You, T.(2024). The influence of educational big data visualization on students' learning initiative. *Journal of Educational Technology Development and Exchange*, *17*(2), 118-133.
https://doi.org/10.18785/jetde.1702.02

The Influence of Educational Big Data Visualization on Students' Learning Initiative

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Abstract: *With the development of educational informatization, a large amount of data has been generated in the field of education through various platforms, which prompted research on educational big data among numerous researchers. The quasi-experimental research method has certain controllability. This study adopts the method of quasi-experimental research to conduct a semester of educational big data visualization experiments teaching students through the learning platform. The purpose is to explore the impact of educational big data visualization on students' learning initiatives. Participants were divided into two different groups, namely an experimental group (52 people) and a control group (40 people) for a 4-month teaching experiment from February 2023 to June 2023. The results indicated that there was no significant difference in the mean value of the learning initiative between these two groups. However, the results for the pre- and post-tests showed one stronger effect on the experimental group and much less compared to the control group. The size effect of the experimental group was 0.314, but the control group was only 0.167. This means that the effect has been stronger for the experimental group than for the control group.*

Keywords: educational big data, data visualization, learning initiative

1. Introduction

In 2012, the United Nations (2012) released a significant document titled "Big Data for Development: Challenges and Opportunities." This document highly praised the application value of big data, predicting that it would play a pivotal role in numerous fields in the future. In 2016, the Office of Educational Technology in the United States published the National Educational Technology Plan. Zhao et al. (2016) point out this plan explicitly proposed the application of big data technology to learning data analysis.

Data visualization allows administrators, teachers, students, and other education-related personnel to observe data visually within the context of educational big data. Through various graphics and images, Deng et al. (2016) discerned complex cognitive patterns and educational phenomena concealed within the data. This current study integrates data visualization into classroom teaching, employs a quasi-experimental research method, and focuses on freshmen as the research subjects. The aim is to investigate the impact of educational big data visualization on students' learning initiative. Cao and Li (2021) thought that students' learning initiative was a crucial factor influencing their learning outcomes and the overall quality of talent training in schools. The researchers for this study hope that it can offer insights and recommendations to enhance students' learning initiative.

Although some research on data visualization in the field of education exists, the amount is not large, and only focuses on it as a tool and technology without further in-depth research. This study further explores the impact of data visualization on students' learning initiative by applying it to teaching. There are a lot of studies on students' learning initiative, but not from the perspective of data visualization.

Based on relevant research literature, studies on students' learning initiative mainly focus on the status quo of learning initiative in different school age groups, training methods of learning initiative, and the weaving of learning initiative scales, etc. Chen et al. (2017) found some people have summarized the influencing factors of learning initiative from the perspectives of learning subjects, schools, and families. No studies have been found to explore the influence of learning initiative from the perspective of data visualization teaching methods. Therefore, this study adopts the visualization of educational data to conduct teaching quasi-experiment, observing the changes of the learning initiative of the experimental group and the control group, to speculate whether the visualization of educational data can have an impact on the learning initiative of students.

2. Literature Review

2.1 Big Data Visualization in Education: A Modern Pedagogical Tool

Matcha et al. (2019) divided the application objects of educational big data visualization into three categories. When learners' learning data is collected and visually presented, students can find their cognitive problems from it, and teachers can reflect on their teaching effects from the results of data visualization. Administrators generally control the educational level and quality of schools through the results of data visualization. Corrin and De Barba (2014) visualized data with the participation of online community users to reflect users' contributions and participation in community activities. Charleer et al. (2016) believed that teachers could timely understand students' learning participation and completion through data visualization, and appropriately change the teaching process according to students' situations. Starting from the classification of regional big data, Yang et al. (2020) pointed out that the visualization of educational big data could provide managers with more efficient data interpretation methods, and could timely grasp the education situation of the whole region to carry out scientific educational decision-making.

Jivet et al. (2018) summarized some functions of the dashboard, which were concluded after some learner-learning analysis, and explored how these functions fit into the cognitive development of individuals. This study showed that most dashboards could effectively support and promote learners' metacognitive levels. Xia et al. (2019) embedded the PeerLens interactive visual analysis system through the LeetCode online question bank, which could recommend customized adaptive practice questions for learners. Chaparro-Peláez et al. (2019) proposed the Data Extractor design module through the application of online self-assessment and peer assessment mode in the field of learning analysis, which as a plug-in, could supplement the functions of Moodle Workshop in data analysis and visualization. Kuosa et al. (2016) introduced two interactive visual learning management system (LMS) tools to improve the learning and teaching effects of online courses.

2.2 Types of Educational Big Data Visualization

Zhao et al. (2008) thought that text data visualization was to find some meaningful information through text analysis, visualize the information, and use computer technology to present it graphically, to facilitate people to understand the implied content or relationship of the text . According to the characteristics and application scenarios of text information, Wise et al. (1995) subdivided text visualization into text visualization based on word frequency statistics, text visualization based on clustering algorithm, and text visualization based on semantics. Chang et al. (2016) proposed a label cloud method based on learners' video viewing logs and subtitles, and weighted keywords to form a keyword cloud of learning topics. Collins et al. (2009) created DocuBurst, a visual method for reflecting semantic content. It is a radial, spatially filled subsemantic layout that can reflect the internal structure and semantic relations of text. Hoque and Carenini (2014) proposed ConVis, a visual exploratory text analysis system for blogs, which closely integrated interactive visualization with text mining technology specifically for processing conversational data to meet the information needs of users when exploring conversations.

Dos Santos and Brodlie (2004) pointed out that multidimensional data visualization could reflect the attributes of multiple information and the relationship between these attributes and show more attribute characteristics of abstract information. To facilitate people to build images of multi-dimensional information in their minds, Sun et al. (2008) used some technical methods to reduce multi-dimensional information to low-dimensional information to achieve visualization, which mainly includes geometric-based technology, pixel oriented technology, icon-based technology, hierarchy-based technology, graph-based technology, and dimensional-reduction mapping technology. Vivian et al. (2015) analyzed and visualized the emotions of the experimental subjects through a radar map. The emotion analysis mainly included anger, expectation, disgust, fear, joy, sadness, surprise, and trust. Wu et al. (2016) visualized some multidimensional data of students through the parallel coordinate system, which mainly came from the number of students' visits to the forum, the number of posts in the forum, and the frequency of interaction with other students, and found the correlation between students' learning behavior and academic performance through the visualization of these data.

Wang and Ren (2017) thought that network data relationship was also a common type of data visualization. In the network structure, every point represents an individual, and the connection between points represents the relationship between individuals, which can be represented by tree structure or network structure. Pardos and Kao (2015) visualized the flow of the course and the structure of the course content in the form of a tree diagram. Saqr and Alamro (2019) used directional arrows to connect nodes to express the degree of interaction of students in course learning. The thicker the directional arrows, the stronger the interaction. Qu and Chen (2015) used the force layout diagram to make a visual analysis of large-scale student social networks, representing a student as a dot, the size of the dot representing the level of student participation in activities, the color of the dot representing the student achievement, and the links between dots representing the interaction between students, through which the impact on student achievement can be found.

In addition, Qi and Wu (2015) also put forward the concepts of time series data visualization and geospatial data visualization. Visualization of time series data consists of a set of data with time attributes, which show certain rules as time changes. Common visualization methods of time series data mainly include Sankey chart, calendar chart, spiral chart, and more.

Goggins et al. (2015) developed a visual tool that allowed teachers to visualize the formal process of group learning, understand how group cooperative learning changes over time, and explore the historical information of learners' learning activities in the form of a calendar graph. Zhou et al. (2018) thought that visualization of geospatial data was generally used to describe some data information with spatial location distribution laws, and i common to use point maps or thermal maps to visualize geospacers. Emmons et al. (2017) used a dot map to visualize the data of students' origin, and the area size of the dot circle represented the number of students participating in learning in a certain area.

2.3 Current Situation of Learning Initiativ-e Research

The study of the concept of learning initiative is also different, and researchers give different definitions from different perspectives. Fay and Frese (2001) believed that learning initiative refered to a kind of behavior and psychological state in which students actively and spontaneously took various ways to overcome learning difficulties and setbacks in order to complete learning goals and tasks. Fazey (2001) held that to understand the nature of students' learning initiative, we should first pay attention to students' learning ability, learning motivation, and learning control. The development of students' positive psychological characteristics is influenced by personal and environmental factors, and individual differences in psychological characteristics are influenced by learning experiences. Clifford (1999) found that if students were encouraged to take the initiative to learn independently in universities, faculty and staff needed to change from the role of knowledge experts to the role of resources and facilitators, and new teaching and learning concepts and new skills could be formed. Through the problem-based learning (PBL) teaching method, Martin et al. (2008) studied the influence of learners' mental constructs related to proactive learning and found that a short-term PBL course could cultivate learners' initiative and other key employability skills as well as the application of content knowledge. Smith (2008) pointed out that the concept of learning initiative first appeared in the early 1970s and was developed through practice by faculty researchers at the Centre de Recherches et d 'Applications Pe´dagogiques en Langues (CRAPEL) at the University of Nancy in France, and the learning initiative was the ability of people to take charge of their learning. Through research, Little (2007) found that the development of learner initiative and the improvement of target language ability not only supported each other, but also combined and incorporated the learning initiative into language teaching to form a set of general teaching principles, which could better improve specific language teaching and learning process effects.

Tam and Song (2016) believed that data visualization, when initially applied to the field of education, could significantly improve students' learning and analysis capabilities. However, no one has yet found out how to select the content of data visualization and how to present it to students so they could find the fun of learning and thus, improve their learning initiative. Leal-Flores and Gonzalez-Guerra (2020) proposed that learning styles and learning environments in the new era cannot remain unchanged. They proposed schools should strive to design and implement strategies that conformed to students' learning habits in the new era, and to facilitate them to acquire knowledge and skills necessary for future career development. To explore and discover the change in students' learning initiatives through data visualization is an attempt to discover the influence of learning styles in the new era on students' learning habits.

By integrating educational data visualization into the classroom teaching process, on the one hand, it is convenient to record the students' learning footprint of the whole course and then analyze the students' learning effect; on the other hand, through this form of teaching, the study explores whether the change of students' mental state of learning initiative is significant. The researchers hope that this paper can provide some new ideas and references for the research of educational big data visualization and learning initiatives.

3. Method

3.1 Research Participants

This study takes the information technology course of two classes in the first year of a higher vocational college in Shanghai, China as an example. The information technology course was selected for the convenience of experimental design. From the perspective of experimental design, different classes led by different teachers would have a certain impact on the experiment due to the different teaching styles of teachers. To avoid the error of the experimental results caused by different teachers, the classes participating in the study were taught by the same teacher.

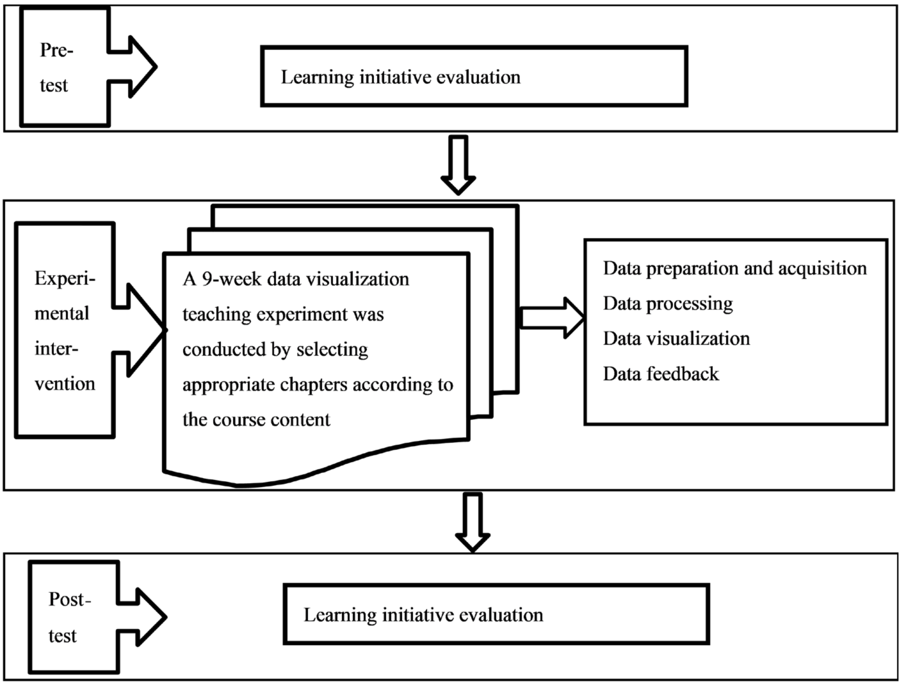
Before the educational big data visualization teaching experiment begins, it is necessary to confirm that there is no significant difference in learning initiative between the two classes involved in the study. Therefore, Huang and Xie (2013) first tested learning initiatives by using the Questionnaire on College Students' Learning Initiatives with good reliability and validity. The results showed that there was no significant difference between the scores of students in the two classes on the learning initiative scale. On this basis, two classes were randomly assigned, with one class as the experimental group and the other as the control group. The experimental group consisted of 41 participants (34 males and 7 females); the control group consisted of 35 people (19 males and 16 females).

3.2 Experimental Design Process

This study adopted the experimental process of time series with a two-group design, and the experimental design flow chart was divided into three stages by referring to Figure 1:

Figure 1

Experimental design process



1) Pre-test of learning initiative: In the first week, the two groups of students first took the pre-test of learning initiative as the initial degree value before the experiment intervention.

2) Experimental intervention: From the second week to the tenth week, the experimental intervention was carried out for nine weeks, the class time was 120 minutes per week, and the students' learning time on the platform was also recorded before and after class. From the perspective of data processing, the implementation process of experimental intervention was divided into four stages: data preparation and acquisition, data processing, data visualization, and data feedback. The details are as follows:

a. Data preparation and acquisition. Before class, the teacher made a short case teaching video according to the course objectives and course content and upload it to the learning platform. After the short video, some resources and test questions related to the teaching content were set. Students watched the video and answered the test questions. In class, teachers activated the attendance and sign-in function through the learning platform to record students' attendance. During the teaching process, teachers interacted with students through the selection and response functions of the learning platform to record students' participation in classroom activities. After class, teachers published homework and discussion topics through the learning platform, students submitted homework in groups or individuals and published their views on each learning topic, and the background records students’ learning after class. Finally, the teacher guided the learning record of the weekly course from the platform.

b. Data processing. To facilitate subsequent data analysis, after the teacher exported the data from the platform in the form of Excel, the data needed to be cleaned and processed. The teacher could screen, merge, supplement, and unify the data according to the teaching needs, and remove some irrelevant data.

c. Data visualization. For students to visualize their weekly course learning, teachers needed to visualize the processed data. As Excel itself has a powerful chart display function and the raw data is also stored in the form of Excel documents, it is convenient to visualize the data directly in Excel. Through data visualization, teachers can have an intuitive grasp of students’ learning situations, so that they can give targeted guidance to students. As shown in Figure 2, teachers can learn that most students are most likely to log in to the learning platform to study from 12 a.m. to 4 p.m. The Y-axis represents the number of times the class studied chapters on the learning platform. The more times a chapter is studied, the higher the lines will be. As shown in Figure 3, teachers know the performance of each group, so they can reasonably adjust the groups to improve the cooperation of group members in completing the homework. The Y-axis shows the score of group work in a group activity. Grouping in class is equivalent to one class activity. The teacher can determine the grouping of this class group activity according to the previous group performance. Because the group activities can be freely selected, each group situation may not be the same. As shown in Figure 4, by comparing the performances of the two students, the teacher can find out which knowledge points student 1 is not good at, to give targeted guidance to them. For student 2, it can be found that this is a student with high enthusiasm for learning, and can be praised. The numbers from 1 to 9 correspond to nine chapter tests with different knowledge content. Each circle represents the magnitude of the score. The larger the circle, the higher the score.

Figure 2

Class Performance

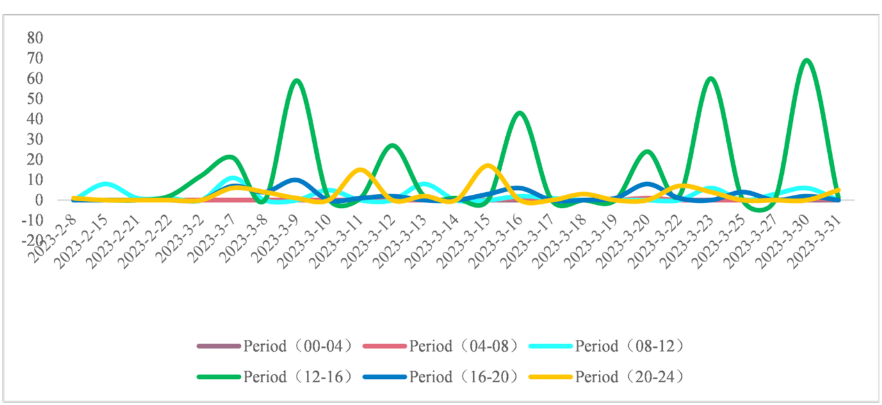


Figure 3

Group Performance

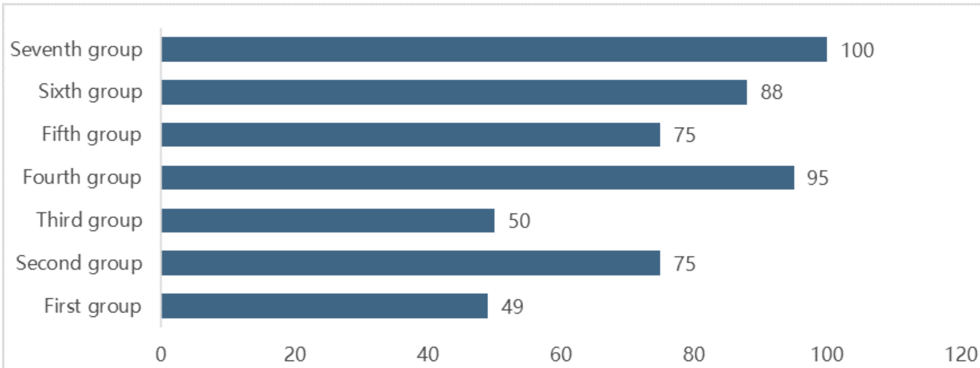
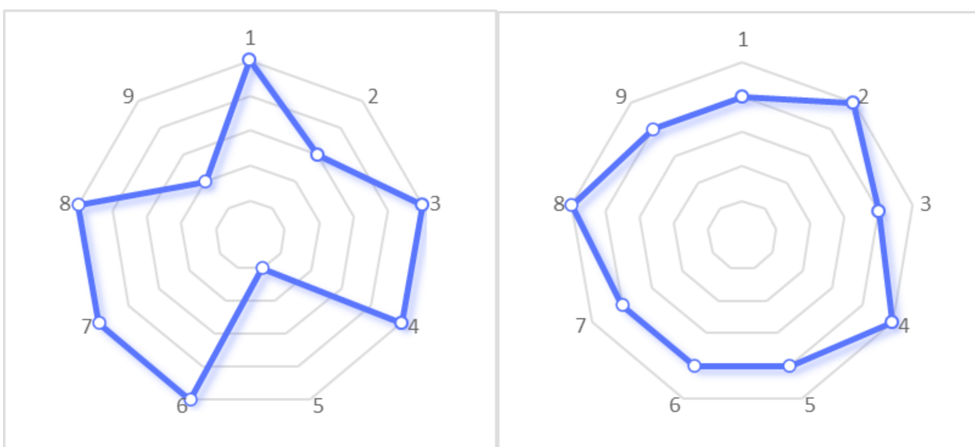


Figure 4

Individual Performance



d. Data feedback. The teacher sends the visualized results to the course group or send them individually to the students by email so that the students could understand their performance this week. In the learning platform, there was the function of sending email notification, through which students could check the progress of emails, which students have checked and which students have not checked. Teachers could also send one-click alerts to students who have not checked their emails. A control group of students did not participate in these sessions. In this way, the teacher would remind the students who did not complete the study well, and praise and encourage the students who did well in the study.

3) Post-test of learning initiative: The students in the experimental group and the control

group were tested after the intervention of the experiment.

3.3 Measuring Tool

The Questionnaire of College Students' Learning Initiative compiled by Huang and Xie was used as the measuring tool in this study. The questionnaire contained 17 questions and the answers divided into four levels: very inconsistent, not very consistent, basically consistent, and very consistent. The score was 4, 3, 2, and 1, and the higher the score, the lower the learning initiative. Huang and Xie (2013) proved that confirmatory factor analysis of the scale structure showed that the final scale had good structural validity, and the model fitting index was as follows: $x2/df = 398.95/113 = 3.53 < 5$, CFI = 0.96, RMSEA = $0.043 < 0.05$, NNFI = $0.95 > 0.90$, IFI = 0.96. The reliability coefficient of the scale reached 0.814, and the correlation coefficient between each question and the total table ranged from 0.34l to 0.648 ($p < 0.01$). The specific contents of the research tool are shown in the Appendix.

3.4 Data Analysis

The statistical software SPSS 25.0 was used to analyze the collected effective results. As the experimental intervention was conducted in this study to test the impact of data visualization on learning initiative, it was necessary to control the initial degree of students' learning initiative before experimental intervention to avoid interference with the interpretation of results. In the single-factor analysis of variance, the post-test of learning initiative was taken as the dependent variable and the pre-test of learning initiative as the covariate, and covariate analysis was conducted. To verify whether there was a significant difference in learning initiative between the experimental group and the control group before and after the experiment, a t-test was needed. The independent sample t-test was also conducted in this study. Therefore, in addition to quasi-experimental teaching methods, descriptive statistics, covariance analysis and independent sample t-test are also used in this study.

4. Results

4.1 Descriptive Statistical Analysis

The descriptive statistical results are shown in Table 1. After the deletion of invalid samples by the pre-test learning initiative, there were 76 valid samples in total. The number of effective pre-test samples in the control group was 35, with an average of 49.97 and a standard deviation of 9.69; the number of effective pre-test samples in the experimental group was 41, with an average of 50.14 and a standard deviation of 8.85. After the post-test learning initiative deleted the invalid samples, the number of effective samples was 66. The number of effective samples in the control group was 35, with an average of 51,48 and a standard deviation of 8.37. The number of effective samples in the experimental group was 31, with an average of 50.74 and a standard deviation of 8.70. The reason for the inconsistent sample size between the pre-test and post-test may be that some students have changed majors, suspended studies, or dropped out.

Table 1

Descriptive Statistics

Group		*N*	Range	Average	*SE*	*SD*
Control	Pre-test	35	45	49.97	1.63	9.69
	Post-test	35	29	51.48	1.41	8.37
	Number of valid cases (column)	35				
Experimental	Pre-test	41	30	50.14	1.38	8.85
	Post-test	31	31	50.74	1.56	8.70
	Number of valid cases (column)	31				

4.2 Result of ANCOVA

After conducting a statistical analysis, the researchers confirmed that the assumption of homogeneity of regression coefficients in ANCOVA was met, allowing them to proceed with the analysis. As shown in Table 2, when controlling for the covariate (pre-test learning initiative), the independent variable (visualization of educational big data) did not significantly influence the dependent variable (post-test learning initiative), evidenced by an F value of .057. Despite different experimental treatments across sample groups, there was not a significant variance in post-test learning initiative levels. This suggested that while the post-test learning initiative might fluctuate based on the received experimental treatment, such as educational big data visualization, these differences were not statistically significant.

Table 2

List of Covariate Analysis ANCOVA

Source	Type III SS	df	MS	*F*	SIG	Partial Eta squared
Modified model	90.72a	2	45.36	0.62	0.53	0.01
Intercept	4506.10	1	4506.10	62.05	0.00	0.49
Pre-test	81.62	1	81.62	1.12	0.29	0.01
Group	4.11	1	4.11	0.05	0.81	0.00
Error	4575.05	63	72.62			
Total	177251.00	66				
Revised total	4665.77	65				

Note: a. R square = .01(Adjusted R square = -.01)

4.3 Result of T-Test

Table 3 shows that there is no significant difference between the average values of pre-test learning initiative and post-test learning initiative in the control group, $t(35) = -0.612$, $p = .544$, d = -.167, and the results of t-test analysis on dependent samples were as follows. There was no significant difference between pre-test learning initiative ($M = 49.97$, $SD = 9.69$) and post-test learning initiative ($M = 51.48$, $SD = 8.37$). There was no significant difference in the mean value of the activity, t(31) = -0.505, p = .616, d = -.314, and no significant difference between the pre-test learning initiative (M = 48.00, SD = 8.74) and post-test learning initiative (M = 50.74, SD = 8.70). However, from the value of effect size, the experimental group d = 0.314, the control group d = 0.167, the difference in learning initiative of the experimental group was larger.

Table 3

T-test

Dimension	***M* (*SD*)**		**df**	***t***	***p***	**Effective size**
	Pre	**Post**				
Control	49.97(9.69)	51.48(8.37)	39	-0.61	0.54	-0.16
Experimental	48.0(8.74)	50.74(8.70)	49	-0.50	0.61	-0.31

5. Discussion

According to the analysis results in this study, the difference between the pre-test learning initiative and post-test learning initiative of the control group was not significant, and the difference between the pre-test learning initiative and post-test learning initiative of the experimental group was not significant. However, after the teaching method of data visualization, the overall effect value of the experimental group was significantly higher than that of the control group, indicating that the learning initiative of the experimental group was still higher than that of the control group. Because the experimental group adopted the visual teaching form of educational data, the learning initiative of pre-test and post-test was a quite different. The control group did not adopt this form, and there was no significant difference in the learning initiative measured pre-test and post-test. The comparison of results showed that visualization of educational big data could improve students' learning initiative.

There were some limitations in this study. For example, the study did not use an anonymous survey for the students who participated in the experiment. Students answering questions under their real names may give untrue answers. These would have some effect on the results. Necessary is to avoid such problems in the future related research. The sample size of participants in the study was relatively small, and larger sample sizes from multiple cultural contexts may enhance the generalizability of the findings. The timing of the investigation may have been inopportune. The survey was conducted during the holiday period, with a period of time between the start and end of the experiment. The time interval may reduce the students' perception of the course learning. Therefore, suggested that relevant researchers interested in data visualization teaching should carry out reasonable experimental design and choose a suitable time point for investigation.

Though educational data visualization can improve students' learning initiative to a certain extent, there may be other reasons that lead to the improvement effect. Interested researchers can conduct in-depth research on this topic to find out some specific reasons that may be related. In addition, due to the limitations of the level of researchers and the schedule of courses in the process of specific teaching experiments, the selection of teaching materials and the arrangement of teaching contents, as well as the length of each class period, these factors may also have a certain impact on the enthusiasm of students to learn. Such as the difficulty of the textbook, the degree of students' acceptance of the teaching content, the length of students' concentration time in class, and more, subsequent relevant research can also be carried out around these contents.

In the process of quasi-experimental teaching, due to the complexity of the links involved, unavoidable objective factors such as students' learning environment and personal development could interfere with the results to a certain extent. For example, students come from different regions and have different learning experiences before university, which would be reflected in their personal characteristics and learning styles and enable students to make different choices when facing the same problem or dilemma. Jin (2017) thought that some students have no learning initiative in school because of the learning environment created by their family background and some habits formed since childhood, or they thought that the professional content of the course had little significance for their future development, and the teacher found difficult to improve their learning initiative. The shortcomings of this study are summarized to provide reference for future research.

6. Conclusion

How can educators help students improve their learning initiative? Through this experimental research, helping students improve their learning initiative can be done from the following aspects. First, teachers should be proficient in their professional knowledge. Only when teachers are proficient in the contents taught can they better transform this knowledge and teach it in a way that students can accept and be willing to accept. Only in this way can they attract students. This also requires teachers to have a certain familiarity with their students. Second, teachers' ability to control the classroom is also a very important factor. In the limited time and space of the classroom, teachers need to not only impart knowledge, but also observe and feel the state and psychological changes of students and draw students' attention to the classroom promptly. This requires teachers to possess various skills so that students will not be interfered with by other factors in the classroom. It is for the improvement of their teaching effect and students' learning effect. Finally, schools can take more measures to encourage teachers to try more new technologies in their classrooms, and create a strong learning atmosphere for students, so that the development of schools can keep up with the trend of the times. Teachers and students can feel that their development is closely related to the development of the whole society.

In summary, the findings of this study underscore the importance of leveraging educational big data visualization to enhance student learning initiatives. By incorporating data visualization techniques into teaching practices, educators can promote student engagement, personalize learning experiences, and drive continuous improvement in educational outcomes. This research has the potential to shape the development of innovative educational tools and strategies that prioritize data-driven decision-making and student-centered learning approaches.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the author.

Acknowledgments: N/A

Funding statement: N/A

Conflicts of Interest: The author declare no

Participation consent statement: N/A

Permission to reproduce materials from other sources: N/A

Clinical trial registration: N/A

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Appendix

Research Tool

Serial	Item
1	My study goal is very clear
2	I feel learning is very meaningful
3	I feel very happy to study
4	I am quite satisfied with my current major
5	I am very interested in study
6	I take the initiative to speak up in class
7	I often take the initiative to communicate with teachers
8	I often take the initiative to communicate with my classmates
9	In learning, I dare to question and criticize
10	I often skip class
11	I often arrive late and leave early
12	I can take my homework seriously
13	I can always stay focused in class
14	I can preview myself before class
15	I can review after class voluntarily
16	I spend a lot of my spare time on study
17	I like to read a lot of books