Research Team Characteristics as Drivers of Algorithm Innovation

Authors: Tian Jingwen, Yin Xinping, Zhai Yujia, Yin Xinping

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Abstract

Purpose/Significance: Integrating research teams with algorithmic innovation and analyzing the impact of research team characteristics on algorithmic innovation from the perspective of team traits can help enhance the academic capabilities of research teams, thereby promoting algorithmic and scientific innovation. Methods/Process: Three measurement indicators for research teams were established—team size, number of institutions, and institution type—along with two evaluation indicators for algorithmic innovation: algorithm performance and academic output. Taking 543 research teams in the image classification task within the machine learning domain as an example, non-parametric tests and multiple linear regression models were employed to explore the effect of research team characteristics on algorithmic innovation, and recommendations for enhancing team research performance and promoting algorithmic re-innovation were proposed based on empirical results. Results/Conclusions: All measurement indicators of research team characteristics exhibit influence effects on algorithmic innovation, mainly manifested as: research team institution type has a significant impact on algorithmic innovation, with hybrid-type teams demonstrating optimal performance in algorithm model accuracy and enterprise-type teams showing optimal performance in citation counts of algorithm papers; research team size has a positive influence on both algorithm performance and academic output; the number of institutions in a research team shows a positive correlation with academic output but a negative correlation with algorithm performance.

Full Text

Algorithm Innovation Driven by the Characteristics of Scientific Research Teams

Jingwen Tian[1], Xinping Yin[1], Yujia Zhai[1],[2]
[1]Tianjin Normal University, School of Management

[2]Wuhan University, School of Information Management

Abstract

[**Purpose/Significance**] This study combines scientific research teams with algorithmic innovation, exploring the influence of research team characteristics on algorithm innovation from the perspective of team traits. This approach helps enhance the academic capacity of research teams and thereby promotes algorithmic and scientific innovation. [**Method/Process**] We established three measurement indicators for research teams—team size, number of institutions, and institution type—and two evaluation indicators for algorithm innovation: algorithm performance and academic output. Taking 543 research teams in the image classification task within the machine learning domain as our sample, we employed non-parametric tests and multiple linear regression models to explore the impact of research team characteristics on algorithm innovation. Based on the empirical results, we propose recommendations for enhancing team research performance and promoting algorithmic reinnovation. [**Result/Conclusion**] All measurement indicators of research team characteristics affect algorithm innovation, primarily manifested as follows: institution type has a significant impact, with hybrid teams achieving optimal performance in algorithm model accuracy and enterprise-type teams performing best in paper citations; team size positively influences both algorithm performance and academic output; the number of institutions correlates positively with academic output but negatively with algorithm performance.

Keywords: Research team characteristics; Algorithm innovation; Nonparametric test; Multiple linear regression
Classification Number: G203

1. Introduction

In recent years, digital technologies based on algorithms and big data have been rapidly applied and continuously innovated across various social domains, driving an intelligent revolution in human society and adding tremendous momentum to social development [1]. At the Sixth World Internet Conference in 2019, Yu Siying, Vice President of Alibaba Group, noted that algorithm innovation has become a global high ground for innovation. Against this backdrop, computer science research centered on algorithms has emerged as a new focus in academia. By continuously exploring new algorithmic mechanisms, developing novel algorithm models, and advancing new algorithmic applications, researchers provide strong impetus for the development of an intelligent society. However, as scientific research deepens, researchers face increasing difficulty, leading more scholars to seek collaboration through research teams. Relying on collective strength to achieve research goals and produce strong academic outcomes, algorithm research conducted by research teams has gradually gained prominence.

Although teamwork helps researchers achieve breakthroughs in scientific innovation, the collaboration process presents numerous challenges, including member diversity, deep knowledge integration, large scale, goal differences, open boundaries, geographic dispersion, and high task interdependence [2]. These challenges undoubtedly affect the effectiveness of research team collaboration, making the study of research teams an inevitable outcome of the strengthening trend toward scientific collaboration [3]. Multiple studies have shown that team characteristics (such as size, institutional or national diversity) significantly influence the impact, quality, and novelty of research outcomes [4]. In other words, the internal environment and conditions of research teams also affect algorithm innovation. However, most studies still treat algorithms as rational and objective technical models, thereby overlooking the potential diversity of algorithms themselves and the complexity of how this diversity evolves under environmental influences [5]. Moreover, algorithms are not simply objective instructions, and the relationship between algorithms and humans cannot be ignored [6].

In summary, although research on both scientific teams and algorithms has emerged, the two have not yet been integrated, particularly regarding studies examining how research team characteristics influence algorithm innovation [7]. What impact research teams have on algorithmic research and what relationship exists between team characteristics and algorithm innovation remain unresolved questions. Therefore, this study attempts to explore the driving forces behind algorithm innovation from the perspective of research team characteristics, with the primary goal of enhancing the academic capacity of research teams and thereby promoting algorithmic and scientific innovation.

2.1 Research Team Trait Measurement Indicators

Scholars have proposed a series of quantitative indicators to measure research team traits and their impact on team outputs, focusing primarily on team size, structural characteristics, and type traits.

First, quantifying team size is straightforward—the number of researchers in a team constitutes its size, typically measured using statistical variables such as maximum, minimum, and mean values. Additionally, Zeng Deming et al. [8] constructed a research team size measurement method based on the net Shapley Value to dynamically analyze factors influencing optimal team size. Second, institutional and national diversity traits: Liao Qingyun et al. [9] proposed institutional diversity and national diversity indicators when studying the impact of team diversity on performance. Third, disciplinary traits: Research team interdisciplinarity is measured by calculating cross-disciplinary characteristics from team members' disciplines. Zhang Lin et al. [10] proposed a method for extracting disciplinary classifications from co-author institutional addresses to measure interdisciplinary collaboration. Tanmoy Chakraborty et al. [11] used Shannon entropy to propose a reference diversity indicator for quantifying the interdisciplinarity of individual scientific papers. Finally, other common traits: Dae Sung Lee et al. [12] calculated team age, gender, professional, and role diversity using entropy-based diversity indices. Li Gang et al. [13] selected indicators from personnel and output perspectives to measure the collaboration characteristics of academic leaders and their impact on research output. Yi Bu et al. [14] quantified collaborator diversity through thematic and impact diversity dimensions when studying scientific team collaboration patterns.

In summary, beyond team size, current classifications of team structure and type often overlap. There is no unified classification system for research team traits, with researchers emphasizing different perspectives based on their research content and themes. This study focuses on three dimensions: research team size, number of institutions, and institution type, measured through a series of quantifiable indicators.

2.2 Algorithm Innovation Evaluation Indicators

Although no unified definition of algorithm innovation exists in academia, its connotation is clear. In this study, each performance improvement, modification, and optimization of an algorithm model is considered an algorithm innovation. Consequently, evaluation indicators for algorithm innovation largely align with those for algorithm performance. Due to the diverse application domains of algorithm models, scientists deploy the most suitable algorithms for different tasks in various environments [15], resulting in diverse and heterogeneous performance evaluation metrics.

Literature review reveals that accuracy [16], precision [17], recall [17], F1-score [17], average precision [18], and mean average precision [18] are among the most common evaluation metrics in machine learning, widely used in algorithm model research for tasks such as image classification, recognition, segmentation, and object detection. For specific research problems and application scenarios, scholars propose additional metrics. Wen Jing Kang et al. [19] established quantitative metrics including illumination variation, scale change, and target movement length to test single-target visual tracking algorithms. Bryar A. Hassan et al. [20] analyzed performance from four dimensions: initialization parameters, problem dimension, search space, and problem queue when comparing backtracking search optimization algorithms. Duraipandian [21] evaluated MANET routing algorithm performance based on transmission delay, energy consumption, and packet delivery rate.

Although algorithms emphasize application, academic papers remain a crucial channel for dissemination and diffusion. Therefore, beyond algorithm performance metrics, academic output evaluation constitutes another dimension of algorithm innovation assessment. Academic output evaluation includes qualitative and quantitative assessments of output quantity and quality. Qualitative evaluation primarily employs peer review to assess paper innovation, scientific rigor, and practicality [22]. Quantitative evaluation relies on metrics such as citation frequency, journal impact factor, and H-index. Citation frequency, first proposed by Garfield [23], has become a recognized quantitative evaluation indicator. This study primarily uses this metric for academic output-based algorithm innovation evaluation.

2.3 Research on the Impact of Team Characteristics on Algorithm Innovation

Currently, research on research teams and algorithms remains confined to their respective domains, with few studies examining algorithm research teams or factors influencing algorithmic outcomes. Below, we review research on research team output evaluation, algorithm research teams, and factors influencing innovation in machine learning.

First, studies on how research team characteristics affect research output include: Huang Yufang et al. [24] used social network methods to construct team knowledge-sharing networks and structural equation modeling to examine relationships between knowledge-sharing structure, team emotion, and team performance. Wang Lei et al. [25] studied factors influencing individual creativity in university research teams using questionnaires and multilevel linear models. Second, studies on algorithm research teams or AI research teams include: Wang Yuefen et al. [26] studied collaboration patterns in AI field-leading teams based on scholars' collaboration numbers and social network indicators. Zou Bentao et al. [27] found significant "small group" collaboration phenomena in high-yield AI teams across different periods. Piorkowski et al. [28] identified communication challenges among AI developers in multidisciplinary teams, noting that overcoming these barriers is key to bridging psychological gaps. Finally, studies on scientific innovation influencing factors include: Lü Dongqing et al. [29] used logistic regression to explore how interdisciplinary knowledge fusion affects the D-index. Du Xingye et al. [30] studied core elements affecting knowledge innovation in data-intensive research environments, proposing a data capability model to promote knowledge innovation.

Overall, although research on research teams and algorithms has emerged, studies integrating the two to explore how team characteristics influence algorithm innovation have not reached unified conclusions. As research collaboration becomes increasingly common, the impact of research teams on scientific progress becomes more pronounced. Research on teams should no longer be limited to macro-level management studies but should focus on more specific and targeted micro-level research. For algorithm research, algorithm innovation is influenced not only by internal model parameters and training conditions but also by external environmental factors. To continuously improve algorithm innovation levels, in-depth analysis of influencing factors is necessary.

3. Research Design and Data Processing

This study examines research teams and algorithms in the machine learning field, using datasets obtained from Papers With Code, Scinapse, and Semantic Scholar to explore relationships between teams and algorithm innovation from multiple perspectives. Specifically, we first collect data and analyze team characteristics to establish measurement indicators for team traits and evaluation indicators for algorithm innovation. Second, we employ non-parametric tests and multiple linear regression models to explore the impact of team characteristics on algorithm innovation. Finally, based on the analysis results, we propose recommendations for enhancing team research performance and promoting algorithmic reinnovation.

We selected algorithm models from the Image Classification task under the Computer Vision domain on the Papers With Code platform. With the rapid development of internet multimedia technology and the proliferation of digital devices, image data has exploded, giving rise to computer-automated image recognition and classification methods. Consequently, an increasing number of algorithm models have been applied to this task [Figure 1: see original paper], making our selection representative.

Data were primarily obtained from Papers With Code, Scinapse, and Semantic Scholar through web scraping and manual collection. First, we used web crawlers to collect algorithm model and paper information from Papers With Code, including model names, accuracy, parameter counts, paper titles, and publication years. Second, we supplemented author information (names, institutional affiliations, H-indices) on Scinapse based on collected paper titles, simultaneously obtaining author and institution counts. Third, we searched Semantic Scholar using paper titles to supplement citation data. Due to some papers being unretrievable or having incomplete information, certain author and institution details were obtained from original papers, and author H-indices were retrieved from both Scinapse and Semantic Scholar. In total, we collected information on 851 research teams, including team size, number of institutions, institution type, average member H-index, algorithm model accuracy, parameter count, paper title, publication year, and citation count.

Data were then imported into Stata for preprocessing. Since Papers With Code occasionally lacks parameter count data, entries with missing values were deleted. Additionally, we identified extreme values in citation counts that were uncommon. To generalize findings and ensure they wouldn't significantly impact results, we removed these outliers. After handling missing and anomalous values, we obtained 543 valid data entries for subsequent empirical analysis.

[Figure 1: see original paper] Data Acquisition and Preprocessing Flowchart

4.1 Establishment of Research Team Trait Measurement Indicators

Drawing on previous definitions of scientific teams, this study defines a research team as a group of two or more researchers collaborating to solve scientific problems and produce scientific papers. In our context, all authors of an algorithm innovation paper constitute a research team—specifically, an algorithm research team. Based on literature review and integration, combined with our research content and characteristics, we established three measurement indicators: research team size, number of institutions, and institution type.

(1) Research Team Size
Team member quantity affects team output. Disregarding internal collaboration atmosphere and communication effectiveness, larger teams can exert greater collective strength and potentially achieve better outcomes. Therefore, team size is a fundamental and essential measurement indicator. Our team size distribution is shown in and [Figure 2: see original paper]. The average size is approximately 6 members, ranging from 2 to 29. Overall, 83.4% of teams have 3–8 members, with 6-member teams being most common (103 teams). Teams exceeding 12 members are rare, indicating an optimal team size range and highlighting the importance of size control in scientific research.

Descriptive Statistics of Research Team Size
[Figure 2: see original paper] Histogram of Research Team Size Distribution

(2) Number of Research Team Institutions
In algorithm research, collaboration between internet companies, AI firms, and universities continues to strengthen, with teams exhibiting multi-institutional, cross-unit composition characteristics. Collaboration between institutions with different capabilities and backgrounds undoubtedly affects overall team research levels. Therefore, the number of institutions in a team is another focus. Our institution count distribution is shown in and [Figure 3: see original paper]. Teams with 2 institutions are most numerous (216), while over 30% have only 1 institution (no cross-institutional collaboration). Overall, aside from a few teams with 4+ institutions, the variation across teams is relatively small.

Descriptive Statistics of Number of Institutions
[Figure 3: see original paper] Distribution of Number of Institutions

(3) Research Team Institution Type
With increasing numbers of internet and AI companies capable of conducting scientific research and collaborating with universities, we classified teams by member institutional affiliation to examine performance differences. Classification criteria: If all members' primary affiliations are enterprises or enterprise-affiliated research institutes, the team is classified as enterprise-type; if all are universities, as university-type; if mixed, as hybrid-type. Our institution type distribution is shown in and [Figure 4: see original paper]. Enterprise-type, university-type, and hybrid-type teams account for 30%, 15%, and 55% respectively. Hybrid teams are most numerous, exceeding the sum of the other two types, reflecting the popular trend of university-enterprise collaboration. Among the remaining two, enterprise-type teams far outnumber university-type teams, demonstrating the strong competitiveness of AI companies.

Distribution of Research Team Institution Types
[Figure 4: see original paper] Distribution of Research Team Institution Types

4.2 Establishment of Algorithm Innovation Evaluation Indicators

(1) Algorithm Model Accuracy
As previously discussed, algorithm innovation evaluation indicators largely align with algorithm performance metrics. Each performance improvement or optimization constitutes innovation. Our selected models' performance metrics include Top1 Accuracy, Top5 Accuracy, and Number of Parameters. In image classification, models predict class probabilities and rank them. Top1 Accuracy refers to accuracy when the top-ranked class matches the actual result; Top5 Accuracy refers to accuracy when the actual result appears within the top five predictions. Number of Parameters indicates model complexity. Since Top1 Accuracy and Number of Parameters data are relatively complete, we selected Top1 Accuracy (hereinafter "accuracy," ACC) as an algorithm innovation evaluation indicator and Number of Parameters (hereinafter "parameter count," NOP) as a control variable.

shows our algorithm model accuracy distribution. The average accuracy is 81.9%, with a minimum of 61.5% and maximum of 91.1% [31]. Spanning 10 years, this demonstrates significant performance improvements. [Figure 5: see original paper] illustrates the upward accuracy trend from 2018–2022.

Descriptive Statistics of Algorithm Model Accuracy
[Figure 5: see original paper] Algorithm Model Accuracy Change Chart

(2) Algorithm Paper Citation Count
Citation count is a crucial bibliometric indicator measuring academic visibility and influence. Guided by normative theory, previous studies often use citation frequency as a proxy for innovation, with high citations being a basic characteristic of innovative outputs [32]. Algorithm model improvements are accompanied by academic paper production, with papers serving as effective dissemination vehicles. Higher citation counts indicate stronger paper influence and, by extension, greater algorithm innovation. Therefore, we selected paper citation count (Cited Quantity, CIT) to evaluate algorithm innovation from an academic output perspective.

shows our algorithm paper citation distribution. The average citation count is 137.2, with a maximum of 947—a relatively high level. However, due to varying publication years and algorithm performance, citation gaps between papers are substantial. Earlier papers generally accumulate more citations. [Figure 6: see original paper] shows the citation distribution, with most papers receiving fewer than 400 citations and some remaining uncited.

Descriptive Statistics of Algorithm Paper Citations
[Figure 6: see original paper] Distribution of Algorithm Paper Citations

4.3 Model Construction for Impact of Team Characteristics on Algorithm Innovation

(1) Model for Institution Type Impact on Algorithm Innovation
Since both algorithm accuracy and paper citations are non-normally distributed and institution type is a multi-categorical variable, we used the Kruskal-Wallis test [Figure 7: see original paper] to analyze relationships. Two models were constructed: Model 1 with institution type (TOI) as the independent variable and accuracy (ACC) as the dependent variable; Model 2 with institution type (TOI) as the independent variable and citation count (CIT) as the dependent variable.

The testing process involved: (1) Shapiro-Wilk tests and boxplots to examine normality; (2) Levene's test for homogeneity of variance; (3) Kruskal-Wallis tests when data were non-normal and variances were heterogeneous, followed by statistical inference based on results.

[Figure 7: see original paper] Schematic Diagram of Institution Type Impact Model

(2) Model for Team Size and Institution Count Impact on Algorithm Innovation
We constructed multiple linear regression models to examine team size and institution count impacts. Since we measured algorithm innovation from performance and academic output perspectives, we built two regression models: Model 3 (algorithm performance, dependent variable: accuracy) and Model 4 (academic output, dependent variable: citations), both including team size (TMS) and institution count (NOI) as independent variables.

To enhance explanatory power, we added control variables. Publication year (YEA) affects both algorithm performance and citation accumulation, so it was included in both models. For Model 3, parameter count (NOP, in millions) significantly affects model performance and was included as a control variable. For Model 4, average team member H-index (AHI) was included as a control variable due to its strong correlation with citations . Parameter count averaged 175.9M (1.759 billion), ranging from 1.2M to 120M. Average H-index averaged 22.6, ranging from 2.5 to 66.5.

Descriptive Statistics of Parameter Count and Average H-Index

We established the following regression models:

Model 3 (Algorithm Performance):
(4.1)

We used hierarchical regression for accurate analysis. Model M1 included control variable publication year (YEA) and dependent variable accuracy (ACC). M2 added parameter count (NOP). M3 added team size (TMS). M4 added institution count (NOI), where β represents regression coefficients and represents error terms.

Model 4 (Academic Output):
(4.2)

Model 4 also used hierarchical regression. M5 included control variable publication year (YEA) and dependent variable citations (CIT). M6, M7, and M8 sequentially added average H-index (AHI), team size (TMS), and institution count (NOI).

[Figure 8: see original paper] Schematic Diagram of Team Size and Institution Count Impact Model

5. Impact of Research Team Characteristics on Algorithm Innovation

Based on the two evaluation dimensions of algorithm innovation, we examined the impact of team characteristics on algorithm performance and paper citations. Data were imported into Stata, non-parametric tests and multiple linear regression commands were executed, and results were analyzed.

5.1 Impact of Institution Type on Algorithm Innovation

(1) Impact on Algorithm Performance
We classified teams into enterprise-type, university-type, and hybrid-type. According to Kruskal-Wallis test principles, we first examined data normality using Shapiro-Wilk tests.

shows normality test results for accuracy across three groups, with P-values of 0.00046, 0.00006, and 0.00000 (all <0.01). Combined with boxplots [Figure 9: see original paper], we confirmed non-normal distributions. Levene's test yielded $F=3.088$, $P=0.046<0.05$, indicating heterogeneous variances, permitting Kruskal-Wallis tests.

Normality Test Results for ACC
[Figure 9: see original paper] Boxplot of Accuracy

shows Kruskal-Wallis test results. With $P<0.01$, significant differences exist between groups, indicating institution type affects algorithm performance. Hybrid teams outperform others in accuracy, though the gap with enterprise-type teams is small. University-type teams show the lowest accuracy, approximately 3 percentage points lower than the other two types, reflecting weaker competitiveness and potential bottlenecks in university algorithm research. Enterprise members appear to promote accuracy improvements.

Kruskal-Wallis Test Results for ACC

(2) Impact on Academic Output
Similarly, we examined citation normality using Shapiro-Wilk tests . All three groups showed P-values <0.01, with non-normal distributions confirmed by boxplots [Figure 10: see original paper]. Levene's test yielded $F=5.327$, $P=0.005<0.01$, indicating heterogeneous variances, permitting Kruskal-Wallis tests.

Normality Test Results for CIT
[Figure 10: see original paper] Boxplot of Citations

shows Kruskal-Wallis test results. With P<0.01, significant differences exist between groups, indicating institution type also affects citation counts. Enterprise-type teams outperform others in citations, contrary to our expectations. However, university-type teams again show the lowest citations, far below the sample average. Overall, hybrid and enterprise-type teams outperform university-type teams in both accuracy and citations, highlighting the need for university algorithm research teams to enhance competitiveness.

Kruskal-Wallis Test Results for CIT

5.2 Impact of Team Size and Institution Count on Algorithm Innovation

We continued examining team size and institution count impacts using multiple linear regression.

(1) Impact on Algorithm Performance
shows regression results with accuracy as the dependent variable. Model M4 indicates team size positively correlates with accuracy (β=0.003, P<0.01), while institution count negatively correlates (β=-0.005, P<0.01). The absolute value of the institution count coefficient exceeds that of team size, indicating a stronger impact. Control variables (publication year, parameter count) are also significant at the 1% level.

Model diagnostics show F-values for M1-M4 are significant at P<0.01, confirming linear relationships. R^2 increases with added variables, reaching 0.293 in M4, indicating that 29.3% of accuracy variance is explained. Variance inflation factors (1.18, 1.10, 1.08, 1.02) are all below 10, indicating no multicollinearity and reliable results.

Multiple Regression Results with ACC as Dependent Variable

(2) Impact on Academic Output
Since citation counts don't follow a standard normal distribution [33], we transformed them using log(CIT+1) before regression, following Thelwall's recommendation [34].

shows regression results with log(CIT+1) as the dependent variable. Model M8 indicates team size positively correlates with citations (β=0.027, P<0.05), and institution count also positively correlates (β=0.055, P<0.10). Institution count shows a stronger impact than team size. Control variables (publication year, average H-index) are significant at the 1% level, with year showing a negative coefficient (as expected) and H-index showing a positive coefficient.

F-values for M5-M8 are significant at P<0.01. R^2 increases substantially with average H-index addition, reaching 0.340 in M8, indicating that 34% of citation variance is explained. Variance inflation factors (1.11, 1.11, 1.05, 1.04) are all below 10, indicating no multicollinearity.

Multiple Regression Results with log(CIT+1) as Dependent Variable

5.3 Results Analysis and Discussion

(1) Institution type significantly affects algorithm innovation. Hybrid teams achieve optimal algorithm performance, while enterprise-type teams achieve optimal citations. Regarding algorithm performance, hybrid teams' superiority aligns with Martínez-Plumed et al.'s [35] finding that "hybrid" groups dominate state-of-the-art model domains. Hybrid teams possess high-quality algorithm researchers from both universities and enterprises. Since algorithm performance improvement is enterprises' essential goal, they continuously recruit capable researchers who may focus more intensively on algorithm research than university researchers. Additionally, hybrid teams have access to necessary hardware and resources—enterprise members bring funding and equipment that support competitive research outcomes. However, university-enterprise collaboration faces challenges including process complexity, goal alignment, and technical feasibility, making control and management crucial for project success [36].

Regarding academic output, enterprise-type teams' citation advantage was unexpected. This may occur because: (1) Most enterprises in our sample are large internet companies with long research histories that accumulate more citations, while hybrid teams' superior but newer models haven't had sufficient time to accumulate citations; (2) Enterprise-type teams are generally larger, and internal cross-citation may boost citation counts.

(2) Team size positively correlates with algorithm performance, while institution count negatively correlates.
The positive team size-performance correlation aligns with expectations. Algorithm performance improvement requires multi-domain knowledge and skills; increased team size meets these knowledge demands and enhances problem-solving capacity for complex research tasks [37]. Additionally, algorithm research demands high innovation, and larger teams can contribute more to innovation.

The negative institution count-performance correlation resembles Cummings et al.'s [38] findings. Unlike team size, increased institution count means stronger member heterogeneity, lower background fusion, reduced group identity, and higher communication costs. Especially in large teams, while increased institution count may form hybrid teams, the negative effects eventually outweigh hybrid team benefits, reducing overall output. Moreover, excessive institution counts may create remote teams, and Lin et al. [39] found that remote teams are less likely to integrate existing knowledge to generate breakthrough ideas, which is detrimental to algorithm research.

(3) Both team size and institution count positively correlate with academic output.

The positive team size-citation correlation aligns with Zhang Lingling et al.'s [40] findings. Similar to the performance mechanism, increased team size enhances overall productivity and creates more academically influential work with higher citations, potentially benefiting from internal cross-citation.

The positive institution count-citation correlation contrasts with its negative performance impact. Increased institution count may broaden dissemination channels and expand research impact, making papers discoverable by researchers across fields and institutions, increasing citation likelihood. Besides internal self-citation, inter-institutional citation among team members' affiliations may also contribute. Larivière et al. [41] confirmed that the number of addresses in author bylines helps increase article citations.

6. Conclusions and Implications

This study employed non-parametric tests and multiple linear regression to establish impact models of research team characteristics on algorithm innovation, analyzing the effects of team size, institution count, and institution type. Results show that institution type significantly affects algorithm innovation, with hybrid teams achieving optimal accuracy and enterprise-type teams achieving optimal citations. Algorithm performance is influenced by team size (positively) and institution count (negatively), along with parameter count and publication year. Academic output is influenced by team size and institution count (both positively), along with average H-index and publication year.

Based on these findings, we propose: (1) Encourage cross-institutional research without blind promotion. Hybrid teams promote algorithm innovation through complementary strengths and resource sharing, but enterprise-type teams also show citation advantages, indicating that cross-institutional collaboration isn't always optimal. Respect single-institution teams' autonomous research while encouraging cross-institutional collaboration. (2) Optimize team structure and strengthen collaboration. Since team size positively affects algorithm innovation, appropriately expand team size when forming teams, but establish thresholds to prevent excessive complexity that hinders communication. In increasingly diverse teams, strengthen member communication, enhance identity and belonging, and foster long-term sustainable collaboration. (3) Improve technical skills and emphasize innovative thinking. Algorithm innovation depends heavily on members' technical levels, so conduct training and exchanges to enhance skills. Teams should also monitor latest research developments, update knowledge reserves, maintain technology leadership, and encourage members to try new ideas and methods.

This study has limitations. First, our team characteristic measurement and algorithm innovation evaluation indicators are not sufficiently comprehensive. Second, our sample comprises algorithm research teams and papers in machine learning image classification, potentially limiting generalizability. Future research could incorporate more indicators, such as dynamic measures of team fluidity and stability, and innovation diffusion-based evaluation metrics. Additionally, comparative studies across multiple domains could analyze outstanding teams' composition patterns, operational mechanisms, and collaboration models to provide new insights for scientific collaboration and improve team output levels.

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Author Contributions

Jingwen Tian: Conceptualized the framework, processed data, and wrote the initial draft; Xinping Yin: Revised and finalized the manuscript; Yujia Zhai: Conceived the research topic, proposed the research design, and revised and finalized the manuscript.

Note: Figure translations are in progress. See original paper for figures.