment. Most studies focus on quantitative analysis of SRL behavior interactions and regulatory effects. They have not yet explored the dynamic process of SRL behavior and could not directly observe the metacognitive process occurring in different stages of SRL.

2.4. This Study

As the researchers pointed out, the frontier analysis method related to the temporal and temporal characteristics of SRL may enhance our understanding of the nature of SRL and has formed a new direction in the field of SRL [2,3,41,42]. Most importantly, advances in analytical techniques provide new insights that traditional statistics cannot achieve, for example, with time, students' behaviors, cognition, and metacognition in learning and whether some learning modes are superior to other learning modes. The lag sequence analysis method is a good example of the technology for evaluating the temporal correlation of SRL behaviors. The lag sequence analysis method describes the behavior pattern and emphasizes how SRL behavior interacts with time. A literature review shows that lag sequence analysis has been used in customer behavior preference analysis in e-commerce, patient behavior analysis and treatment in the medical field, and player game behavior analysis in the gaming field. In recent years, this method has attracted the wide attention of educational researchers and has been applied to the field of education. For example, Huang et al. used lag sequence analysis to explore the differences in the mode conversion of learners' metacognitive behavior in 3D modeling courses [43]. Chen et al. used lag sequence analysis to investigate learners' performance in real and virtual English competitions based on game learning [39]. In conclusion, the lag sequence analysis method can reveal not only the learning behavior path of learners at different levels but also the mechanism of the generation of learning patterns to enhance the new understanding of students' SRL in the network environment.

This study uses Zimmerman's SRL model as a theoretical framework to examine students' self-regulation process. As the primary theoretical and conceptual basis of SRL, this model paves the way for understanding SRL in specific areas or tasks [44]. This model is used because this highly practical and clear model can be adjusted and extended to study the adjustment process of specific areas in specific learning activities. The Zimmerman model takes SRL as a dynamic loop process, which can properly explain students' behavior according to our online learning research background. It is worth noting that the three stages are recursive and weakly ordered. This means that these three stages do not necessarily unfold in a linear order but may occur dynamically at the same time as students participate in a task.

3. Experimental Design

3.1. Data Sources

The data of this study come from the online learning platform of 69 students' in a physics course in the fall semester of the United States Naval Academy. The online learning of the course is based on the Andes learning platform. In this process, students learn by themselves, without teacher guidance and peer help, so we used this online data as the study of students' self-regulated learning. Andes is an online learning platform with multiple feedback mechanisms that record learners' learning processes in detail and provide timely feedback. The Andes learning log records all kinds of behavioral information in the learners' physical learning process, including 132,852 data, such as setting goals, answering questions, viewing materials, and viewing feedback. Andes platform requires learners to choose their learning objectives and physics learning variables required in exercises so as to provide learners with sufficient self-learning space. The overall learning activity lasted one semester.

3.2. Behavior Coding

This study refers to Zimmerman's self-regulation theory model, related SRL behavior coding methods, and online learning platform learners' behavior characteristics. Finally, the SRL behavior stage was divided, and the coding scheme was formulated (Table 1). On this basis, we analyzed fine-grained tracking data of self-regulated learning behavior and self-regulated learning behavior sequence patterns and compared the use of self-regulated learning strategies. According to the division of online platform self-regulated learning behavior stage, stage confusion may occur and affect the final analysis results. This study assumes that a learning behavior corresponds to only one self-regulated learning stage to avoid this problem. Based on the above classification rules, two professional researchers completed the text coding work after full discussion, and the consistency of the two coding records was tested.

3.3. Tools and Methods

Firstly, the study used Python 3.8 programming algorithm and the agglomerative hierarchical clustering algorithm in machine learning to determine different student groups according to the frequency of SRL behavior of students. Secondly, we used lag sequence analysis to explore SRL behavior patterns of different learning groups and compare their differences. Finally, SPSS 21.0 was used to compare the performance differences among different learner groups.

Table 1. SRL behavior coding scheme.

SRL Stage	Behavior	Coding	Detail
Preplan	Setting goals	VR	Define the objectives of the task and consider the purpose of the task
Behavioral expression	Draw the force diagram	AX	Draw the diagram according to the learning requirements so as to solve the problem later.
	Formula derivation	EQ	Reasoning physical formulas and writing detailed equation
	View information	CP	View information related to the learning task
	Help tips	EF	View tips when learning tasks encounter difficulties
Reflection and evaluation	Answer the solution	AS	Answer the solution required by the relevant task
	View feedback	SV	Submit answers and view system scores and feedback
	Click question	WR	Click on the system feedback question so as to obtain the relevant analysis.

Firstly, according to the SRL behavior and SRL behavior frequency extracted from Andes online platform, this study used the hierarchical agglomerative clustering to identify and classify different learning groups. Hierarchical agglomerative clustering is a bottom-up method. Each data point starts with a separate cluster, and each loop merges the two closest clusters into one cluster. We repeat the iteration until all individuals gather together to form a large class. This algorithm avoids the selection of the number of clusters and initial points and does not fall into local optimum. In addition, the complete method used in this study is used to calculate the similarity between individuals, which can well-separate the data sets containing noise between clusters.

On this basis, the lag sequence analysis (LSA) method was further used to identify the significant SRL behaviors of different learning groups and to explore the differences in SRL behavior sequence patterns. We can dynamically understand the whole process of learners' self-regulated learning strategies by using the LSA method to analyze the explicit and implicit behaviors of learners on the online learning platform. In this study, the lag sequence analysis tool GSEQ 5.1 was used to calculate the occurrence frequency and probability of the sequences formed by the SRL behaviors of different learning groups, and the drawing tool Visio was used to draw the transformation map of SRL behaviors of different learning groups.

Finally, we used SPSS 21.0 software to carry out one-way analysis of variance on related achievements. Then, we took the learning group category in the clustering results as the independent variable and the academic performance as the dependent variable to explore the relationship between SRL populations and learning outcomes and specific differences in learning outcomes.

4. Experimental Results and Analysis

4.1. Cluster Analysis of Self-Regulated Learning Behavior

In order to explore the SRL behavior pattern in online learning platform, this study uses the condensed hierarchical clustering method to cluster SRL behavior based on the SRL behavior coding scheme and related behavior frequency in Table 1. Contrary to some top-down segmentation clustering algorithms (such as k-means clustering algorithm), hierarchical agglomerative clustering algorithm does not need to assume the number of clusters. Because the amount of behavior frequency data is huge, the order of magnitude is different in order to prevent clustering errors caused by ignoring the small range of data during clustering. Therefore, standardization of the data is needed; though standardized processing of data are the same, each data set follows the standard normal distribution, i.e., the average ($\mu = 0$, $\sigma = 1$). The calculation of Equation (1) is as follows:

$$\mathrm{BF} = (x - \mu)/\sigma \quad (1)$$

Among them, the BF represents the standard score, x represents the original data, μ represents the set of data of average, and σ represents the standard deviation of the data.

According to the hierarchical clustering tree graph generated by Figure 1,and orange, green and red represent cluster 1, cluster 2, cluster 3. We group the similar cases with a given distance metric and finally determine the number of clusters is 3. Among them, cluster 1, cluster 2, and cluster 3 contain 18, 25, and 26 students, respectively. The frequency of various SRL behaviors and the overall average level of class students are shown in Figure 2.

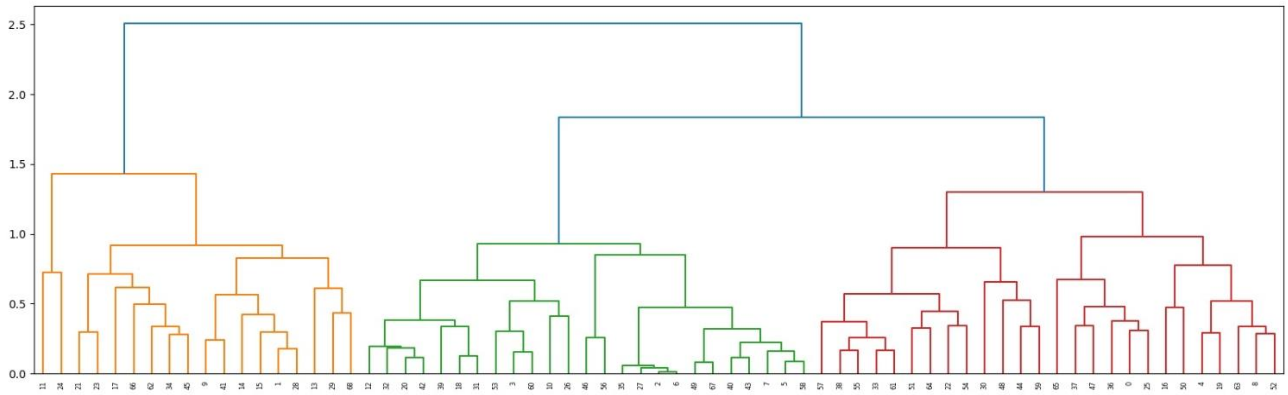

Figure 1. Dendrogram of the clustering result.

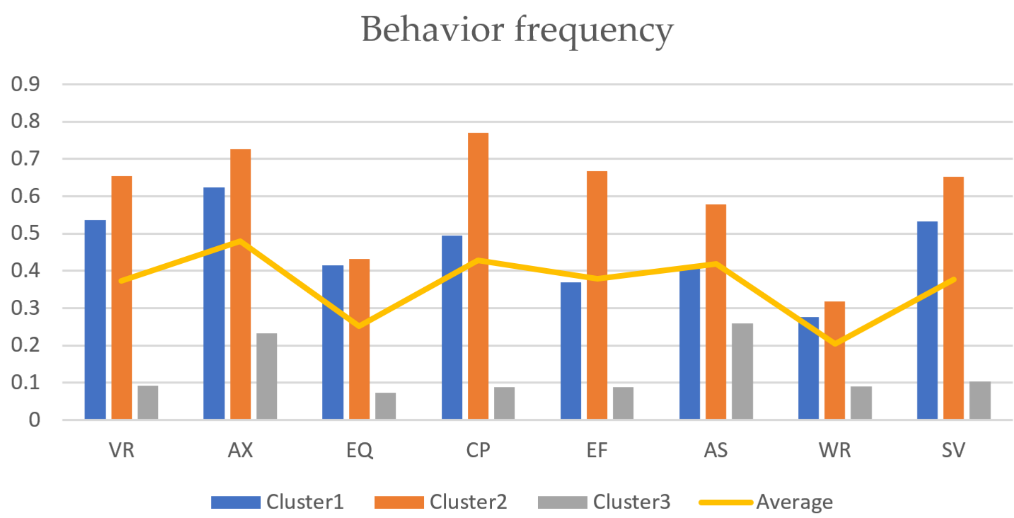

Figure 2. Comparison of behavior frequency of different clusters.

Among the three types of learning groups, the learning behavior frequency of cluster 1 learning group is basically at the average level. The learning group of cluster 2 was relatively active, and the behavior frequency was higher than the average level. The activity of group 3 was the lowest, and the behavior frequency was lower than the average level. In particular, the most frequent of all behaviors in cluster 1 is the formulation of goals and drawing diagrams in the pre-planning stage; the most frequent behavior in cluster 2 is the viewing data in the performance stage; and the most frequent behavior in Cluster 3 is the question answering in the performance stage. This indicates that SRL behavior is significantly different among different learning groups in the online environment. Cluster 1 tended to make plans and think about tasks. In order to achieve their own learning goals, they made learning plans and analyze learning tasks by themselves. Cluster 2 tended to find information and prompt help from Andes online platform and combined the information and prompt feedback provided by the platform to reach a deeper level of cognition. Cluster 3 tended to answer the questions given by online platforms directly, with less planning and reflection.

4.2. Analysis on the Difference of Sequence Patterns of Self-Regulated Learning Behaviors

Self-regulated learning is not a single, independent learning event but a dynamic and iterative process. Therefore, the study further used the lag sequence analysis method to count the sequence transfer frequency and sequence transfer conditional probability of the specific behavior time sequence of the three groups of students, thus obtaining the adjusted residual table. Then, we selected the most statistically significant (Z-score > 1.96, the higher the Z-value, the stronger the significance) sequence behavior for visual analysis (Figure 3). Among them, the arrow represents the direction of behavior transfer, and the number represents the Z-value of the sequence. The thicker the arrow, the larger the Z-value of the corresponding sequence, that is, the more active the learning group is in the sequence.

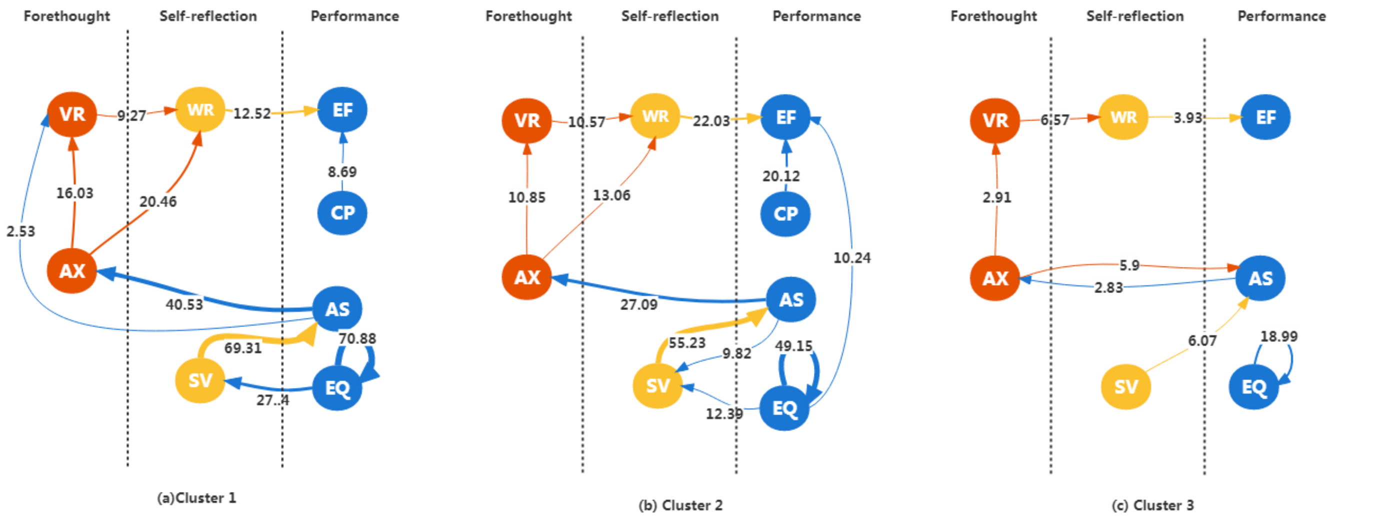

Figure 3. SRL behavior transition diagram of different learning groups. ((**a**) cluster 1 behavior transition diagram; (**b**) cluster 2 behavior transition diagram; (**c**) cluster 3 behavior transition diagram).

Cluster 1 learning group has a clear learning path and good self-guidance. In the pre-planning stage, the SRL behavior path of this group is the most abundant and the most obvious. Learners show clear problem-solving paths (AX→VR→WR→EF, AX→WR→EF), which indicates that such learners have more self-regulated learning strategies. In the behavioral performance stage, the most significant behavior of this cluster is to repeatedly deduce formulas, constantly reason and internalize knowledge, have a clear understanding of their own learning process and SRL strategies, and rely less on prompts and materials. After deducing the formula, this kind of learner can often submit answers and obtain systematic feedback (EQ→SV). In the reflection stage, such learners improve the answer according to system feedback (SV−>AS).

Cluster 2 learning group has the largest number of SRL behavior sequences and transformation types, and all behaviors are closely related to form a large cycle. This group is more likely to look at various feedbacks from online platforms. In the behavior stage, the group is more inclined to view the data and help tips (EQ→EF, CP→EF) to reflect and deepen the understanding of knowledge. It is worth noting that the characteristics of such learning groups are prominent in the reflective evaluation stage. Compared with the other two groups, this kind of learning group has richer behavioral paths in the reflection stage. They tend to re-answer (SV→AS) after looking at the final feedback and reflect more explicitly (VR→WR) after setting learning goals. This phenomenon shows that the group can often improve their learning content and further deepen their knowledge after viewing platform feedback and tips.

The SRL behaviors of the cluster 3 learning group are relatively independent and weakly connected. In the three stages of self-regulated learning, the group shows the smallest behavior path and the lowest visibility. This group mainly completes the question answering (AX→ AS, SV→ AS) and only focuses on the passive completion of online platform tasks. In addition, compared with other groups, this group tended to redraw the object map (AS→AX) when answering questions, indicating that the knowledge mastered by this group was not solid, and the learning route was not clear. Most of these learners' explicit behavior(Z-score>1.96) is short and passive learning caused by systematic feedback because their knowledge construction level is not deep enough.

4.3. The Difference Analysis of the Learning Effect of Self-Regulated Learning Groups

The study further adopted one-way ANOVA, clustering results as independent variables and academic performance as dependent variables to explore the relationship between SRL groups and academic performance. The results of the homogeneity test of variance are shown in Table 2, P = $2.7 \times 10^{-3} > 5 \times 10^{-2}$, and the difference between the three groups is the same, so subsequent one-way analysis of variance was carried out. The results of one-way ANOVA (F = 11.560, $p = 0 < 5 \times 10^{-2}$) showed that there were significant differences in academic performance among different SRL groups, as shown in Table 3.

Table 2. Homogeneity test of variance.

Levene Statistics	df1	df2	Significance
1.336	2	66	2.7×10^{-1}

Table 3. One-way ANOVA.

	Sum of Squares	df	Mean Square	F	Significance
Group to group analysis	11,466.383	2	5733.192	11.560	0
Analysis within a group	32,731.388	66	495.930		
Total number	44,197.771	68			

In order to further analyze the differences in the learning effects of different learning groups, this study conducted a pairwise comparison of the learning performance of the groups. As shown in Table 4, there were significant differences between cluster 3, cluster 1, and cluster 2 ($p < 0.05$), and there was no significant difference between cluster 1 and cluster 2 in academic performance. The distribution of all kinds of academic performance is shown in Table 5, in which the excellent line represents the number of people with scores of 80 and above in all groups; the pass line indicates the number of people whose online platform scores are above 60.

Table 4. Pairwise comparison of academic performance of different SRL groups.

(I) Complete Method	(J) Complete Method	Mean Value Difference (I−J)	Standard Error	Significance	95% Confidence Interval	
					Lower Limit	Upper Limit
1	2	5.354	6.828	4.36×10^{-1}	−8.28	18.99
	3	28.650	6.238	0	16.20	41.10
2	1	−5.354	6.828	4.36×10^{-1}	−18.99	8.28
	3	23.296	6.884	1×10^{-3}	9.55	37.04
3	1	−28.650	6.238	0	−41.10	−16.20
	2	−23.296	6.884	1×10^{-3}	−37.04	−9.55

Table 5. Distribution of academic performance.

Related Performances	Cluster 1 (N = 18)	Cluster 2 (N = 25)	Cluster 3 (N = 26)
Average score	52.880	47.530	24.230
Standard deviation	24.370	22.461	19.693
Highest score	95.000	86.000	87.000
Lowest score	5.000	15.000	0.000
Excellent (score $\geq$ 80)	3 (11.53%)	2 (11.11%)	1 (4.00%)
Pass (score $\geq$ 60)	13 (50.00%)	6 (33.33%)	1 (4.00%)

In general, although there is no significant difference in the overall level of academic performance between cluster 1 and cluster 2, the excellent rate and pass rate of the behavioral group represented by cluster 1 are significantly higher than those of cluster 2 from the perspective of the distribution of academic performance (see Table 5) This shows that SRL behavior group represented by cluster 1 is more desirable in this learning platform. It further verifies the advantages of cognitive oriented learners in academic performance; that is, they have the best self-regulated learning strategies. The group of negative moderators was the lowest in three groups whether in average (24.23), proportion of outstanding achievement (4.00%), or proportion of pass (4.00%). It verifies the characteristics of negative-regulated learners in learning effect, indicating that such students do not actively adjust themselves to participate in learning in online learning. Therefore, this kind of students should be the focus of teachers in subsequent teaching.

5. Discussion and Recommendations

5.1. Discussion and Conclusions

The study showed that the SRL behavior displayed by students in Andes can be grouped into three groups through clustering analysis. Specifically, Figure 2 proves that there are significant differences in SRL behavior among different learning groups in the online environment. Cluster 1 with average behavior frequency showed a more proactive attitude toward online learning. They think about learning tasks, formulate learning objectives, and carry out deep learning effectively driven by strong motivation. Cluster 2 with the highest frequency of behavior tends to rely on online environmental feedback, and they complete online learning better with the help of system data and tips. Cluster 3 has the lowest frequency of behavior, showing passive completion of learning tasks.

The unique and important contribution of this study is to use the lag sequence method to determine the SRL behavior sequence patterns of three students. Specifically, cluster 1 is less dependent on systematic tips and information and shows a positive and clear learning deployment in the three SRL stages of planning, performance, and reflection; solves learning tasks in multiple ways; and shows more self-regulated learning strategies. Hence, they present a clear path of “cognitive oriented” sequential pattern. Compared with the other two groups, cluster 2 was more inclined to seek various prompt feedback from the online platform during the learning process, which showed a “reflective oriented” sequential pattern. However, this does not mean that such learners’ learning is passive because the group tends to re-improve learning objectives, supplement task answers, and improve in trial and error after viewing various platform feedback. Consistent with research from the University of Leuven, Belgium [31], help-seeking behavior can increase learners’ awareness of the actions and skills required to perform goal-directed learning behaviors, and the calibration of relevant cues can induce a learner’s perception of their own abilities. The group represented by cluster 3 is not completely SRL-free learners. Their learning behavior is relatively independent, the level of knowledge construction is not deep enough, and they tend to obtain learning results passively, without a clear type of learning deployment and learning reflection. That is, it shows a “negative regulated” sequence pattern. When students receive internal or external feedback on tasks, they will have self-reflection. Self-reflection will trigger the momentum or obstacles of SRL’s further efforts. For example, learners who think they do not perform well in their tasks can respond positively by making more effort to achieve better learning outcomes or react negatively by reducing their motivation for the task or even their motivation to learn. This also explains the iterative and cyclic properties of SRL process.

In addition, the study found that the scores of reflective oriented learners were higher than those of negative regulated learners. This finding is not surprising because reflective learners have better performance in both frequency and sequential patterns of SRL behavior. Previous studies have shown that students with better scores more consciously accept and reflect on their weaknesses and are motivated to make up for these gaps by actively adapting to various learning needs [45]. It is worth noting that this study does not find significant differences in academic performance between cognitive oriented learners and reflective oriented learners. However, the excellent rate and pass rate of cognitive oriented learners are significantly higher than those of reflective oriented learners. This is similar to the existing research conclusions [46]. This study shows that successful learning is often related to the positive and clear deployment of regulatory activities in the learning process, such as goal setting and planning.

Based on Zimmerman's self-regulation model, this study classifies, encodes, and analyzes learners' SRL behavior data. Through hierarchical cluster analysis and lag sequence analysis, this paper divides learning groups into three sequential patterns: cognitive oriented, reflective oriented, and negative regulated so as to mine the differences in SRL behavior and sequential patterns of learners in online environments and analyze the differences in learning effects among different groups on this basis.

The results show that: (1) the group with average frequency of behavior tend to actively deploy and solve online tasks. They present a "cognitive oriented" sequence pattern, which performs best. (2) The group with more active behavior frequency tend to reflect and improve in trial and error. They present a "reflective oriented" sequence pattern, which performs better. (3) The group with the lowest behavior frequency tend to passively complete the learning tasks. They present a "negative regulated" sequence pattern, which performs poorly.

5.2. Limitations and Suggestions

In this study, there are still shortcomings and limitations in the coding, classification, analysis, and in-depth insight of the groups' self-regulated learning behaviors and their sequential patterns. Firstly, this study used the system log file as a single data source to identify and observe students' SRL behavior at multiple time points. Even in an online environment where learner behavior is registered, it is not possible to capture all the behaviors involved in the learner's learning process. For example, some goal setting or problem seeking help may occur outside the learning platform. In addition, the coding mechanism of self-regulating behavior needs to be optimized to improve the accuracy and reliability of self-regulating behavior pattern identification. Based on the above discussion, this study puts forward the following optimization suggestions for the improvement of online learning platform and student training.

(1) Construct a self-regulated learning intervention mechanism.

The analysis of self-regulated learning strategies can enhance learners' understanding of the complex processes they adopt and inform future intervention options to advance research in online course design. Past studies have shown that students' self-regulation can be learned or improved through educational interventions [47]. Timely teacher intervention in online learning can promote students' use of cognitive, metacognitive, and SRL strategies.

(2) Add constructivism learning environment.

Learner-centered constructivist learning environment can enhance students' experience and encourage self-regulation of learning behavior. Studies have shown that problem-based learning can effectively promote students' SRL and in-depth learning methods [48].

Adding problem-based learning to the learning platform enables students to use SRL strategies to guide and monitor the process of problem solving.

(3) Provide self-regulated learning support.

For negative regulated learners, if the learning platform can provide personalized learning feedback in time and apply learning analysis to support learners' self-regulated learning, it will help to cultivate students' better understanding of self-regulated learning ability. Feedback is not only an important measure to realize the integration of learning and evaluation but is also a necessary means to ensure the quality of online learning. Therefore, it is important for future research to explore the use of learning analytics and examine learner behavior in SRL-supported online learning platforms based on current approaches in order to gain a comprehensive understanding of how learners can be better supported to self-regulate learning in online learning environments.

Author Contributions: Conceptualization, Z.Y.; methodology, Y.L. and H.C.; formal analysis, L.J.; investigation, Y.L. and G.Z.; writing—original draft, L.J. and Z.Y.; project administration, Z.W. and H.C.; funding acquisition, G.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by 2021 School-level teaching reform Project of Zhejiang Institute of Economics and Trade JG21311 and JG21106, in part by of Zhejiang China Vocational Education Association (ZJCV2022A21) and Zhejiang Institute of Economics and Trade and Technical College of provincial and ministerial level and above education cultivation project (21SBJP02).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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