Big data assisted eco-learning environment framework for inclusive education

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ABSTRACT

Big data is profoundly changing education under inclusive education. Classroom interaction, a vital component in education, is gaining increased emphasis, driving research into learning environments that better meet interaction needs. Therefore, exploring the construction of a big data-assisted eco-learning environment for classroom interaction is a prospective study. This research focuses on constructing a big data-assisted ecological learning environment based on affordance theory. It examines the relationship among learning environment, classroom interaction, and learning outcomes, using SmartPLS for validation. Through controlled experiments, surveys, teacher-student interaction analysis, and interviews, the study explores learner behavior data. Findings show the big data-assisted eco-learning environment enhances English classroom interaction, thereby further improving learning outcomes, across dimensions like learning space, resource accessibility, technical support, and emotional support. Integrating big data with ecological theory offers insights into educational digitization, supporting flexible classroom interaction, and promoting education equity, inclusivity, and sustainable education through data-driven resource management.

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1. INTRODUCTION

The advent of information technology, including big data-based learning, has transformed modern education into a dynamic and personalized experience that addresses the specific needs of individual learners [1]. Big data has become essential for educators, researchers, and administrators seeking to enhance educational quality and effectiveness. Data analytics offers insights into student behavior, learning patterns, and performance, enabling educators to tailor teaching methods to individual needs and maximize potential [2]. Importantly, creating a harmonious ecological learning environment and an efficient teaching model based on big data is crucial for enhancing teaching quality [3]. The learning environment plays a pivotal role in implementing teaching activities and ensuring teaching quality [4], making it essential to understand the interrelationship between education and its ecological surroundings [5]. The affordance theory in educational ecology is a ground-breaking concept that explains how learning environments can be transformed through a process of perception, interpretation, and action [6], [7]. Prior studies have shown that by understanding the potential opportunities and limitations presented by a particular environment, educators can develop effective teaching strategies and design learning environments that promote student success [8]. Classrooms can be viewed as self-contained ecosystems with unique characteristics [9]. Educators can integrate big data with multi-activity settings to gain valuable insights into how students perceive and interact with their environment. A big data-assisted ecological learning environment grounded in affordance theory is designed to provide students with the resources they need to succeed while enabling teachers to foster a more engaging classroom experience and ultimately improve learning outcomes. This study aims to explore the relationships among the learning environment, interaction behavior, and learning outcomes.

An efficient learning environment significantly impacts students' academic achievement [10]. Big data disrupts traditional education, expanding learning beyond the regular classroom to a mix of resources and formats. Despite this, the traditional model, where teachers lead and students are passive, remains prevalent, hindering the development of a dynamic ecological learning environment [11]. Educational theories like behaviorism, cognitivism, and constructivism provide important insights but have limitations. Behaviorism overlooks student initiative, cognitivism ignores the external environment, and constructivism emphasizes internal sense-making. All these theories fail to address the dynamic adaptive relationship between the learner and the learning environment.

A widely accepted notion in higher education research and practice is that the quality of education is largely influenced by the interactions between teachers and students in the classroom. Despite the rapid development of information technology providing numerous databases and tools for educational research [12], [13], selecting, analyzing, and interpreting this data to understand classroom interactions remains a challenge [14], [15]. Addressing this issue by introducing new perspectives and methods in classroom interaction studies is urgent.

As a core concept of educational ecology, affordance is a continuous cycle of interaction among perception, interpretation, and action [16]. Students perceive learning resources, interpret them, and take action to convert them into affordances, which can vary widely for individuals or over time [17]. However, big data-based research on learning environment ecology is limited. Previous studies have investigated the impact of big data on student engagement and classroom interaction, but they did not explicitly address its influence on learning outcomes in an ecological learning environment. Therefore, this research seeks to explore the effects of big data on sustainable education through an ecological approach. Most literature focuses on educational data mining and learning analytics, with few studies exploring affordances in language acquisition [18]–[21]. There is a notable lack of empirical research on the practical application and efficient switching paths of affordance.

This study used the college English classroom as an example and conducted quantitative and qualitative research on affordance actualization in the college learning environment with the support of big data. It attempts to construct a multi-dimensional model of classroom interaction in an ecological learning environment, providing theoretical support and practical exploration for the study of big data-assisted ecological learning environments, and addressing the gap in current research on how ecological theories can be effectively applied to enhance learning outcomes.

The hypotheses in this study are i) RH1: the application of big data has a positive effect on establishing the eco-learning environment; ii) RH2: positive affordance is a positive indicator of classroom interaction in the eco-learning environment; and iii) RH3: interaction Competence has a positive effect on learning outcomes in the eco-learning environment.

This study constructed an analytical framework to examine the impact of the learning environment on university students' learning outcomes as shown in Figure 1. It analyses three primary variables: the dimensions of the learning environment, classroom interactions, and learning outcomes. By analyzing their relationships, it proposed a theoretical mode of "learning environment-classroom interaction-learning outcomes" to validate the hypotheses. The model suggests that an ecological learning environment, with classroom interactions mediating and big data as a supplementary tool, impacts college students' learning outcomes. Drawing from the four recognized elements of the learning environment and embracing the perspective of affordance theory, this study's interpretation of the classroom learning environment encompasses the learning space, resource accessibility, technological support, and emotional support. These factors are all perceptible to students and have the potential to exert direct or indirect effects on their learning. According to affordance theory, individuals perceive and interact with their environment based on the affordances for action that the environment offers. Interaction competence within this framework encompasses three dimensions: behavioral interaction, affective interaction, and cognitive interaction. They provide a comprehensive understanding of how students engage with learning opportunities in the classroom, facilitating the creation of supportive environments conducive to meaningful learning experiences and holistic development. The learning outcomes of college students are the value-added of student development after receiving higher education. The value-added is both specific and quantifiable, encompassing: the knowledge acquired through the study of a specific course; the advancements in professional skills attained through the study of a particular major; and the experiences gained through university education.

Building upon this foundation, the current study focuses on the value-added development of university students resulting from their experiences in higher education. It excludes consideration of individual growth and maturation that may occur independently.

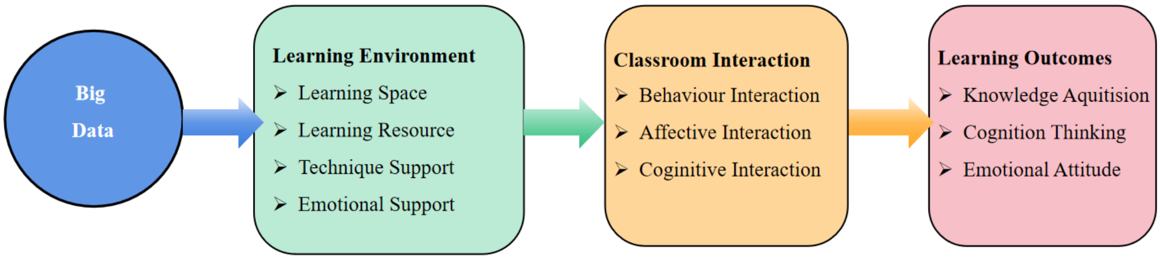

Figure 1. Model hypothesis

2. RESEARCH METHOD

This study used a mixed-method approach-questionnaires, observations, and interviews-to examine ecological learning environments in classroom interactions [22]–[24]. To ensure reliability and validity, this study utilized established tools like the Dundee ready educational environment measure (DREEM) [25], [26] and the college and university classroom environment inventory (CUCEI) [27]. These tools were adjusted and improved based on research needs. Experts in student development and educational management reviewed and refined the questionnaire items, resulting in a finalized survey for vocational college student learning assessment. The quantitative relationship of the mode was further verified through SmartPLS [28], [29].

Classroom observation is a common method in education research. Observers use their senses to perceive the dynamic interactions without intervening [30]. Despite subjectivity, it's user-friendly, suitable for teachers, and allows in-depth study with smaller samples. Face-to-face interviews were conducted with six students across different proficiency levels in both experimental and control groups. The experimental study involved four natural classes of first-year students at Jiangsu Medical College, totaling 88 non-English majors with the same L1 background. A one-semester English teaching experiment used the practical English test for colleges (PRETCO) as a pre- and post-test to ensure consistent score analysis. PRETCO is a national standardized English as a foreign language (EFL) test for higher vocational colleges and specialized post-secondary institutions. In the experiment, a single teacher taught the same English course to both groups over 15 weeks, employing distinct learning modes as shown in Figure 2. Classroom observations gathered data, focusing on interaction behaviors categorized by the information technology-based interaction analysis system (ITIAS): teacher talking, student talking, silence, and technology use. Statistical analysis involved coding and interpreting these records. Besides, this experiment included interviews with both students and teachers.

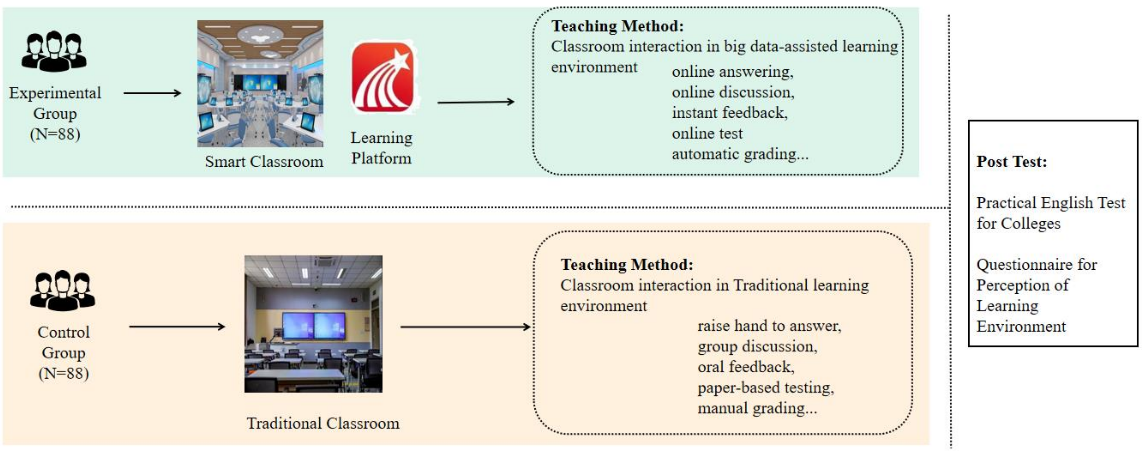

Figure 2. Experimental process

3. RESULTS AND DISCUSSION

The formal questionnaire on the application of big data in the learning environment for English learning was open for about a month, and 202 respondents completed the questionnaire (95% confidence level, 5% margin of error). The survey data indicated that the age distribution reflected homogeneity within the sample (Figure 3), enhancing the external validity of the findings to age-matched groups as presented in Figure 3(a). A high degree of consistency across respondents' regions indicated the robust reliability of the questionnaire as shown in Figure 3(b). Regarding information technology access, most began using information technology (IT) for educational purposes in junior or senior high school as shown in Figure 3(c). Over 77.20% of respondents frequently use digital products for learning English as presented in Figure 3(d), demonstrating that students have developed adequate digital literacy to adapt to the new learning system assisted by big data.

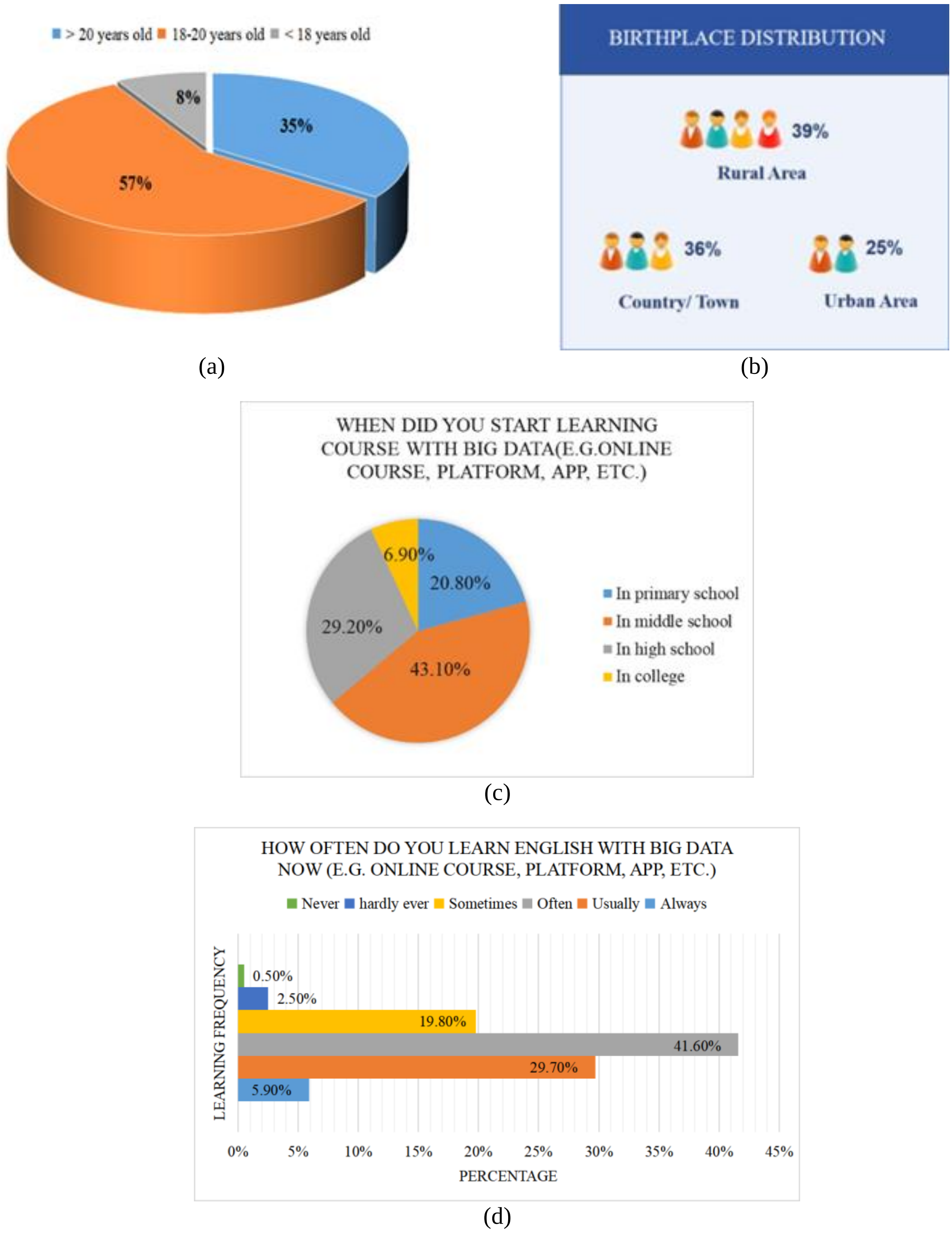

Figure 3. Respondent demographics of (a) age group, (b) regional distribution, (c) learning experience, and (d) learning frequency

By utilizing SmartPLS 4.0 software for detailed analysis, the theoretical framework obtained is depicted in Figure 4 [30]. Seven variables were under consideration, namely big data (BD), learning space (LS), resource accessibility (RA), technical support (TS), emotional support (ES), positive affordance (PA), behavioral interaction (BI), affective interactions (AI), cognitive interaction (CI), and learning outcomes (LO). The internal consistency measurement of the model shows that Cronbach's alpha values for all 10 variables exceed 0.7, and all measurement items have outer loadings above 0.7. This indicates that the data collected from the questionnaire has a high level of reliability.

P-values assess model fit and the relationships between variables in hypothetical models. A smaller p-value provides stronger evidence against the null hypothesis, supporting its rejection. If the p-value exceeds the significance level, the null hypothesis is not rejected, indicating non-significant observed differences [31], [32]. The learning environment consists of four dimensions: LS, RA, TS, and ES. The results indicate a positive correlation between big data and the learning environment across its four dimensions ($P<0.01$; T:[8.995, 6.294, 5.62, 4.716]; M:[0.511, 0.426, 0.376, 0.367]; SD:[0.056, 0.067, 0.066, 0.0767]), suggesting that big data significantly enhances these dimensions. Interaction competence includes behavioral, affective, and cognitive interactions. The positive correlation between learning environment affordance and interaction competence ($P<0.01$; T:[11.906, 4.468, 5.126]; M:[0.599, 0.26, 0.34]; SD:[0.05, 0.075, 0.067]) implies that improving the learning environment enhances all three interaction dimensions. Furthermore, a positive correlation exists between interaction competence and learning outcomes ($P<0.01$; T:[3.75, 3.074,3.792]; M:[0.309, 2.245, 0.296]; SD:[0.082, 0.079, 0.078]), indicating that increased interaction competence significantly improves learning outcomes, while decreased interaction competence results in poorer outcomes as shown in Table 1. Within the big data context, positive affordance from the learning environment has a significant impact on both interaction competence and learning outcomes.

Using pre-test scores as observed variables, descriptive statistics and t-tests were conducted. The experimental group had a mean score of 63.923 (SD=10.051), and the control group had a mean of 63.902 (SD=9.785). The mean difference was minimal at 0.018. The homogeneity of variance test (Sig.=0.4049>0.05) indicated homogeneous variances between groups. The independent samples t-test (Sig.=0.9903>0.05) showed no significant difference in pre-test scores between the groups. Post-test scores showed notable improvement compared to pre-test scores. The control group had a mean post-test score of 68.534, while the experimental group achieved 83.261. The non-significant Sig. A value of 0.071 suggests a similar variance in post-test scores between groups. The t-test for equality of means yielded a significant p-value of 0.000, indicating a significant difference in post-test scores. Thus, students in the big data-assisted ecological learning environment showed substantial score improvement compared to those in the traditional setting, achieving higher overall scores. This is consistent with the findings of Miao *et al*. [33], indicating that students' performance in a big data-assisted teaching model significantly surpasses that in traditional teaching settings.

An analysis of classroom interaction behaviors in both the experimental and control groups was conducted using the ITIAS. This system records interaction codes every 3 seconds during a 40-minute class, generating approximately 800 codes per session., which chronologically document teaching structures and behavioral patterns. Interactions among teachers, students, and technology in real teaching scenarios are complex and often simultaneous, with a focus on documenting student behaviors throughout the teaching process. The experimental group recorded 769 instances of various behaviors and the control group captured 733. As depicted in Figure 5, from the teacher's perspective, the frequency of teacher talk was lower in the experimental group, suggesting a willingness of teachers to allocate more time to student participation, thereby enhancing students' active engagement in classroom instruction. From the student perspective, student-initiated actions such as responding actively (6.35%), questioning actively (4.12%), and discussing with partners (18.23%) accounted for 86.32% of student talk. This highlights the strong initiative demonstrated by students in their learning environment. In contrast, in the control group, the frequency of student talk was 119, constituting 16.25% of the total interactions, with student-initiated actions accounting for 57.97% of student talk. This comparison indicates a higher level of learning initiative among learners in the experimental group. Regarding technology, the frequency of technology use was 205 in the experimental group, accounting for 26.65% of the total interactions. In comparison, in the control group, the frequency of technology use was 127, constituting 17.32% of the total interactions. This comparison reveals a higher frequency of technology use in the experimental group, with a relatively higher proportion impacting students' learning.

After a semester of experiments, six students (S1, S2, S3 in the experimental group, S4, S5, S6 in the control group) were interviewed to understand their classroom experiences. The experimental group highlighted the benefits of big data-supported learning environments. They appreciated the wealth of online resources, like learning platforms, software, and social media, which broke time and space constraints (S1) and allowed personalized learning through various formats like short videos and animated demonstrations

(S2). A strong learning atmosphere and diverse activities in class encouraged participation (S1), and real-time feedback boosted confidence and study habits (S3). Conversely, traditional learning environments were perceived negatively due to the pressure from abundant course content, fast pace, and challenges faced by students with weaker foundations (S6). Limited interactive opportunities made some students reluctant to participate (S4), and the focus on textbook content increased concerns about future exams (S6). Students often passively received knowledge, with limited interaction (S5). Associate Prof. Hu, teaching both groups, was satisfied with the big data-assisted learning environment. She noted that the interactive process brought joy and motivation, creating a positive cycle. The environment provided richer resources and tools, promoting active and collaborative learning. Hu mentioned that her role was to guide, allowing students to learn and construct knowledge independently. While traditional methods offer stability, they can be monotonous. Despite the challenges, Hu is eager to further explore integrating technology and teaching to enhance her abilities, viewing it as an inevitable trend.

The empirical research results indicate that compared to traditional learning environments, the big data-assisted ecological learning environment has a significantly positive impact on improving learners' academic performance and facilitating classroom interactions. Additionally, it indirectly influences learning outcomes through the mediation of classroom interactions. Specifically, the big data-assisted ecological learning environment first enhances the level of classroom interactions through emotional interactions, which in turn affects the unfolding of behavioral interactions and cognitive interactions. The experimental results strongly support these hypotheses. Meanwhile, feedback was collected from both learners and teachers through interviews. Learners expressed satisfaction with the teaching activities conducted based on the big data-assisted ecological learning environment classroom interaction model. They believed that big data provides flexible and diverse learning methods, offers rich resources, creates a lively and active learning atmosphere, and has a positive impact on knowledge acquisition, cognitive thinking, and emotional attitudes. Similarly, teachers believed that in the big data-assisted ecological learning environment, utilizing various advanced information technology and abundant teaching resources for classroom activities results in a more active teaching process and better teaching effectiveness.

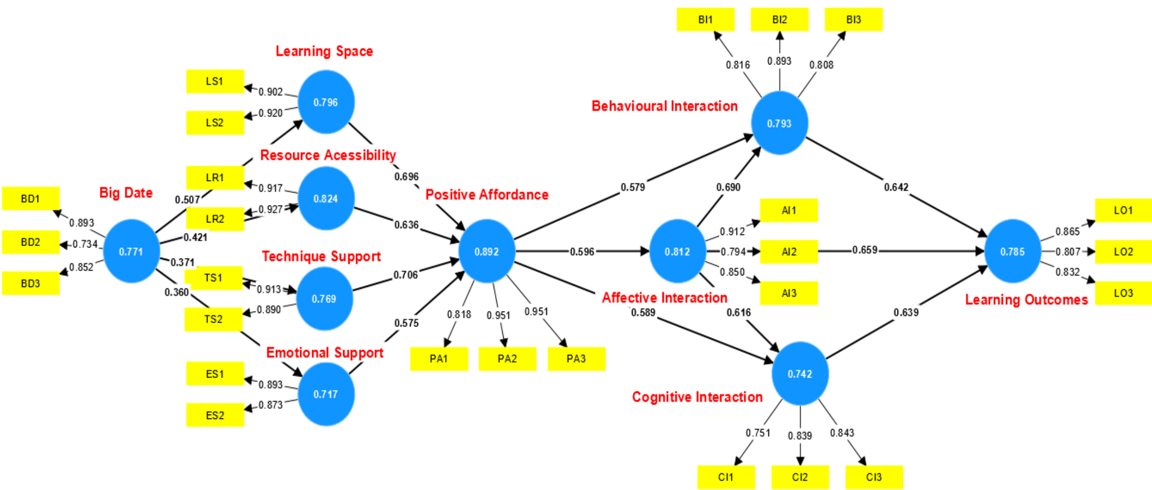

Figure 4. Visualization of partial least squares-structural equation modeling (PLS-SEM) model

Table 1. Hypothetical structure model

Hypothesis		PLS Paths	Original Sample(O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (IO/STDEV)	P-Values	Hypothesis Accepted
H1	H1-1	BD->LS	0.507	0.511	0.056	8.995	0.000	Accepted
	H1-2	BD->RA	0.421	0.426	0.067	6.294	0.000	Accepted
	H1-3	BD->TS	0.371	0.376	0.066	5.620	0.000	Accepted
	H1-4	BD->ES	0.360	0.367	0.076	4.716	0.000	Accepted
	H2-1	PA->AI	0.596	0.599	0.050	11.906	0.000	Accepted
H2	H2-2	PA->BI	0.260	0.260	0.075	3.468	0.001	Accepted
	H2-3	PA->CI	0.343	0.340	0.067	5.126	0.000	Accepted
	H3-1	AI->LO	0.309	0.309	0.082	3.750	0.000	Accepted
H3	H3-2	BI->LO	0.242	0.245	0.079	3.074	0.002	Accepted
	H3-3	CI->LO	0.297	0.296	0.078	3.792	0.000	Accepted

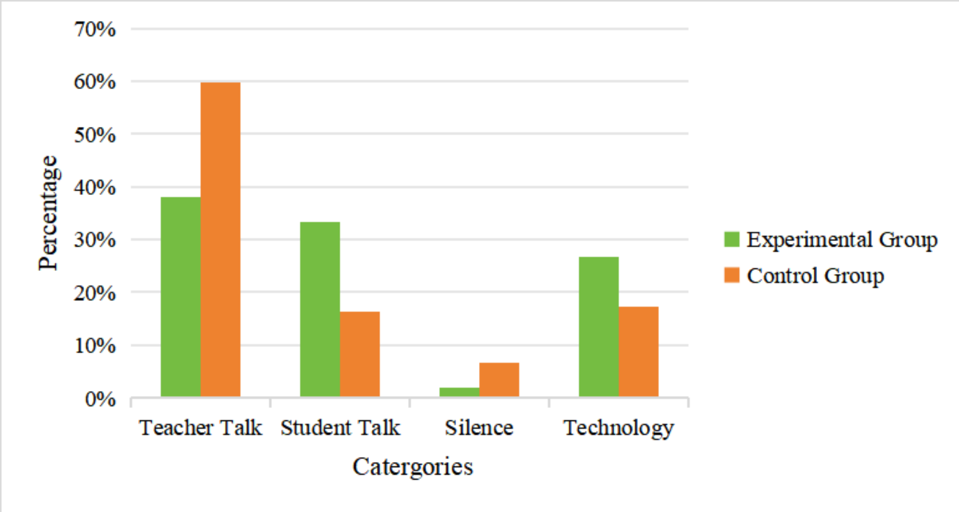

Figure 5. Comparison chart of classroom interaction

4. CONCLUSION

Recent findings indicate that big data significantly enhances eco-learning environments by providing flexible spaces, accessible resources, technical support, and emotional assistance. Classroom interaction, evaluated through behavioral, emotional, and cognitive indicators, is positively influenced by these environments. With the support of big data, classroom interaction positively impacts learning outcomes, with knowledge acquisition, cognitive engagement, and emotional attitudes serving as key indicators. Thus, classroom interaction mediates the relationship between the learning environment and outcomes, with big data-assisted eco-learning environments enhancing this interaction and improving learning results. The research holds significant potential to contribute across multiple dimensions. By integrating affordance theory with big data, it provides deeper insights into learner-environment interactions. In management, big data enables the customization of teaching strategies and informs policy-making, thereby enhancing equity and facilitating efficient resource allocation. On a societal level, it promotes inclusivity by addressing educational disparities through data-driven decision-making. Furthermore, it improves resource utilization, minimizes reliance on printed materials, and fosters collaboration, all of which contribute to sustainability efforts.

The research took a student-centered approach, exploring their views on the big data-assisted ecological learning environment. Recognizing teachers' crucial role, future research should include data from their perspectives for more thorough validation. Due to time and resource constraints, the current study only involved a first-year public English course at a vocational college for one semester. This limited scope and sample size may result in incomplete conclusions. Future research should conduct broader exploratory teaching practices across disciplines and stages to comprehensively evaluate the model.

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