# Relationship between Team Diversity and Innovation Performance in Interdisciplinary Research Teams within the Field of Artificial Intelligence: Decision Tree Analysis

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## Abstract

Interdisciplinary research teams are crucial in solving complex problems by providing creative solutions that single-discipline teams cannot achieve. Previous studies have primarily focused on the linear relationship between independent variables and team innovation performance, neglecting the non-linear aspect. To address this gap, this paper examines the non-linear relationship between diverse factors and the innovative performance of interdisciplinary research teams in artificial intelligence. By utilizing the Classification and Regression Tree (CART) model, the study reveals that activity diversity and interdisciplinary research team innovation performance exhibit a U-shaped relationship in terms of "novelty" innovation performance. Furthermore, this relationship is influenced by research interest diversity. Specifically, low research interest diversity leads to low innovation performance as activity diversity increases. Meanwhile, research interest diversity emerges as the most critical factor impacting innovation performance. The importance of member diversity, institutional diversity, and activity diversity on innovation performance should not be ignored. Through decision tree analysis, this paper extends research on the multifactor combination, complex nonlinear relationships, and multipath influence mechanism of team diversity on interdisciplinary research teams' innovation performance.

## KEYWORDS

Interdisciplinary research team, Team diversity, Innovation performance, Classification and regression tree (CART) model

## 1. Introduction

Growing globalization and intense market competition have transformed the scientific model and increased the number of specialized research teams. In order to enhance the efficiency and quality of scientific research, more research teams are transitioning from single teams to diversified teams[1]. Interdisciplinary research has become a necessary choice in this context[2], allowing teams to draw upon a wide range of disciplines and expertise to address complex scientific questions. The diversity of team members from various disciplines and backgrounds contributes to greater knowledge and innovative results[3]. Thus, effective interdisciplinary collaboration is crucial for achieving scientific and innovative breakthroughs[4].

Previous research highlights the significance of diversity as a crucial factor influencing the success of interdisciplinary research teams[5]. Diversity can be broadly categorized as demographic diversity and task-related diversity[6]. Demographic diversity encompasses variations in team members' demographic attributes, such as age, gender, and institutional backgrounds[7]. Task-related diversity pertains to the diverse qualities that team members bring to their academic or professional pursuits, including workplace functions, knowledge, and education[8]. Creating successful teams with demographic and task-related diversity is not a straightforward process of simply combining individuals from different disciplines. Horwitz et al.[6] discovered that while demographic diversity did not significantly impact team performance, task-related diversity positively influenced it. Diverse teams struggle with issues such as gender differences, team conflict, and collaboration[9]. Given these contradictory findings, our focus is on investigating the impact of both demographic diversity and task-related diversity on the innovation performance of interdisciplinary research teams, while analyzing the varying importance of different diversity factors. Existing studies have primarily focused on exploring the linear relationship between independent variables and team innovation performance, overlooking the nonlinear aspect. The nonlinear relationship between these characteristics and team innovation performance, especially in the context of demographic diversity and task-related diversity in interdisciplinary research teams, remains unclear.

This paper aims to investigate the impact and decision-making mechanisms of team diversity on the innovative performance of interdisciplinary research teams. Firstly, team innovation performance is divided into novelty and impact[10]. Second, we

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will investigate the influence of team diversity on the interdisciplinary research team's innovation performance in terms of both the demographic diversity and task-related diversity of team members. From a social categorization perspective, we assume that gender diversity, national diversity, and institutional diversity are included in the demographic diversity in this context. Meanwhile, relying on the informational decision-making perspective, we hypothesize that task-related diversity includes sociability diversity, activity diversity, research interest diversity, and member diversity. Specifically, we address the following research questions in this paper: RQ1: What is the complex relationship structure among demographic diversity, task-related diversity, and the innovative performance of interdisciplinary research teams? RQ2: What combinations of characteristics promote high levels of team innovation performance? RQ3: What diversity characteristics should researchers focus on to enhance the innovation performance of interdisciplinary research teams?

# 2. Data and methods

This paper investigates the impact of team diversity on interdisciplinary research teams' innovation performance. The basic process is shown in Figure 1. Firstly, raw data is processed to form authors' collaborative relationship data and measure each author's collaborative tie strength. Second, stable collaborative relationships are identified using a pre-set threshold (super tie). Then, members of interdisciplinary research teams are identified, and the diversity index of each team is measured. Again, team innovation performance is divided into novelty and impact to be measured. Finally, by using team diversity as the conditional attribute and innovation performance as the decision attribute, the impact of team diversity on the interdisciplinary research team's innovative performance is explored using the CART model.

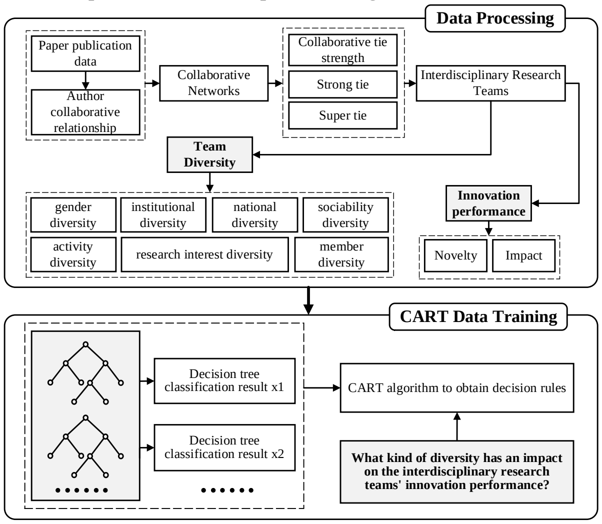


**Figure 1:** Research Framework

## 2.1 Data collection

This paper focuses on empirical research in the field of artificial intelligence (AI). The dataset is derived from the information of the most influential scholar award winners on the AMiner website (https://www.aminer.cn/ai2000) 2023 AI 2000 annual list. There are three reasons for selecting these scholars as the subjects of the study. Firstly, AI research is inherently interdisciplinary[11]. Second, since its launch in 2006, the AMiner platform has already been used by many researchers[12]. Third, since 2017, the AMiner platform has been publishing the annual AI 2000 most influential scholar list. The purpose of this list is to annually rank the 2000 scholars who are expected to be highly cited in the field of AI over the next ten years (2020-2029).

## 2.2 Team Recognition

Firstly, we obtain the dataset from the AMiner website, which covers information on the most influential scholars in the 2023 AI 2000 annual list. The dataset consists of 195 selected scholars and their collaborators, with five of these scholars receiving awards in two or more subfields. The public information of the selected scholars is obtained from their personal websites and academic social networking platforms. The papers of selected scholars are downloaded from the Web of Science database. Finally, 25,285 papers are submitted by 195 selected scholars.

Second, we conduct community detection on the author co-occurrence network for each selected scholar using the Louvain algorithm. This algorithm divides the nodes in the network into different communities based on modularity metrics, which assess the collaborative relationships between the nodes. The algorithm identifies strong connections within the same community and sparser connections between different communities. In the network, each co-author is represented as a node, and edges represent collaborations between selected scholars and co-authors who have published papers together. Figure 2 shows the author co-occurrence network for Silver, D selected scholars. Different colors in the figure represent various communities determined by modularity, with the community to which Silver and other selected scholars belong shown in purple.

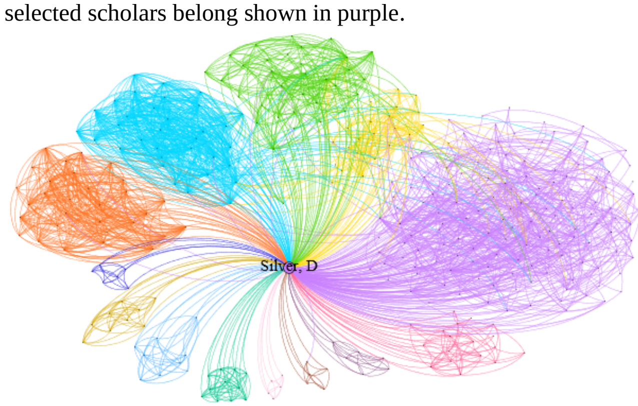


**Figure 2:** Collaboration Network of Silver, D scholar

Next, we calculate the collaborative tie strength among the nodes in each community to filter out the core collaborators of each selected scholar. Collaborative tie strength, also known as a "super tie", has been extensively studied in scientific collaborative networks[13]. It represents a long-term and stable collaboration, similar to life partners, characterized by high intensity, close ties, and long durations[14]. To identify the core collaborators among the 195 selected scholars, we calculate the super tie for each community. Specifically, when a member's collaborative tie strength exceeds his or her community's super tie threshold, that member is referred to as a super tie collaborator and core team member. Equations 1 and 2 demonstrate the formula for calculating the super tie[14]. Additionally, we employ the Anderson-Darling test to examine the distribution of collaborative intensity $K_{ij}/K_i$ among the members. Our analysis indicates that the statistical distribution $P(K_{ij})$ of all members' collaborative intensity conforms to an exponential distribution, with the average collaborative strength of members being 2.83.

$$\langle K_i \rangle = S_i^{-1} \sum_{j=1}^{S_i} K_{ij} \tag{1}$$

$$K_i^c = (\langle K_i \rangle - 1) \ln S_i \tag{2}$$

Where the collaborative tie strength $K_{ij}$ is defined as the cumulative number of papers co-authored by the selected scholar in community $i$ and scholar $j$ over the time between their first and last paper. $S_i$ represents the number of different co-authors of selected scholars in the community $i$. $\langle K_i \rangle$ represents the average collaborative tie strength $K_{ij}$. Each scholar $j$ with $K_{ij} > K_i^c$ is labelled as a super tie collaborator of community $i$.

Eventually, we identify 195 research teams and their 1,217 core members. Figure 3 shows the distribution of team sizes for 195 teams. The largest team size is 57 members, and 165 teams are smaller than 10 members, which represents 85% of all teams. Previous research defines interdisciplinary teams as groups of scientists from different disciplines who collaborate to address complex problems[15]. To verify the interdisciplinarity of these teams, we utilize a method that maps member affiliations to disciplinary classifications[16] to more accurately determine the disciplinary backgrounds of the members. Specifically, we extract secondary institutions from each member's address, retain the disciplinary terms in the secondary institution names, and match these terms to the discipline field in the OECD classification scheme. In this way, each member's institution can be precisely matched to his or her research discipline. The results indicate that 165 teams have members from two different disciplinary backgrounds, 27 teams have members from three different disciplinary backgrounds, and 3 teams have members from four different disciplinary backgrounds, thus reinforcing that the 195 teams in this study are interdisciplinary research teams. Table 1 demonstrates the distribution of members from different disciplinary fields. Specifically, 71.18% of the members are from the field of computer and information science, 21.80% are from the fields of electrical engineering, electronic engineering, and information engineering, while other fields encompass environmental engineering, nanotechnology, and physical sciences, among others. To explore the factors influencing the interdisciplinary research teams' innovation performance, we download each team member's papers from the Web of Science database and collect 91,025 papers from all teams.

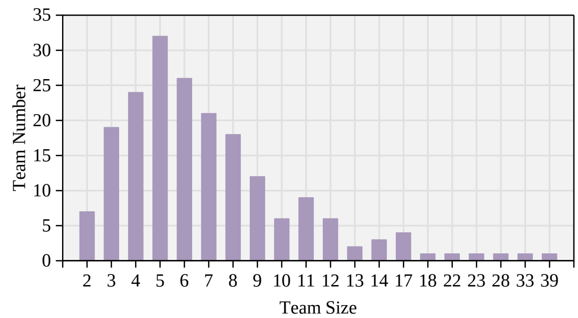


**Figure 3:** Size Distribution of Interdisciplinary Research Teams

**Table 1**
Distribution of Members from Different Disciplinary Fields

| Discipline | Percentage of members |
|---|---|
| Computer and information science | 71.18% |
| Electrical engineering, electronic engineering, information engineering | 21.80% |
| Environmental engineering | 2.03% |
| Nano-technology | 1.52% |
| Physical science | 1.09% |
| Health science | 0.94% |
| Clinical medicine | 0.51% |
| Mathematics | 0.36% |
| Materials engineering | 0.22% |
| Medical engineering | 0.22% |
| Basic medicine | 0.14% |

## 2.3 Variables

### 2.3.1 Dependent variables

We calculate the degree of team novelty using the novelty index proposed by Lee et al.[10]. This index measures the novelty of a team's paper based on the rarity of prior citation pairs. The calculation involves two steps.

Complete the first step of the operation on the paper level. (1) List all paired reference combinations for each paper. (2) Record the corresponding journal pairs. (3) Aggregate the pairs of journal combinations published from year t-2 to year t as $U_t$ set. The time window from year t-2 to year t is chosen to ensure data robustness. We then calculate the commonness value using Equation 3[10]. (4) This equation assigns each paper a range of commonness values. The commonness values of each paper are ranked, and the 10th percentile is taken as the commonness value of the paper. Using the 10th percentile instead of the minimum value helps reduce noise and increase the reliability of the measure. (5) The commonness value is transformed using a natural logarithm to obtain an approximately normally distributed variable. The final novelty value for that paper is obtained by adding a negative sign.

$$\text{Commonness}_{ijt} = \frac{observed\ number\ of\ pairs_{ijt}}{expected\ number\ of\ pairs_{ijt}} = \frac{N_{ijt}}{\frac{N_{it}}{N_t} \times \frac{N_{jt}}{N_t} \times N_t} = \frac{N_{ijt} \times N_t}{N_{it} \times N_{jt}} \tag{3}$$

Where $N_{ijt}$ is the number of occurrences of journal pairs (i, j) in $U_t$ set. $N_{it}$ is the number of journal pairs in $U_t$ set that contain journal $i$. $N_{jt}$ is the number of journal pairs in $U_t$ set that contain journal $j$, and $N_t$ is the number of all journal pairs in $U_t$ set.

Calculating novelty at the team level is the next stage. The number of paper publications by each team is counted and divided by the team size to calculate the team's novelty value.

We measure a team's impact using forward citations[10]. High-impact papers are defined as those in the top 1% of citation distribution. This definition follows Uzzi et al.[17] and considers the use of short citation time windows can lead to the incorrect identification of highly cited papers[18]. First, the process of identifying high-impact papers are completed at the paper level. (1) Rank all papers from highest to lowest citation count. (2) By using a five-year moving window, we define papers in the top 1% of the rankings from year t-5 to year t as high-impact papers. (3) We use a dummy variable to indicate whether each paper is a high-impact publication, assigning a value of 1 if it is and 0 otherwise. Next, the number of high-impact papers per team is counted and divided by the team size to finally obtain the team's impact value.

### 2.3.2 Independent variables

Gender diversity refers to the subjective or objective similarities and differences between team members in terms of gender[19]. National diversity is defined as having team members from different national backgrounds, which introduces sociological categorization and the potential for diverse cognitive perspectives[20]. Institutional diversity refers to the presence of a variety of members in different institutions[21]. All of the above demographic diversity indicators mentioned above are measured using the Simpson index, which is calculated using Equation 4.

$$H = 1 - \sum_{i=1}^{n} P_i^2 \qquad (4)$$

Where $n$ is the total number of categories, $P_i$ is the percentage of members of the group $i$. The higher the $H$ value, the greater is the value of the diversity.

Using the AMiner platform, we algorithmically obtain data on sociability, activity, and research interest diversity indices to assess the academic proficiency of members. Definitions and formulas for these indicators are provided[22].

The sociability index is derived from considering both the number of scholars' collaborators and their collaborative papers, as shown in Equation 5.

$$sociability(A) = 1 + \sum_{each\ coauthor(c)} ln(\#copaper_c) \qquad (5)$$

Where the $\#copaper_c$ is the number of papers co-authored between scholar and co-authors.

The activity index measures a scholar's frequency and number of recent publications, along with the significance of each paper, as shown in Equation 6.

$$\text{activity(A)} = \sum_{each\ year(n) in\ recent\ N\ years} \text{IS}(G_n) \times \text{weight(n)} \qquad (6)$$

Where, in $n$ years ($n$ belongs to near $N$ years), $G_n$ is a group of papers published by scholars in n years, $\text{weight(n)} = \alpha^{\text{this year}-\text{n}}$, and the following principles are applied to the values of $n$ and $\alpha$: if the current month is in the first half of the year (month<July), it is set $N = 4$ and $\alpha = 0.75$; if the present month is at the second half, it is set $N = 3$ and $\alpha = 0.85$.

To assess the diversity and differences in a team's overall sociability and activity, we utilize Equation 4 to calculate the diversity of these two evaluation indicators.

The research interest diversity of scholar is based on the breadth of the field of interest. Using the topic model, we identify each scholar's field of study and assign their papers to relevant topics. The $P_A(\text{t})$ topic distribution is obtained by Equation 7, and the research interest diversity is defined as the threshold of the distribution of the $P_A(t)$, which is calculated by Equation 8.

$$P_A(\text{t}) = \frac{\#papers\ of\ A\ belong\ to\ topic\ t}{\#all\ paper\ of\ A} \qquad (7)$$

$$\text{research interest diversity(A)} = -\sum_{t \in all\ topic\ of\ A} P_A(t) log P_A(t) \qquad (8)$$

Member diversity refers to the extent of diversity in collaborative relationships among team members. A low diversity indicates frequent collaboration with the same co-authors, while a high diversity reflects collaboration with diverse co-authors, as calculated by Equation 9[23].

$$\text{member diversity} = \frac{relation_i}{coauthor_i(non{-}duplicate)} \qquad (9)$$

Where $relation_i$ refers to the number of collaborations in published journal articles, and $coauthor_i(non-duplicate)$ represents the total number of non-replicating co-authors. Table 2 is the examples of co-authors' member diversity of member A.

**Table 2**

Examples of Co-authors' Member Diversity of Member A

| | Article 1 | Article 2 |
|---|---|---|
| Author | A, B, C, D | A, C, D |
| Relation | A-B, A-C, A-D | A-C, A-D |
| Coauthor(non-duplicate) | A, B, C, D | |
| Member diversity | 5/4=1.25 | |

## 2.4 Data Characteristics and Analysis

Table 3 provides the results of the exploratory analysis, including averages, mediums, minimum, and maximum values for calculated indicators. Figure 4 and Figure 5 provide correlation plots between diversity indicators and interdisciplinary research teams' innovation performance. There is no strong correlation between population diversity, task-related diversity and innovation performance.

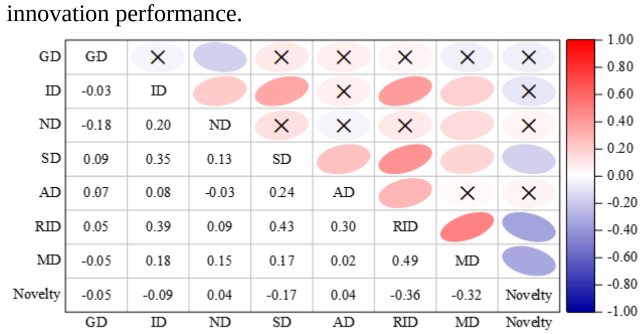


**Figure 4:** Correlation between Diversity Indicators and Team's Novelty

Note: GD = gender diversity; ID = institutional diversity; ND = national diversity; SD = sociability diversity; AD = activity diversity; RID = research interest diversity; MD = member diversity.

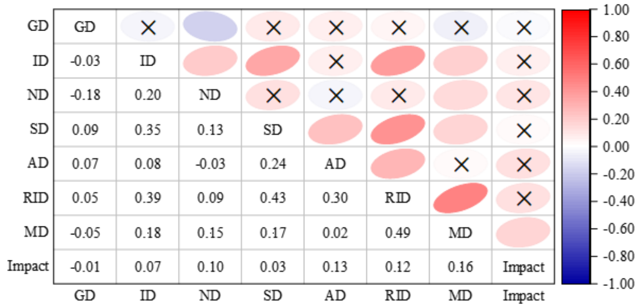


**Figure 5:** Correlation between Diversity Indicators and Team's Impact

**Table 3**

Descriptive Statistics Analysis

| Variable | Sample | Mean | Std.Deviation | Max | Min |
|---|---|---|---|---|---|
| Gender diversity | 195 | 0.13 | 0.17 | 0.50 | 0.00 |
| Institutional diversity | 195 | 0.70 | 0.16 | 0.92 | 0.00 |
| National diversity | 195 | 0.25 | 0.25 | 0.75 | 0.00 |
| Sociability diversity | 195 | 0.81 | 0.10 | 0.97 | 0.50 |
| Activity diversity | 195 | 0.79 | 0.11 | 0.97 | 0.00 |
| Research interest diversity | 194 | 8.94 | 5.93 | 46.31 | 0.16 |
| Member diversity | 195 | 36.40 | 25.78 | 210.93 | 3.59 |
| Novelty | 195 | -293.80 | 536.83 | 561.74 | -5668.35 |
| Impact | 195 | 3.90 | 7.93 | 62.00 | 0.00 |

## 2.5 Base Classifier Model-Classification and Regression Tree

### 2.5.1 Idea of a CART Decision Tree

The CART model is a supervised machine learning model proposed by Breiman[24]. It is a classification regression method generated based on the regression of the fork decision properties. It is commonly used in data analysis and evaluation, including project performance assessment[25]. When studying the factors that influence the innovative performance of interdisciplinary research teams, we often face the challenge of dealing with multivariate and nonlinear relationships. Traditional regression models, while useful in revealing relationships between independent and dependent variables, may have limitations in handling complex relationships. These models rely on the least squares method, which requires rigorous hypothesis testing and variable control[26]. In the context of understanding how diversity impacts the teams' innovation performance, it is crucial to consider multiple independent variables and potential interactions among them. Incorrect selection of control variables or omission of important variables may lead to biased results in regression analysis. In contrast, the CART model offers a more flexible and robust solution[27]. It constructs a decision tree using recursive binary splitting, dividing data subsets into smaller subsets[24]. This nonparametric approach eliminates the need for rigorous hypothesis testing and variable control, as it automatically selects partitioning rules based on the actual distribution and characteristics of the data[28]. As a result, the CART model can capture nonlinear relationships and higher-order interactions[29], providing a more accurate understanding of the impact of diversity on team innovation performance.

### 2.5.2 Design of the CART Decision Tree

The paper categorizes the data based on innovation performance and divides it into training and test samples in an 8:2 ratio. Alongside the CART model, several baseline models are trained on the dataset, and their performance on the test set is compared to select the optimal model. These baseline models include the C4.5 model, CART model, Random Forest model, and Gradient Boosting Tree model. The C4.5 model is similar to the CART model but uses information entropy as the partitioning criterion. The random forest model combines multiple decision trees to optimize classification, while the gradient boosting tree model iteratively trains weak classifiers and combines them into strong classifiers. To enhance the model's performance, the paper utilizes the grid search method to systematically explore various hyperparameter combinations and determine the optimal parameter configurations. The accuracy of each model, after grid search, exceeds 0.6, indicating that over 60% of the samples are correctly predicted by the model. Among the models, the CART model demonstrates superior performance with accuracy rates of 0.73 and 0.68 in measuring the novelty and impact of the team, respectively. Based on these results, the CART model is selected for use in this paper.

# 3. Results and Discussion

## 3.1 Model Result Analysis

Through the CART model, a decision rule table for innovation performance can be constructed between on the variables of "novelty" and "impact". Table 4 shows that a high decision result indicates that the novelty and impact of the team with the current decision rule are higher than the median novelty and impact of all interdisciplinary research teams, respectively.

**Table 4**

Innovative Performance Decision Rules

| | Demographic diversity | | | | Task-related diversity | | | Decision results | Support | Confidence |
|---|---|---|---|---|---|---|---|---|---|---|
| | GD | ID | ND | SD | AD | RID | MD | | | |
| Novelty | - | - | - | - | > -0.40 | > -0.31 | - | Low | 29.00% | 61.00% |
| | - | - | - | - | > -0.40 | <= -0.31 | - | High | 12.00% | 79.00% |
| | - | - | - | - | <= -0.40 | - | - | High | 14.00% | 66.00% |
| Impact | - | <= -0.72 | - | - | - | <= 0.47 | <= -0.08 | Low | 9.00% | 78.00% |
| | - | > -0.72 | - | - | - | <= 0.47 | <= -0.08 | High | 31.00% | 60.00% |
| | - | - | - | - | - | > 0.47 | <= -0.08 | Low | 7.00% | 86.00% |
| | - | - | - | - | - | <= -0.29 | > -0.08 | High | 8.00% | 93.00% |
| | - | - | - | - | - | (-0.29,0.08] | > -0.08 | Low | 5.00% | 70.00% |
| | - | - | - | - | - | (0.08,0.47] | > -0.08 | High | 19.00% | 74.00% |

Firstly, in the "novelty", interdisciplinary research teams have a higher proportion of high innovative performance ratings. In the “impact”, there is a higher proportion of interdisciplinary teams with a low innovation performance rating than in the “novelty” innovation performance. Secondly, activity diversity and member diversity split as root nodes, which are key factors affecting the novelty and impact of a team, respectively. Third, the confidence coefficients for most of the decision rules are above 60%, indicating that the weight of the sample size supporting the current decision rule in the leaf node’s sample size is 60% or more. This suggests that the results are highly interpretable.

Figure 6 shows that there are a total of two rules to determine whether a team has high or low innovation performance. The CART model divides data into approximately two branches based on whether the most important feature “activity diversity” is less than or equal to -0.40. The results show that with lower activity diversity, team members can focus more on their original thinking, enhancing team innovation performance without the need to be concerned about publication frequency and quantity. When activity diversity is higher, an increase in research interest diversity contributes to teams achieving high levels of innovative performance. Horizontal comparison reveals that activity diversity is a crucial factor influencing innovation performance. Interdisciplinary research teams with low activity diversity are not influenced by research interest diversity, whereas interdisciplinary research teams with high activity diversity are impacted by research interest diversity.

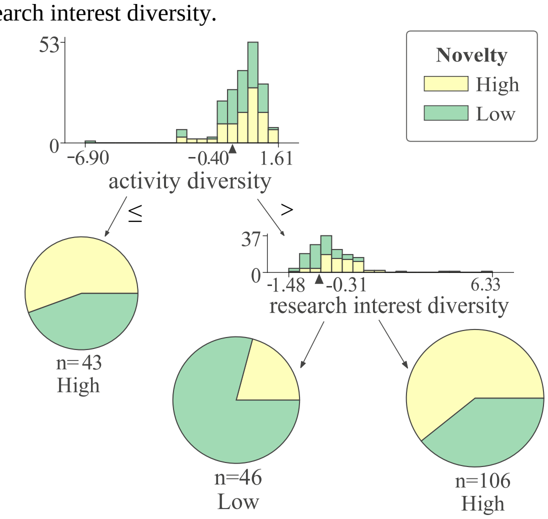


**Figure 6:** Decision Tree for Team’s Novelty

Figure 7 shows six rules to determine whether a team has high or low innovation performance. The CART model divides the data into two branches based on whether the most important feature “member diversity” is less than or equal to -0.08. The results reveal that interdisciplinary research teams with member diversity more than -0.08 need to control research interest diversity to achieve high innovation performance. For interdisciplinary research teams with member diversity smaller than -0.08, institutional diversity is a key influence on innovation performance. Horizontal comparison shows that member diversity is a key factor influencing innovation performance. Interdisciplinary research teams with low member diversity tend to prioritize the diversity of institutions represented within the teams.

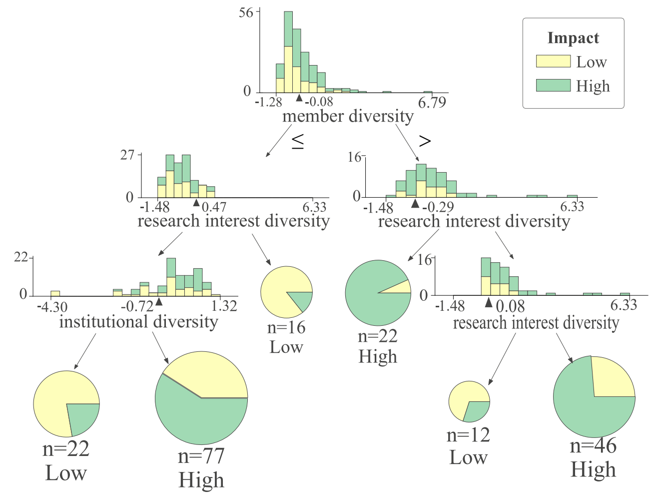


**Figure 7:** Decision Tree for Team’s Impact

## 3.2 Feature Importance Analysis

The model’s final characteristic importance for explanatory variables is presented in Figure 8. Among the factors affecting a team’s novelty, research interest diversity has the highest characteristic importance of 0.97, while activity diversity has a characteristic importance of 0.03. Among the factors affecting a team’s impact, research interest diversity has the highest characteristic importance of 0.48. Member diversity and institutional diversity closely followed with 0.30488 and 0.22, respectively. This result shows that research interest diversity is most strongly associated with interdisciplinary research teams' innovation performance. This shows that team members' diverse expertise backgrounds enable knowledge integration and reconfiguration, which are crucial elements in innovation performance[21].

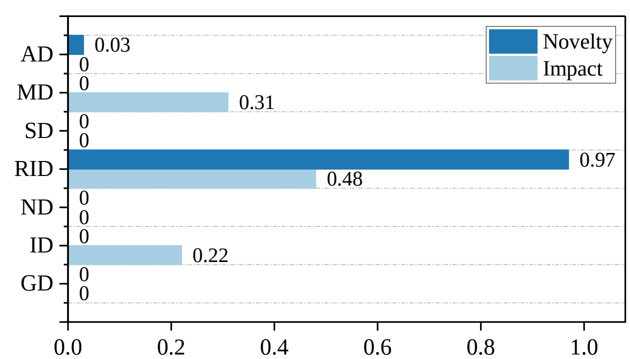


**Figure 8:** Characteristic Importance of Explanatory Variables

# 4. Conclusion

This paper finds a U-shaped relationship between activity diversity and team innovation performance in “novelty” innovation performance. However, this relationship is impacted by research interests diversity. Specifically, interdisciplinary teams with low activity diversity are able to improve their innovative performance independently of research interest diversity. In contrast, low research interest diversity leads to low innovative performance when activity diversity increases. In terms of "impact" innovation performance, increasing member diversity and managing the range of research interests can be beneficial. In addition, interdisciplinary research teams with low member diversity need to focus on the institutional diversity of team members, as institutional diversity has a positive impact on the team's effectiveness.

In the evaluation of various factors, research interest diversity emerges as the most significant determinant of innovative performance in interdisciplinary research teams. This implies a close association between research interest diversity and the team's ability to innovate. Researchers with distinct research themes bring a diverse range of knowledge and contribute to the reconfiguration of knowledge by identifying and integrating insights from different fields[30].

Managers should consider research team diversity when developing it. To create a healthy innovation environment, they should pay attention to the heterogeneity of different organizational and disciplinary backgrounds to which team members belong and strive to optimize the level of knowledge diversity in the team. Furthermore, managers should encourage and promote activity diversity. Meanwhile, the costs of too much research interest diversity need to be noted to avoid the phenomenon of "too much of a good thing". This is because knowledge diversity among collaborative members in different research fields is often considered a double-edged sword. As Wang et al have found, increasing knowledge diversity leads to a decline in social influence after a certain peak[21].

Our study has limitations. Firstly, it focuses solely on the AMiner platform in AI, limiting its scope and generalizability. Future studies should broaden the research fields. Secondly, the sample of 195 interdisciplinary teams may not fully reflect AI team diversity and complexity, potentially suffering from sampling error. A more representative sample is needed. Thirdly, while we focused on diversity within teams, future research could explore diversity in other research team activities. Lastly, our team recognition method overlooks member turnover dynamics. Future studies should introduce a dynamic analysis of member flow for more accurate core member identification.

## ACKNOWLEDGMENTS

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