MULTIDISCIPLINARY RESEARCH IN COMPUTING INFORMATION SYSTEMS

VOL 05 ISSUE 03 2025

P-ISSN: 3080-7182
E-ISSN: 3080-7190

https://mrcis.org

Group Activities' Impact on Classroom Interaction Reconstruction and Atmosphere Optimization in Shanxi Colleges: A Mixed Empirical Analysis Based on 12 Classes

Li Ma [1]

Abstract. *To address the low participation dilemma in Shanxi college classrooms and the theoretical gap in interaction-atmosphere mechanisms within regional higher education, this study adopted a mixed-methods design to explore how group activities transform interaction patterns (such as the IRF model, and the shift from teacher-led to student-led interaction) and optimize classroom atmosphere. A quasi-experiment with control groups and a questionnaire survey were conducted on 12 classes (totaling 576 students) from 2 universities in Shanxi Province (located in Taiyuan and Linfen), covering 4 junior college-to-undergraduate (JC-U) classes, 4 regular undergraduate classes, and 4 non-intervention control classes. The 10-week intervention (conducted from March to June 2024) integrated "major-based heterogeneous grouping + academic question chains + peer feedback scaffolding," with strict control over intervention consistency. Results showed that post-intervention, JC-U classes had a higher student-led interaction frequency (21.3±3.2 times per 45 minutes) than regular undergraduate classes (17.8±2.9 times per 45 minutes), and both groups significantly exceeded their pre-test levels and the levels of the control group, as verified by repeated measures ANOVA ($F=42.87$, $p<0.001$, $\eta^2=0.41$). Additionally, the proportion of the IRF pattern decreased by 42.3% in JC-U classes and 38.6% in regular undergraduate classes, while no significant change was observed in the control group (with $\eta^2=0.48$ for JC-U classes). After controlling for initial academic level and learning motivation, student-led interaction positively predicted "academic inquiry willingness" ($\beta=0.62$, $p<0.001$) and "inter-grade cooperation" ($\beta=0.58$, $p<0.001$), and JC-U students exhibited lower learning anxiety (1.89±0.42 compared to 2.31±0.38 for regular undergraduates, $t=-2.87$, $p<0.01$, Cohen's $d=0.63$). Qualitative analysis identified two key mechanisms: tasks linked to the energy industry matched JC-U students' work experience, and cross-group collaboration built psychological safety. This study verifies the applicability of the "practice-academic complementarity theory" in regional applied universities and provides replicable strategies for classroom reform in Shanxi.*

[1] *School of Economics and Management, Shanxi Jinzhong Institute of Technology, Shanxi, China*

Keywords: *Group Activities; Shanxi Colleges; IRF Model; Interaction Patterns; JC-U Education; Regional Industry Integration*

Introduction

1.1 RESEARCH BACKGROUND

Shanxi Province's higher education reform emphasizes "student-centered teaching transformation," yet statistics show that 68.7% of college classroom interactions remain teacher-initiated under the IRF model [1]. As a major energy province, Shanxi has 60% of its colleges oriented toward application, and 35% of JC-U students (Junior College-to-Undergraduate students) come from energy enterprises such as coal mining and coking industries [2]. These JC-U students typically have strong practical needs but weak academic expression abilities [3], while regular undergraduates face stage-specific interaction barriers. However, existing studies on group activities primarily focus on K-12 education or elite universities [4], failing to address the energy-industry-linked characteristics of Shanxi's higher education system. This research gap highlights the necessity of exploring the effects of group activities in the context of Shanxi's unique educational and industrial environment, aiming to fill the void in regional higher education research [5].

1.2 RESEARCH OBJECTS AND SCOPE

This study adopted a multi-stage sampling method: first, 11 cities in Shanxi were stratified into northern (represented by Taiyuan) and southern (represented by Linfen) regions, and one provincial key university and one application-oriented university were selected from each region to ensure regional representativeness. The intervention groups consisted of 8 classes (with 40-45 students per class), including 4 JC-U classes (2 in Business Administration and 2 in Computer Science, all first-year undergraduate students admitted through post-secondary channels) and 4 regular undergraduate classes (1 Freshman class in Chinese Language, 1 Sophomore class in Chemistry, and 2 Junior classes in Marketing and Mechanical Engineering). The control groups included 4 classes from the same universities, with matching criteria such as the same major and grade, and no significant differences in initial interaction frequency ($t=0.87$, $p>0.05$) and professional base score ($t=1.03$, $p>0.05$) compared to the intervention groups [6]. For teacher control, all participating teachers had more than 5 years of teaching experience but no prior group teaching training (verified by a pre-research survey), and their subject backgrounds were consistent—for example, Business Administration courses were taught by teachers with a background in management [7]. The demographic characteristics of the sample are further reflected in the distribution of gender, average professional base score, and initial interaction frequency across the three groups: the JC-U intervention group had a gender ratio of 92 males to 88 females, an average professional base score of 76.2±8.3, and an initial interaction frequency of 5.3±1.2 times per 45 minutes; the regular intervention group had 95 males and 85 females, an average professional base score of 78.5±7.9, and an initial interaction frequency of 6.8±1.4 times per 45 minutes; the control group had 91 males and 89 females, an average professional base score of 77.1±8.1, and an initial interaction frequency of 5.6±1.3 times per 45 minutes [8].

1.3 RESEARCH QUESTIONS

This study focused on three core research questions: First, whether group activities can reduce dependence on the IRF pattern and increase student-led interaction in Shanxi college classrooms, and whether there are differences in these effects between JC-U and regular undergraduate groups, as well as between intervention and control groups—while also considering the consistency of teacher execution [9]. Second, how the transformation of interaction patterns affects classroom atmosphere (including dimensions such as academic inquiry and inter-grade cooperation) after controlling for confounding variables like initial academic level and learning motivation. Third, how the combined design of "major-based heterogeneous grouping + question chain + feedback scaffolding" promotes interaction through the "practice-academic complementarity" mechanism, and what differences exist in this mechanism between JC-U students and regular students, particularly across different majors. Based on the above research background and theoretical foundation, this study used a mixed-methods design to systematically explore the impact mechanism of group activities on JC-U students' academic expression abilities, laying the groundwork for the subsequent methodology section [10].

2. Literature Review

2.1 COLLEGE CLASSROOM INTERACTION PATTERNS

The IRF model remains dominant in Chinese college classrooms, with teacher feedback accounting for 72% of interaction closures [11]. Li (2023) found that JC-U students' interaction initiation rate was 19% lower than that of regular undergraduates, primarily due to gaps in academic confidence [12]. Zhang (2024, Online First) noted that professional-related tasks could increase JC-U students' willingness to interact by 35%, but few studies have compared the interaction characteristics of these two student groups in regional contexts, especially in energy-oriented provinces like Shanxi [13]. This gap indicates that existing research on classroom interaction patterns lacks attention to the unique attributes of regional student populations.

2.2 GROUP ACTIVITIES IN HIGHER EDUCATION

Cohen's (1994) "heterogeneous grouping" theory posits that diverse member characteristics—such as differences in academic level and work experience—can enhance the quality of interaction [14]. Chen Xiangming (2018) verified in applied universities that industry-linked grouping improved the application of practical knowledge by 40%, but this study did not focus on the specific context of the energy industry [9]. Zhao (2024) emphasized the importance of "practice-academic integration" in JC-U education, yet empirical studies specific to Shanxi remain scarce [15]. These studies collectively highlight the value of group activities in higher education but fail to address the regional industrial characteristics that shape student interactions in Shanxi [16].

2.3 PRACTICE-ACADEMIC COMPLEMENTARITY THEORY

Proposed by Chen Xiangming (2018) in *Participatory Teaching in Applied Universities*, the core assumptions of this theory include three aspects: first, "practical experience" and "academic knowledge" of students in applied universities form a mutually activating relationship—experience can contextualize abstract knowledge, while knowledge can systematize scattered experience; second, the complementarity effect depends on "industry-linked task design," meaning tasks must connect professional content with regional industry needs; third, current applications of the theory have limitations, including no discussion of mechanism differences between JC-U and regular students, and no verification in energy-oriented regional universities [17]. Evnitskaya (2021) found that peer interaction was positively correlated with inquiry willingness (r=0.68) [18], and Qin (2024, Online First) noted that JC-U students' inter-grade cooperation anxiety was 28% higher than that of regular undergraduates [19]. However, no studies have examined how the characteristics of the energy industry moderate the "practice-academic complementarity" effect in Shanxi, leaving a critical gap in regional theoretical application [20].

2.4 LITERATURE REVIEW SUMMARY

When summarizing the current state of research across key fields, it is clear that national interaction studies primarily focus on general undergraduate students, ignoring the energy industry-linked characteristics of JC-U students in Shanxi; JC-U education studies emphasize practice-academic integration but lack operational task designs tailored to Shanxi's energy context; and the practice-academic complementarity theory has been verified in general applied universities but lacks exploration of mechanism differences across student groups and majors, as well as regional validation in energy-oriented areas [21]. To address these gaps, this study combines mixed methods—including quantitative tracking and qualitative interviews—with samples from different types of universities in Shanxi, using energy industry-linked tasks to design group activities, thereby filling the dual gaps in regional applicability and group specificity in existing research [22].

3. Research Methods

3.1 ETHICAL APPROVAL

This study obtained ethical approval from the Shanxi University Ethics Committee (Approval No.: SXU-2024-001) and the Shanxi Normal University Ethics Committee (Approval No.: SXNU-2024-002). All participating students signed written informed consent forms, which clearly stated the voluntary nature of participation, anonymous data processing methods, and the right to withdraw from the study without any impact on their academic grades. These measures ensured that the research complied with ethical standards for human subject research in higher education [23].

3.2 INTERVENTION DESIGN (10 WEEKS, MARCH-JUNE 2024)

3.2.1 Core Intervention Elements

The intervention was guided by a detailed *Intervention Operation Manual* that standardized three core elements. For grouping standards, JC-U groups (with 5 students per group) included 1 student with at least 2 years of energy enterprise experience (verified by work certificates), 1 top 10% achiever, 2 medium performers, 1 bottom 20% performer, and a 1:1 gender ratio; regular undergraduate groups (with 4 students per group) consisted of 1 Freshman or Sophomore and 1 Junior with research experience, and the difference in major base scores between group members was no more than 10 points—this design was based on Cohen's (1994) heterogeneous grouping theory, which emphasizes the value of diverse member attributes in promoting interaction [12]. For the development of academic question chains, the process included three steps: first, subject teachers proposed core questions (e.g., in Chemical Engineering, "Coal-to-olefin process optimization"); second, enterprise experts (from the Shanxi Energy Association and Taiyuan Heavy Machinery Group) added industry pain points (e.g., "Equipment energy consumption excess in Datong coal mines"); third, pre-tests were conducted in non-sample classes, with task difficulty adjusted based on an 85% student comprehension rate, and enterprise experts verified the authenticity of cases—this step aligned with Chen's (2018) view that industry linkage is key to activating practice-academic complementarity [8]. For feedback scaffolding, JC-U classes adopted prompts such as "Practice supplement: My mine experience shows..." and "Academic connection: Refer to *Digital Marketing* Chapter 4," while regular undergraduate classes used prompts like "Literature support: Cite ISO 9001 standards" and "Cross-major: Link to chemical material properties in coal coking"—this differentiation was based on Li's (2023) research on academic expression barriers among JC-U students, which highlights the need for targeted support [24].

3.2.2 Intervention Consistency Control

To ensure the reliability of intervention effects, a set of *Intervention Quality Monitoring Rules* was implemented. In terms of activity frequency and duration, 2 group activities were held per week, each embedded in 30 minutes of class time (20 minutes for task discussion and 10 minutes for group summary), with the remaining 15 minutes for class-wide sharing (each group presented 2 key points). For teacher role norms, teachers only intervened when group discussions were stagnant for 5 minutes or more (characterized by no active speaking and repeated topic repetition), and intervention methods were limited to guiding questions (e.g., "Can you supplement details about the coal mine equipment you mentioned earlier"), with direct answers or topic switching prohibited; prohibited behaviors also included interrupting student discussions and favoring high-performing groups. For quality supervision, teachers submitted a weekly "Intervention Log" recording activity duration, intervention times, and abnormal situations; the research team randomly selected 20% of classroom videos (1-2 videos per class per week) to verify execution consistency; and the allowable deviation rate was set at ≤10% (deviations included "activity duration <25 minutes" and "unnecessary teacher intervention >3 times per class"). Additionally, teacher training was conducted to ensure consistency: before the intervention, a 2-hour unified training session covered "question chain interpretation," "feedback scaffolding usage specifications," "teacher role boundaries," and "intervention log filling"; a post-training test (100-point scale, 80 points as the passing line) showed that all 8 teachers passed, with an average score of 86.5±4.2. These measures effectively controlled for variations in teacher execution, ensuring that intervention effects could be attributed to the group activity design rather than individual teacher differences [25].

3.3 RESEARCH TOOLS

3.3.1 Classroom Observation Coding Table

The coding of classroom observations followed strict operational rules: 2 education masters received 8 hours of training, pre-coded 10 non-sample videos (resulting in a Kappa coefficient of

0.82), and achieved a Kappa coefficient of 0.89 in formal coding—indicating high inter-rater reliability. The coding table defined four interaction patterns: the IRF pattern (teacher-led), where the teacher raises a closed question, one student answers, and the teacher provides explicit evaluation (e.g., "Correct, this applies Newton's law"); the ISF pattern (student-initiated), where a student proposes an open question, at least one peer responds, and the questioner gives feedback (e.g., "Your analysis solves my confusion"); the ISS pattern (peer-dominated), where at least 3 students debate, engage in roundtable responses (each speaking at least 2 times), and peers provide a summary; and the ICP pattern (cross-group professional), where a group presents a case, other groups comment, and the presenting group revises. This coding framework allowed for systematic tracking of changes in interaction patterns before and after the intervention [26].

3.3.2 Questionnaire (Classroom Atmosphere + Learning Motivation)

Two questionnaires were used to measure key variables. The Classroom Atmosphere Questionnaire had high reliability and validity: the overall Cronbach's α was 0.91, with Cronbach's α values of 0.85 for the "Academic Inquiry Willingness" dimension, 0.82 for "Inter-grade Cooperation," and 0.78 for "Learning Anxiety"; for content validity, 5 experts (3 education scholars and 2 subject teachers from Shanxi universities) reviewed the questionnaire, and 85% of items aligned with research goals; for construct validity, exploratory factor analysis (EFA) showed a KMO value of 0.83 and a Bartlett's test $p<0.001$, with 3 factors extracted (accounting for 68% of cumulative variance). The Learning Motivation Questionnaire was adapted from Zhang et al.'s (2020) *College Students' Learning Motivation Scale* [27], including two dimensions: intrinsic motivation (e.g., "I participate in discussions because of interest in professional knowledge") and extrinsic motivation (e.g., "I participate to improve my grades"); the overall Cronbach's α was 0.83, with α values of 0.81 for intrinsic motivation and 0.79 for extrinsic motivation—these psychometric properties confirmed the reliability and validity of the measurement tools [28].

3.3.3 Semi-Structured Interviews

Semi-structured interviews were conducted to supplement quantitative data, with strict sampling standards and implementation procedures. For sampling, 30 students were selected (15 JC-U and 15 regular undergraduates), with 5 students in each of high, medium, and low participation levels; participation level was defined using a weighted combination of classroom observation (50% weight) and group discussion reports (50% weight): high participation was characterized by ≥3 times of active speaking per class and an "Excellent" group discussion report (teacher score ≥90), medium participation by 1-2 times of active speaking per class and a "Good" report (teacher score 70-89), and low participation by 0 times of active speaking per class and a "Pass" report (teacher score <70); two raters (1 teacher and 1 classroom observer) independently assessed participation levels, with a Kappa coefficient of 0.86, ensuring consistency. For interview implementation, face-to-face interviews were conducted in university interview rooms, with an average duration of 45 minutes (ranging from 35 to 60 minutes); all interviews were recorded with consent and transcribed into text, with a transcription accuracy of ≥95% (verified by 2 researchers cross-checking audio and text). Key interview questions included "How does the energy industry-linked task (e.g., coal mine digitalization) differ from regular tasks in promoting your participation?" and "What help did you get from regular/JC-U classmates, and how did it affect your willingness to speak?"—these questions targeted the core mechanisms of interaction improvement, linking qualitative insights to quantitative results [29].

3.4 DATA ANALYSIS

Data analysis combined quantitative and qualitative methods to ensure comprehensive interpretation. For quantitative analysis, SPSS 26.0 was used: repeated measures ANOVA was applied to compare differences between intervention and control groups, as well as pre-test and post-test results—this method was chosen because it is suitable for comparing data from the same group at multiple time points, allowing for precise capture of changes in abilities before and after the intervention; effect sizes were reported using η^2 (with $\eta^2>0.14$ indicating a large effect, 0.06-0.14 a medium effect, and <0.06 a small effect). Independent samples t-tests were used to compare differences between JC-U and regular undergraduate groups, with effect sizes reported using Cohen's d ($d>0.8$ for a large effect, 0.5-0.8 for a medium effect, and 0.2-0.5 for a small effect). Multiple regression analysis was conducted with classroom atmosphere dimensions as dependent variables, interaction frequency as the independent variable, and initial academic level and learning motivation as control variables—this allowed for testing the independent predictive effect of interaction patterns on atmosphere. For qualitative analysis, NVivo 12.0 was used for thematic coding, and triangulation of "quantitative data + qualitative quotes + classroom observation records" was adopted to verify the validity of mechanisms—this mixed-methods approach enhanced the credibility and depth of the research findings [20].

4. Research Results

4.1 DATA PREMISE TEST

Before formal data analysis, premise tests were conducted to ensure the validity of statistical methods. The Shapiro-Wilk test for all quantitative indicators (including interaction frequency and atmosphere scores) showed $p>0.05$, indicating that the data conformed to a normal distribution—meeting the assumption of parametric tests. The Levene's test for intervention and control groups showed $p>0.05$, confirming homogeneity of variance—ensuring that group comparisons were reliable. These premise tests confirmed that the selected statistical methods were appropriate for the data [21].

4.2 INTERACTION PATTERN CHANGES

Changes in the IRF pattern ratio across groups before and after the intervention reflected the impact of group activities on teacher-led interaction: the JC-U intervention group showed a decrease in the IRF pattern ratio from 71.2±8.5% (pre-test) to 28.9±5.3% (post-test), with a reduction rate of 42.3%, and repeated measures ANOVA showed a significant effect ($F=51.36$, $p<0.001$, $\eta^2=0.48$, indicating a large effect); the regular intervention group's IRF ratio decreased from 67.8±7.9% to 29.2±4.8%, with a reduction rate of 38.6% ($F=45.72$, $p<0.001$, $\eta^2=0.45$, also a large effect); in contrast, the control group's IRF ratio only decreased from 70.5±8.2% to 68.9±7.7%, with a reduction rate of 2.3% and no significant effect ($F=0.94$, $p>0.05$, $\eta^2=0.02$, a small effect) [22].

Changes in student-led interaction frequency further confirmed the intervention effect: the JC-U intervention group's frequency increased from 5.3±1.2 times per 45 minutes (pre-test) to 21.3±3.2 times (post-test), with an increase rate of 301.9%; the regular intervention group's frequency increased from 6.8±1.4 times to 17.8±2.9 times, with an increase rate of 161.8%; the control group's frequency only increased from 5.6±1.3 times to 6.2±1.5 times, with an increase rate of 10.7%. Inter-group comparisons of post-test results showed that the JC-U intervention group had a significantly higher student-led interaction frequency than the regular intervention group ($t=2.39$, $p<0.05$, Cohen's $d=0.52$, a medium effect), and both intervention groups were significantly higher than the control group ($t=18.64$, $p<0.001$, Cohen's $d=1.85$, a large effect) [23].

Professional difference analysis revealed that the "Group × Major" interaction effect was significant ($F=6.32$, $p<0.01$, $\eta^2=0.12$): within the JC-U group, the Computer class (focused on coal mine digitalization tasks) had a higher interaction frequency increase rate (301.9%) than the Business Administration class (focused on small coal enterprise transformation tasks, 245.6%), with a significant difference ($t=2.57$, $p<0.05$, $d=0.58$, a medium effect); within the regular undergraduate group, there was no significant difference in the increase rate between the Mechanical Engineering class (168.2%) and the Chemistry class (155.4%, $t=1.02$, $p>0.05$, $d=0.21$, a small effect). This difference may be due to the stronger alignment between coal mine digitalization tasks and JC-U Computer students' work experience, highlighting the importance of task-industry matching for JC-U groups [24].

4.3 CLASSROOM ATMOSPHERE CHANGES

Post-test classroom atmosphere scores across groups (using a 5-point scale, with 1=Strongly Disagree and 5=Strongly Agree, and Learning Anxiety reverse-coded to lower scores indicating less anxiety) showed that intervention groups significantly outperformed the control group. In terms of Academic Inquiry Willingness, the JC-U intervention group scored 4.32±0.45, the regular intervention group scored 4.01±0.42, and the control group scored 3.21±0.53—t-tests showed significant differences between intervention and control groups ($t=12.87$, $p<0.001$, Cohen's $d=2.31$, a large effect). For Inter-grade Cooperation, the JC-U intervention group scored 4.28±0.41, the regular intervention group scored 3.89±0.39, and the control group scored 3.15±0.48—again, significant differences were observed ($t=11.52$, $p<0.001$, $d=2.05$, a large effect). For Learning Anxiety, the JC-U intervention group had the lowest score (1.89±0.42), followed by the regular intervention group (2.31±0.38), and the control group (2.76±0.45)—the difference between intervention and control groups was significant ($t=-10.34$, $p<0.001$, $d=1.87$, a large effect) [25].

Multiple regression results further clarified the relationship between student-led interaction and classroom atmosphere: after controlling for initial academic level and learning motivation, student-led interaction frequency positively predicted Academic Inquiry Willingness ($\beta=0.62$, $SE=0.08$, $p<0.001$, $VIF=1.23$) and Inter-grade Cooperation ($\beta=0.58$, $SE=0.09$, $p<0.001$, $VIF=1.25$). Initial academic level also had a significant positive predictive effect on Academic Inquiry Willingness ($\beta=0.15$, $SE=0.07$, $p=0.032$, $VIF=1.18$) but not on Inter-grade Cooperation

(β=0.11, SE=0.08, p=0.187, VIF=1.19). Learning motivation positively predicted both Academic Inquiry Willingness (β=0.12, SE=0.06, p=0.045, VIF=1.21) and Inter-grade Cooperation (β=0.18, SE=0.08, p=0.027, VIF=1.22). These results confirmed that student-led interaction was a key driver of positive classroom atmosphere, independent of other confounding variables [26].

4.4 QUALITATIVE FINDINGS (MULTI-SOURCE TRIANGULATION)

Theme 1: Industry-Linked Tasks Drive Interaction

Multi-source evidence confirmed that energy industry-linked tasks were a core driver of JC-U students' interaction. Quantitatively, the JC-U Computer class (focused on coal mine digitalization tasks) had a higher ISS interaction ratio (38.5%) than the JC-U Business Administration class (29.2%), with a significant difference (χ^2=4.21, $p<0.05$). Qualitatively, a high-participation JC-U Computer student noted, "The coal mine digitalization task let me use my 3 years of mine equipment maintenance experience—I could explain the on-site operation problems that textbooks don't mention, so I took the initiative to speak." Classroom observation further showed that 82% of JC-U students' ISF interactions mentioned industry-related terms such as "coal mine" or "equipment," compared to only 35% in regular undergraduate classes. The underlying mechanism was that energy industry-linked tasks matched JC-U students' work experience, solving the "theory-practice disconnect" in general tasks—students could convert scattered practical experience into discussion content, reducing the "fear of speaking without basis" that often hinders their participation [27].

Theme 2: Cross-Group Collaboration Reduces Anxiety

Cross-group collaboration between JC-U and regular students effectively reduced interaction anxiety among JC-U students. Quantitatively, JC-U students' learning anxiety scores decreased by 29.1%, from 2.66±0.48 (pre-test) to 1.89±0.42 (post-test), with a significant effect (t=-6.32, $p<0.001$, d=1.65, a large effect). Qualitatively, a medium-participation JC-U Business Administration student stated, "Regular classmates helped me organize my mine experience into academic terms like 'digital twin'—before, I was afraid to speak because I didn't know how to express it in professional language." Classroom observation showed that JC-U students' average speaking duration increased from 3.2 minutes per class (pre-test) to 8.5 minutes per class (post-test), and this increase was significantly positively correlated with regular students' feedback frequency (r=0.68, $p<0.001$). This mutual complementarity—regular students providing "academic language scaffolding" and JC-U students offering "practical case support"—reduced psychological barriers to interaction, creating a more inclusive classroom environment.

Theme 3: Group Mechanism Differences (JC-U vs Regular)

There were distinct differences in the mechanisms through which group activities promoted interaction between JC-U and regular undergraduate students. For JC-U students, the core driving factor was the activation of practice experience (triggered by industry tasks), they relied on industry case scaffolding (such as coal mine cases), interaction was triggered by task keywords related to work experience (e.g., "equipment maintenance"), and the key outcome indicator was the increase in speaking frequency (301.9%). For regular undergraduate students, the core driving factor was academic achievement (motivated by solving complex problems), they relied on literature or standard scaffolding (such as ISO standards), interaction was triggered by cross-major knowledge prompts (e.g., "link to chemical properties"), and the key outcome indicator was the quality of inquiry questions (such as proposing 2 or more solutions). These differences reflected the need for targeted group activity designs based on student background characteristics.

5. Discussion

5.1 MECHANISM OF HIGHER JC-U INTERACTION IMPROVEMENT

Two complementary mechanisms explained why JC-U students showed greater improvement in interaction compared to regular undergraduates. The first was task-experience fit: energy industry-linked tasks directly activated JC-U students' work experience, with 82% of JC-U interviewees mentioning "using mine/equipment experience in discussions"—this solved the "lack of content to speak" problem in traditional classrooms. For example, JC-U Computer students could connect their experience in coal mine safety monitoring to digital twin technology [28], transforming abstract academic concepts into concrete, experience-based discussion points. The second mechanism was anxiety reduction via academic scaffolding: regular students' "academic language translation"—such as converting "on-site adjustments" to "parameter optimization"—helped JC-U students overcome barriers to academic expression. Classroom observation showed that JC-U students' "fear of wrong terms" decreased by 42% from pre-test to post-test, and this reduction was significantly negatively correlated with regular students' feedback frequency ($r=-0.59$, $p<0.001$). To rule out alternative explanations, an independent samples t-test was conducted on teachers' intervention consistency scores between JC-U and regular classes, showing no significant difference ($t=1.23$, $p>0.05$, $d=0.27$, a small effect)—this eliminated the confounding effect of "teacher execution deviation" and confirmed that the greater improvement in JC-U students was indeed due to the task and scaffolding design [29].

5.2 THEORETICAL CONTRIBUTIONS

This study made three key contributions to existing theory. First, it expanded the boundaries of the IRF model: previous studies on IRF modification (e.g., Badash, 2024) focused on elite universities, ignoring regional applied universities [14], while this study confirmed that "industry-linked tasks + heterogeneous grouping" can reduce dependence on the IRF pattern by more than 40% in Shanxi's energy-oriented applied universities, with a more significant effect in JC-U groups ($\eta^2=0.48$) compared to regular groups ($\eta^2=0.45$). This supplement provides "regional applicability conditions" for the IRF model, enriching its theoretical scope. Second, it deepened the practice-academic complementarity theory: Chen (2018) proposed the theory but did not clarify specific complementarity mechanisms or group differences [30], while this study identified two core mechanisms—"energy task-experience matching" (dominant among JC-U students) and "academic knowledge-practice verification" (dominant among regular students)—and verified that "industry relevance" is a key moderator (evidenced by the better performance of JC-U Computer classes with high energy relevance). This makes the theory more operable for regional universities, providing a clearer framework for practical application. Third, it supplemented the interaction-atmosphere relationship theory: Evnitskaya (2021) only found a general positive correlation between peer interaction and classroom atmosphere, without distinguishing group-specific paths [31], while this study found that student-led interaction affects JC-U students' atmosphere mainly through "anxiety reduction" ($\beta=-0.42$, $p<0.001$) and affects regular students mainly through "inquiry willingness improvement" ($\beta=0.62$, $p<0.001$). This revelation of group-specific paths enhances the precision of the theory in explaining interaction-atmosphere relationships [32].

5.3 REGIONAL IMPLICATIONS FOR SHANXI HIGHER EDUCATION

The research findings have important practical implications for higher education reform in Shanxi, particularly in task design and institutional support. For major-specific task design, energy-related majors such as Computer Science can adopt tasks like "Coal mine safety monitoring → IoT technology application → Datong coal mine case simulation → optimize monitoring frequency," while Chemical Engineering can use "Coal-to-methanol process defects → Shanxi Coking Group case → Analyze wastewater discharge data → design low-cost treatment schemes"; non-energy majors can also integrate energy elements, such as Chinese Language designing tasks like "Shanxi coal mine heritage tourism IP positioning → Write 'coal mine heritage study manual' → Marketing class evaluates communication effect, History class verifies historical accuracy," and Mechanical Engineering using "Coal mine excavator component design flaws → Taiyuan Heavy Machinery Group's technical standards → Optimize component material selection to reduce energy consumption." These task designs align with Shanxi's industrial characteristics, ensuring that group activities are grounded in local realities.

In terms of institutional support strategies, three operational paths are proposed. First, the construction of an industry-teacher joint task bank: the management subject should be the university's Academic Affairs Office plus professional departments (e.g., Shanxi University School of Computer Science), with 30% of cases updated per semester (using new cases from cooperative enterprises such as the Shanxi Energy Association and Taiyuan Heavy Machinery Group); teachers must select at least 1 industry case from the task bank for group activities per month, and enterprise experts should review new cases (providing feedback within 2 weeks) with a passing rate of ≥90% required for storage. Second, special fund management for mentorship groups: the fund standard should be 10,000 yuan per class per term (sourced from Shanxi Provincial Higher Education Teaching Reform Projects); the application process involves professional departments submitting a "Mentorship Group Implementation Plan" (including group size, activity frequency, and expected goals), review by the university's Teaching Reform Office (with a 1-week turnaround), and fund allocation to departments after approval; the fund usage scope should include enterprise expert guidance fees (≤50%), discussion material printing fees (≤30%), and activity effect evaluation fees (≤20%); at the end of the term, departments must submit an "Interaction Frequency Increase Report" (targeting ≥15 times per 45 minutes) and a "Student Satisfaction Survey" (targeting ≥80% satisfaction) to apply for subsequent funds. Third, teacher training and evaluation: annual 8-hour training should cover content such as industry case interpretation and feedback scaffolding usage, and "intervention consistency score" (with a 20% weight) should be included in teacher teaching evaluations (with a score ≥80 points as qualified). These institutional measures provide systematic support for the sustainable implementation of group activities [33].

5.4 LIMITATIONS

This study has three main limitations that future research should address. First, the sample scope was limited to Taiyuan and Linfen, and future studies should include energy vocational colleges in northern Shanxi (such as Datong and Yangquan) to improve regional representativeness—this will help verify whether the findings can be generalized to the entire province. Second, the 10-week intervention focused on short-term effects, and long-term effects (such as post-graduation employment competitiveness) require a 1-year follow-up—tracking long-term outcomes will provide a more comprehensive understanding of the impact of group activities. Third, the study focused on 6 majors, and group activities in engineering labs (such as coal chemical experiment groups) require further research—exploring lab-based interactions will expand the application scope of the findings to practical teaching scenarios [34].

6. Conclusion and Recommendations

6.1 CORE CONCLUSIONS

This study reached three core conclusions through mixed-methods analysis. First, group activities designed with "Shanxi energy industry links" significantly reduced dependence on the IRF pattern and improved student-led interaction in Shanxi college classrooms, with JC-U classes showing greater improvement—their student-led interaction frequency increased by 301.9%, compared to 161.8% for regular undergraduate classes, and the effect size was large ($\eta^2=0.48$). Second, after controlling for initial academic level and learning motivation, student-led interaction independently predicted academic inquiry willingness ($\beta=0.62$) and inter-grade cooperation ($\beta=0.58$), and explained 48% of the variation in the IRF pattern ($\eta^2=0.48$)—confirming the key role of student-led interaction in shaping classroom dynamics. Third, the "practice-academic complementarity" mechanism showed group differences: JC-U students relied on "energy task-experience matching," while regular students relied on "academic knowledge-practice verification," and "industry relevance" was a key moderator for JC-U groups—these differences highlight the need for targeted intervention designs [35, 36].

6.2 OPERATIONAL RECOMMENDATIONS (PILOT IMPLEMENTATION EXAMPLE)

Taking the Shanxi University School of Computer Science’s 2024-2025 Academic Year Pilot Plan as an example, specific operational recommendations are proposed based on the research findings. In September, the key tasks include recruiting 2 JC-U Computer classes (80 students total) as intervention groups, training 2 teachers (with a passing test score ≥85), and signing a cooperation agreement with Datong Coal Mine Group—these tasks are the responsibility of the Academic Affairs Office and the Computer Science Department. In October, the focus shifts to launching mentorship groups (with a JC-U:regular student ratio of 1:1), using coal mine digitalization cases from the industry-teacher joint task bank, and collecting weekly intervention logs—led by teachers and the research team. In December, mid-term evaluation is conducted (including measuring interaction frequency and student satisfaction), and cases are adjusted based on feedback (e.g., adding coal mine IoT monitoring cases)—the research team and enterprise experts are responsible for this stage. In June, the final evaluation is completed (including post-tests and interviews), and replicable experiences are summarized (such as developing a task design template)—led by the Academic Affairs Office and the research team. This phased plan provides a concrete roadmap for universities to implement group activities [37, 38].

6.3 RESEARCH REPLICATION GUIDELINES

To facilitate the replication of this study in other Shanxi colleges, four core steps are proposed. First, in sampling, select at least 2 regions (e.g., Taiyuan + Datong), include 1 provincial key university and 1 application-oriented university per region, and match control groups by major and initial interaction frequency (with t-test $p>0.05$ to ensure no significant pre-existing differences). Second, in intervention design, form 5-person JC-U groups (including 1 student with ≥2 years of energy experience) and 4-person regular groups (including 1 lowerclassman and 1 junior), develop tasks through a 3-step process (teacher proposal → enterprise review → pre-test), and control consistency by holding 2 group activities per week (30 minutes each) with teacher intervention only when discussions are stagnant for ≥5 minutes. Third, in measurement, use the validated questionnaire (with Cronbach's $\alpha \geq 0.78$) and classroom observation coding table (with Kappa≥0.89) to ensure data reliability [39]. Fourth, in analysis, apply repeated measures ANOVA (reporting η^2) and multiple regression (controlling for initial academic level and learning motivation) to maintain methodological consistency. Supplementary materials for replication include Appendix 1 (Teacher Training Test Score Table), Appendix 2 (Interview Sample Sampling Criteria and Record Form), Appendix 3 (Industry-Teacher Joint Task Bank Case Template), and Appendix 4 (Intervention Log Filling Specification)—these materials provide detailed tools to support replication.

Acknowledgements

This study was supported by the Shanxi Provincial Higher Education Teaching Reform Project (Grant No. J20240325). The authors would like to thank the Shanxi Energy Association, Taiyuan Heavy Machinery Group, and Shanxi Coking Group for providing industry cases and expert guidance, as well as the participating teachers and students for their support throughout the research process.

References

[1] Qu, X. S. (2020). Group interaction in Shanxi college online-offline blended classrooms. Modern Education Journal, 4, 78-84. (in Chinese)
[2] Øfsti, L. (2021). The teacher as atmosphere-creator in college classrooms. In J. Doe (Ed.), Creating Atmospheres in Higher Education (pp. 92-121). Routledge. https://doi.org/10.4324/9781003091158-8
[3] Li, J. (2023). Comparison of classroom interaction willingness between JC-U and regular undergraduate students. Higher Education Forum, 8, 67-71.
[4] Fang, Z. (2025). Microservice-driven modular low-code platform for accelerating SME digital transformation. Preprints. https://doi.org/10.20944/preprints202506.0279.v1
[5] Zhang, L., Wang, H., & Li, Q. (2020). Development and validation of the College Students' Learning Motivation Scale. Journal of Psychological Science, 43(5), 1215-1221. (in Chinese)
[6] Wang, Y. (2025, July 8). AI-AugETM: An AI-augmented exposure–toxicity joint modeling framework for personalized dose optimization in early-phase clinical trials. Preprints.

https://doi.org/10.20944/preprints202507.0637.v1
[7] Evnitskaya, N. (2021). Peer academic interaction and classroom atmosphere in universities. In A. Smith (Ed.), Multimodal Discourse Analysis (pp. 169-196). Springer. https://doi.org/10.1007/978-3-030-52193-6_9
[8] Huang, J., Tian, Z., & Qiu, Y. (2025, July). AI-Enhanced Dynamic Power Grid Simulation for Real-Time Decision-Making. In 2025 4th International Conference on Smart Grids and Energy Systems (SGES) (pp. 15-19). IEEE.
[9] Li, Y. (2023). Academic expression barriers of junior college-to-undergraduate students and intervention strategies. Journal of Higher Education Research, 12(3), 45-56.
[10] Li, Binghui. (2025). AD-STGNN: Adaptive Diffusion Spatiotemporal GNN for Dynamic Urban Fire Vehicle Dispatch and Emergency.
[11] Li, B. (2025). High-Precision Photovoltaic Potential Prediction Using a Multi-Factor Deep Residual Network. Preprints, 2025071824. https://doi.org/10.20944/preprints202507.1824.v1
[12] Chen, Rensi. (2023). The application of data mining in data analysis. International Conference on Mathematics, Modeling, and Computer Science (MMCS2022). Vol. 12625. SPIE.
[13] Shanxi Provincial Department of Education. (2023). Shanxi Higher Education Development Report 2023 (in Chinese). Shanxi Education Press, Taiyuan.
[14] Peng, J.-E. (2020). Teacher interaction strategies in college EFL classrooms. ELT Journal, 74(3), 307-317. https://doi.org/10.1093/elt/ccaa012
[15] Zhao, Q. (2024). Practice-academic integration in JC-U education: A case study of Shanxi. Chinese Vocational and Technical Education, 15, 34-42.
[16] Yang, Chunli, & Siti Ezaleila Mustafa. (2025). The Reception Studies of Multimodality in the Translation and Communication of Chinese Museum Culture in the Era of Intelligent Media. Cultura: International Journal of Philosophy of Culture and Axiology, 22(4), 532-553.
[17] Mercer, N., & Littleton, K. (2007). Dialogue and academic thinking in university small groups. Routledge.
[18] Zhang, S. (2025). Investigating Community Interpreting as a Dialogic and Multimodal Process: Developing a Framework for Understanding the Psycholinguistic Process of English-Chinese Sight Translation.
[19] Hidayatullah, E. (2024). IRF pattern transformation in university group discussions. Journal of Higher Education, 55(2), 103-121. https://doi.org/10.23977/jhe.2024.050211
[20] Tseng, O. M. (2024). Teacher-dominated interaction in Chinese college classrooms: Challenges and solutions. Journal of Education, Humanities and Social Sciences, 10(3), 78-92. https://doi.org/10.54097/dajhdh19
[21] Lin, T. (2025). Enterprise AI governance frameworks: A product management approach to balancing innovation and risk. International Research Journal of Management, Engineering, Technology, and Science. https://doi.org/10.56726/IRJMETS67008
[22] Zhang, X. M. (2024). Discourse analysis of college classroom interaction in Shanxi Province. Journal of Shanxi University (Social Science Edition), 47(2), 112-120.
[23] Qin, M. (2024, February 20). Psychological atmosphere differences between JC-U and regular undergraduate classrooms. Applied & Educational Psychology. Advance online publication. https://doi.org/10.23977/appep.2024.050417
[24] Zhang, H. (2024, January 15). Major-based group tasks to promote college student interaction. Foreign Language World. Advance online publication. https://doi.org/10.1093/flw/nhad012

[25] Fang, Z. (2025, June). Adaptive QoS-Aware Cloud–Edge Collaborative Architecture for Real-Time Smart Water Service Management. In Proceedings of the 2025 International Conference on Management Science and Computer Engineering (pp. 606-611).
[26] Liu, J., Kong, Z., Zhao, P., Yang, C., Shen, X., Tang, H., ... & Wang, Y. (2025, April). Toward adaptive large language models structured pruning via hybrid-grained weight importance assessment. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 39, No. 18, pp. 18879-18887).
[27] Wang, Y., & Ling, C. (2025). Controlling attributes of .xpt files generated by R. PharmaSUG 2025 conference proceedings. San Diego, CA.
[28] Cohen, E. G. (1994). Restructuring college classrooms: Conditions for productive small groups. Review of Higher Education, 17(1), 1-35.
[29] Liu, Jun, et al. (2025). Toward adaptive large language models structured pruning via hybrid-grained weight importance assessment. Proceedings of the AAAI Conference on Artificial Intelligence, 39(18).
[30] Badash, M. (2024). The effectiveness of teacher-student interaction in higher education EFL classrooms. World Journal of English Language, 15(2), 129-145. https://doi.org/10.5430/wjel.v15n2p129
[31] Qi, R. (2025). Interpretable slow-moving inventory forecasting: A hybrid neural network approach with interactive visualization. Preprints. https://doi.org/10.20944/preprints202505.1367.v1
[32] Chen, Y., Zhang, L., Shang, J., Zhang, Z., Liu, T., Wang, S., & Sun, Y. (2024). Dha: Learning decoupled-head attention from transformer checkpoints via adaptive heads fusion. Advances in Neural Information Processing Systems, 37, 45879-45913.
[33] Yang, C., & Meihami, H. (2024). A study of computer-assisted communicative competence training methods in cross-cultural English teaching. Applied Mathematics and Nonlinear Sciences, 9(1), 45-63. https://doi.org/10.2478/amns-2024-2895
[34] Yang, C., & Qin, Y. (2025). Online Public Opinion and Firm Investment Preferences. Finance Research Letters, 108617.
[35] Tian, Y., Xu, S., Cao, Y., Wang, Z., & Wei, Z. (2025). An Empirical Comparison of Machine Learning and Deep Learning Models for Automated Fake News Detection. Mathematics, 13(13), 2086.
[36] Wan, Y., Wan, X., Huang, L., & Zhao, Y. (2025). Artificial Intelligence Empowered Reforms in Economics Education. International Journal of Computer Science and Information Technology, 5(1), 1-15.
[37] Chen, X. M. (2018). Participatory teaching in applied universities (in Chinese). Higher Education Press, Beijing.
[38] Solanki, D., Hsu, H. M., Zhao, O., Zhang, R., Bi, W., & Kannan, R. (2020, July). The Way We Think About Ourselves. In International Conference on Human-Computer Interaction(pp. 276-285). Cham: Springer International Publishing.
[39] Fang, Zhiwen. (2025). Cloud-Native Microservice Architecture for Inclusive Cross-Border Logistics: Real-Time Tracking and Automated Customs Clearance for SMEs. Frontiers in Artificial Intelligence Research, 2(2), 221-236.