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RESEARCH ARTICLE

Close-knit teams foster complex research: A case study of Physics

Yuxia Chu, Hongyi Zhu, Yujia Zhai*

Management School, Tianjin Normal University, Tianjin, China

ABSTRACT

This study explores the association between team familiarity and research topic complexity within a framework of teamwork and complex system science. We introduce a novel' individual connectedness' metric to gauge team familiarity. Research topics are extracted via BERTopic, creating a topic matrix that determines research complexity. Through ANOVA and quantile regression, we analyze the association between team familiarity and research topic complexity across different team sizes. Key findings include the pivotal role of the third author in collaborations and the observation that team familiarity tends to increase over time. This growth is more pronounced in larger teams than in smaller ones. Moreover, larger team sizes correlate with heightened topic complexity. A notable trend is the positive relationship between team familiarity and topic complexity. Different complexity quartiles exhibit diverse rates of familiarity growth, with more complex topics linked to rapid familiarity increases. To optimize teamwork, managing team growth, enhancing member capabilities, and strategically boosting topic complexity are crucial.

KEYWORDS

Team collaboration; Individual connectedness; Team size; Team familiarity; Topic complexity

1 Introduction

When basic disciplines are relatively mature, making breakthrough progress through isolated research becomes challenging (Zeng et al., 2022). Research collaboration involves scientific researchers engaging in activities through resource contribution and teamwork. The trend towards team-based research has become prominent, as it combines knowledge from different disciplines, leading to deeper insights and valuable research outcomes. An increasing number of research achievements owe their success to the efforts of research teams, which has sparked discussions in the academic community about the mechanisms behind the composition of research teams.

Workload distribution among team members directly influences team performance and productivity. Team size studies show that larger teams often focus on developing existing technologies, while smaller teams have a more crucial role in pioneering scientific frontiers (Hamel, 2006). Moreover, research from more novel teams tends to be more original and impactful (Zeng et al., 2021). However, challenges such as team member diversity, knowledge gaps, interest

Corresponding author: zhaiyujiachn@gmail.com

distribution, and team management can hinder research progress (Cooper et al., 2021; van der Vegt et al., 2010). Successful collaboration demands sustained effort, and close-knit team relationships foster continuity and productivity. As a result, people tend to prefer working with fixed team members.

Adding new members can disturb set team structures, but also offer fresh ideas, viewpoints, and problem-solving strategies, giving the team more flexibility in handling diverse situations. Balancing these aspects is key to enhancing team collaboration efficiency (Liu et al., 2022).

Research collaboration is a vital means to drive research innovation. The development of team-based and diverse research approaches has brought infinite possibilities for research innovation, but it also faces challenges (Ebadi & Utterback, 1984). In-depth study of the formation and operation mechanisms of research teams, as well as strengthening cooperation and communication between teams, can enhance the innovative capabilities and research level of research teams, promoting technological progress and social development. Scholars have conducted extensive research on teams, covering team member behaviors, team performance, and more. Over time, the research scope has gradually expanded to encompass larger environmental levels, such as organizational, regional, and national environments.

This study examines the effect of team familiarity on research topic complexity (TC) across different team sizes. We introduce two indicators: individual connectedness (IC), measuring the mix of new and old team members, and team familiarity. We use the TF-IDF algorithm to extract keywords, creating a keyword matrix, which is then transformed into a research TC index using information entropy. We shift from focusing on isolated, static metrics such as literature, authors, and keywords to a dynamic approach, examining research teams and individuals. Using physics literature, we investigate the association between team familiarity and research TC. By understanding this impact, we can offer insights for building research teams, and helping researchers enhance their team's capabilities and competitiveness, which is crucial for the sustainable, healthy development of research teams.

2 Related researches

2.1 Collaboration familiarity on team performance

Scientific collaboration networks can be classified into author, institution, interdisciplinary, and regional networks. High-achieving scientists are the most active group in scientific collaborations. Individually, authors exhibit characteristics of clustered collaboration networks (Liu et al., 2022; Pao, 1992), demonstrating small-world properties (Girvan & Newman, 2001; Telesford et al., 2011) and hierarchical structures (Abbasi et al., 2012). In institutional collaboration networks, scientists are associated with various entities such as universities, research institutions, and government agencies. Numerous studies have found that research institutions play a significant role in institutional collaboration networks, with top-tier universities playing a particularly crucial role in scientific collaborations, both domestically and internationally.

Team familiarity is commonly defined as the degree of knowledge among team members about each other (Akşin et al., 2021; Hackman, 2011), the extent of their collaboration (Huckman et al., 2009; Zhao et al., 2022), and the level of shared experience in the collaboration (Sieweke & Zhao, 2015a). It reflects the quality of team relationships (Gully et al., 1995), the cohesion among members (Forsyth, 2021; Marlow et al., 2018), and the quality of communication within the team (Rico et al., 2008; Shan et al., 2021). Team familiarity differs from "team tenure" which quantifies the time that team members have worked together within a team (Gonzalez-Mulé et al., 2020). It also differs from "perceived closeness”

(Costa et al., 2021; Wilson et al., 2008), which mainly encompasses interactions, shared experiences, or shared knowledge defined by an individual.

The team cognition approach explains the importance of team member familiarity for performance (Akşin et al., 2021; Marques-Quinteiro et al., 2013). The impact of familiarity on team performance can be understood in two ways. Firstly, in high-intensity environments, team members can predict each other's needs and mutual predictions can occur (Salas et al., 2005). This is possible through shared mental models, which develop with increased familiarity (Mathieu et al., 2009; Orasanu, 2022). Secondly, the cognitive emergence in the transactional memory system (TMS) underlies the influence of team familiarity on team performance (Wegner, 1987). TMS is a shared system for encoding, storing, and retrieving information from different knowledge domains. In established teams with mutual obligations (Van Knippenberg & van Ginkel, 2022) based on knowledge distribution, team members share responsibility for processing information from various domains and contribute to the team's work. High levels of familiarity help team members understand each other's expertise, strengths, weaknesses, backgrounds, personalities, and habits, boosting team efficiency and encouraging work and social interactions (Espinosa et al., 2007; Zeng et al., 2022). Team familiarity also influences team innovation. Innovation is increasingly crucial for the survival and competitive advantage of contemporary organizations (Akgün et al., 2005; West & Sacramento, 2023). As team collaboration becomes a key practice for enhancing organizational innovation (Hülsheger et al., 2009), managers are constantly seeking the best approaches to improve team innovation (Alblooshi et al., 2021; Gebert et al., 2010). However, they often encounter dilemmas in practice. For example, many organizations are interested in having experts from different functional departments work together on innovation tasks in the short term. Still, these teams may suffer from process and coordination issues. Other organizations rely on intact teams to achieve their innovation goals (Edmondson & Nembhard, 2009), but these teams may sometimes be hindered by a lack of novel ideas (Katz, 1982).

Team familiarity facilitates the integration of different knowledge within a team (Harrison et al., 2003; Muskat et al., 2022), the development of shared understanding (Taylor & Greve, 2006), and the coordination of team collaboration (Choi et al., 2021; Savelsbergh et al., 2015), enabling the team to transform different ideas into new products or solutions (Lynn & Akgun, 2002). However, team familiarity can also weaken communication (Akşin et al., 2021; Katz, 2015) and limit constructive debates within the team (Sieweke & Zhao, 2015b; Slotegraaf & Atuahene-Gima, 2011), thereby hindering the generation of new ideas (Nemeth & Ormiston, 2007; Xie et al., 2020) and innovative solutions (Argote & Guo, 2016). Specifically, highly familiar teams are more likely to rely on existing practices and conventions, which may interfere with their engagement in innovative and creative team collaboration processes (Nunn et al., 2019). In general, moderate team familiarity is required to maintain a balance between idea generation and implementation. Discussions on the potential negative outcomes of team familiarity and the effectiveness of team familiarity in unconventional tasks, innovation, and creative work are limited.

2.2 Complexity theory on team performance

The definition of complexity has not reached a conclusive consensus (Davis et al., 2000), but it is generally understood as an indicator reflecting the interests of authors (Cilliers, 2004). Cilliers described complexity theory as "characteristics of a system" (Sturmberg & Martin, 2013). Complexity theory emphasizes the role of interactions among system components in studying the system. The interaction between individuals within the system leads to the complexity of the system. Specifically, the interactions among system components lead to the overall behavior of the system. Primarily, this is attributed to the fact that the interactions among individuals are inherently uncontrollable and emerge from individuals adhering to simple rules, which subsequently manifest in the overarching complexity of the system. Furthermore, the system's openness facilitates fluctuations in information and personnel, stemming from the interplay between individuals and their external environment, thereby influencing the dynamics of individual interactions (Hatcher et al., 1989). As a result, new system behaviors are often unpredictable and challenging to trace back to specific reasons.

Work complexity is positively correlated with individual creativity (Joshi et al., 2009a; Shalley et al., 2004). However, existing research has only examined the impact of high-complexity work on individuals and has not extended the investigation to teams.

Team activities are context-dependent and task-specific (Choi, 2002), where task specificity refers to the series of external stakeholders directly involved in the team's task execution. In complex task contexts, collaboration relationships affect team understanding and the performance criteria for task execution but have minimal impact on the performance of simple work (Marrone et al., 2007). Tasks with lower complexity (e.g., simple and repetitive development tasks) have greater generality and structure, allowing for management through standardized operational procedures. On the other hand, complex work often relies on team members' creative thinking to complete tasks. In more complex task contexts, teams gain more knowledge and ideas through collaborative efforts, thereby enhancing team innovation performance (Joshi et al., 2009b). The complexity and uncertainty of research motivate teams to acquire specialized knowledge and information from specific external knowledge owners, including technical knowledge related to research and general information such as trends, opportunities, and threats (Wu et al., 2019). Facing technical challenges, teams often consult external partners like research institutions for joint solutions, applying their solutions and experiences to industry problems to boost research and development efficiency.

To date, various factors such as team size (Klug & Bagrow, 2014), workload (Hsiehchen et al., 2015), the number of participating countries (Gazni et al., 2012), cross-institution (Noorden, 2015), and interdisciplinary collaboration (Guimerà et al., 2005) have been found to significantly impact the outcomes of team collaboration. However, the role of team familiarity in driving scientific development has received limited attention. In team formation models, the mechanism for team assembly determines the structure of collaboration networks and team performance, and this trend varies across different journal papers (Verssimo et al., 2021). Additionally, scientists with relatively lower qualifications in their careers can be considered to have reduced team familiarity. Scientists typically peak in performance in mid-career, and over the past century, the average age at the peak has increased significantly by 24-26 years (Lee et al., 2017). However, most of these studies have focused on individual scientists' careers, and the relationship between team familiarity in research teams and their performance in advancing science remains unclear.

The research complexity of interdisciplinary teams tends to be high. As scientists progress in academic age and tenure, they engage in more intricate investigations. However, scientists do not arbitrarily establish their research combinations. Venturing into a new research domain requires a significant amount of knowledge, and the evolution of scientists' research combinations often follows a path-dependent trajectory, closely tied to the knowledge they acquire or master through collaboration (Tripodi et al., 2020; Zeng et al., 2019). Concurrently, the proportion of interdisciplinary collaboration is increasing. Scientific research teams are becoming increasingly interdisciplinary, with interdisciplinary teams often having more members and adopting greater division of labor (Haeussler & Sauermann, 2020). There is an association between research complexity and team size. Universities with greater diversity in their research portfolios have a competitive advantage in complex disciplines (Robbins et al., 2014). Janavi et al. constructed national domain networks using SCI citation data, grouped by subject areas, to study a country's complexity and identify the most valuable and feasible untapped domains (Janavi et al., 2020). Although some researchers have started using complexity measures for scientific data experimentation, there is still a lack of complexity measurement in research content. Currently, no research has discussed and analyzed the relationship between team familiarity and TC.

Based on the above issues, this study addresses the following research questions: (1) How to quantify IC and team familiarity? (2) How to quantify TC based on research topics of scientific teams? (3) What is the relationship between team familiarity and TC for teams of different sizes?

3 Methodology

3.1 IC

The concept of "team" was first introduced by Robbins in 1994, who defining a team as a formal group composed of individuals who collaborate to achieve a specific goal (Chen et al., 2013). Scientific research teams are one type of team that specifies the requirements for personnel configuration. In practical research, due to various concerns such as time constraints, many researchers choose to define research groups using social network analysis from the output perspective, considering the authors of a paper as a scientific research team. The co-authorship of papers can effectively represent the collaborative research behavior among researchers within the team (Hongshen et al., 2011), and the frequency of co-authorship reflects the level of collaboration familiarity among researchers.

In this study, a scientific research team is defined as a research group composed of two or more researchers who share common research goals, jointly undertake specific research tasks, and share certain resources. The team exhibits close and stable cooperative relationships (Wiersema & Bantel, 1992), and it may be affiliated with a specific organizational or non-organizational entity. To investigate the role of individual researchers within the scientific research team, this study proposes the indicator of "IC". Taking Paper0 as an example, the cooperative relationship was illustrated in Figure 1.

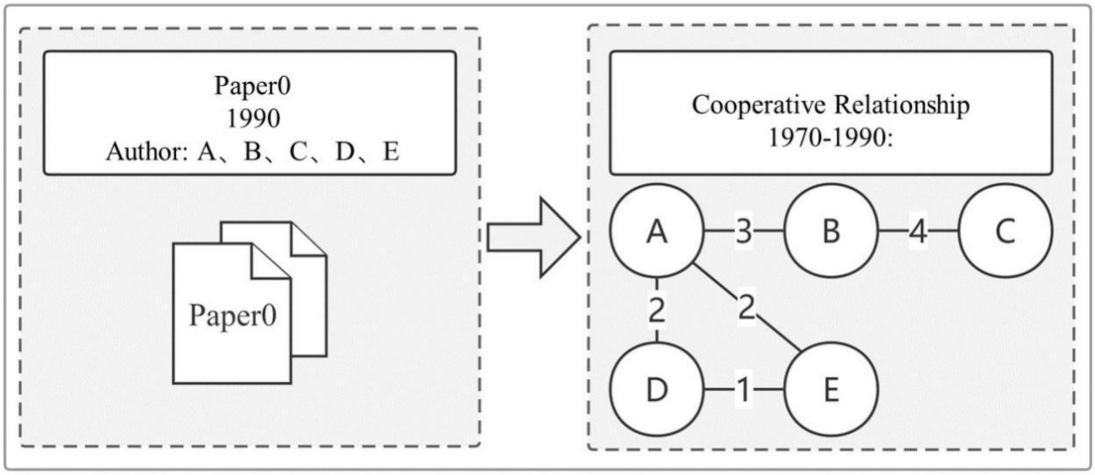

Figure 1 Cooperative relationship in "Paper0"

In "Paper0," the solid lines represent the co-authorship relationships between authors within the past 20 years before co-authoring this specific paper. Let's take author A as an example: Before co-authoring "Paper0" with the team, author A had collaborated with author B three times, with author D two times, and with author E two times. The total number of collaborations among team members was 12. Since the co-authorship relationship is bidirectional, the contribution of author A to the total collaboration within the team is calculated as 7/(12 * 2). This value is defined as the *IC* of author A.

$$IC = \begin{cases} 0 \\ \frac{C_i}{C_{all}\times 2}(\mathrm{C} \neq 0) \end{cases} \tag{1}$$

Where "i"represents any individual author. C_i represents the number of collaboration relationships between author i and other authors. C_{all} represents the total number of collaboration relationships. IC can take on the following values depending on the specific situation within a three-person team: (1) New team: All members have IC values of 0; (2) Addition of new member(s): One member has IC value of 0; (3) Continuing collaboration of an established team: All members have IC values that are not 0.

3.2 Team familiarity

There are various scenarios of collaboration within teams, and team familiarity cannot be simply attributed to the total number of collaborations among team members. For instance, collaborations concentrated among a few individuals versus those spread across a majority, merely comparing the total number of collaborations between two team members is insufficient to determine the level of team familiarity. The entropy value $H(x)$ represents the degree of disorder in the system (formula 2), where p_{x_i} denotes the probability of the random event x_i occurring.

$$H(x) = -\sum_{i=1}^{n} P_{x_i} \log p_{x_i} \tag{2}$$

If we consider a team's collaboration as a universal set of events, with collaborations between different members as random events, and IC as the probability of member collaboration occurring, then according to information entropy, by taking the reciprocal of the formula, we can derive an equation representing the stability of the team collaboration event. The numerical value IC, symbolizing the stability of member collaboration, is viewed as the probability of member collaboration and inserted into the formula. This represents the entropy value of team member collaboration, namely, team familiarity H_f. Additionally, team familiarity is related to both the number of collaborations within the team and the number of team members. In cases where two teams have the same total number of collaborations, a smaller number of members implies more collaborations per member, and teams with a higher frequency of member collaborations have a higher degree of familiarity. Therefore, the formula introduces the variable of the average total number of internal collaborations within the team, denoted as μ. To avoid a zero denominator in the case of IC being zero in a completely new team, 1 is added to the denominator. Consequently, the formula for team familiarity is proposed (formula 3). The higher the value of H_f, the higher the familiarity among team members.

$$H_f = \frac{\mu}{1-\sum_{x=1}^{n} IC_{xy} \log IC_{xy}} \tag{3}$$

IC_{xy} represents the IC of the y-th person in team x; μ denotes the average total number of collaborations within the team. For instance, consider team a as a 3-person team with a total of 12 collaborations. The IC of the three people in team a are 1/2, 1/2, and 0, respectively. The team familiarity is represented as follows: $\frac{4}{1-\left(\frac{1}{2}\times\log\frac{1}{2}+\frac{1}{2}\times\log\frac{1}{2}+0\right)}$.

3.3 TC

In this study, the calculated TC is based on the weight of the text within various topics. By employing topic modeling, the study delves into the deeper meanings and contextual relationships in language, extracting key information from article abstracts and converting this information into numerical values. Each text is associated with a probability corresponding to each topic. TC measures the diversity of topics in the text. BERTopic, based on bidirectional encoder representations from transformers (BERT), offers a more flexible and dynamic representation of topics compared to traditional topic models, such as latent dirichlet allocation. By understanding the different meanings of words in various contexts, BERTopic provides a deeper and more accurate analysis of texts, which is crucial for comprehending complex texts and discerning subtle differences between topics. Additionally, its efficient topic modeling technique rapidly identifies and extracts main topics from a large body of text, making it well-suited for processing extensive document collections. The process is as follows:

First, BERTopic is used to represent each document as an embedding vector in a high-dimensional vector space. When conducting text clustering analysis, each document is assigned to specific topics. Specifically, the model initially generates multiple distinct topics, representing the main concepts and ideas within the document collection. Subsequently, for each document, BERTopic calculates the probability of its association with these topics. This means that each document is not solely related to a single topic but is associated to some degree with every topic. This association is expressed probabilistically, reflecting the document's relevance to each topic. For instance, if a document has a high probability of association with a particular topic, it suggests that the document extensively discusses that topic. Conversely, a low probability of association indicates a weaker relevance to that topic. This probabilistic approach allows for a more nuanced and dynamic understanding of the document's content, reflecting the diversity and complexity of the document across various topics. These embedding vectors capture the semantic information of the documents. Next, to reduce the dimensionality of the embedding vectors and decrease computational complexity, dimensionality reduction techniques are employed to map the high-dimensional embedding vectors into a lower-dimensional space, reducing noise and redundancy while preserving relationships among topics.

In the reduced vector space, clustering algorithms are applied to group documents into clusters. Based on the clustering results, the importance of each cluster (topic score) is computed to extract topics. The topic score depends on the number of documents in the cluster and the distribution of documents within the cluster. To gain a better understanding of the topics, BERTopic employs a TF-IDF transformation to calculate the TF-IDF weights of the topics. This helps identify the most representative keywords and phrases within each topic.

Next, ten topics are formed. Subsequently, the weights of each article on these ten topics are computed (see Appendix Table 1). Finally, the ten weights calculated for each article abstract are inserted into the formula (2) of information entropy. Information entropy is used to measure the complexity of probability distributions, and likewise, this newly derived function is utilized to assess the quality or diversity of the document-topic matrix. In this study, it is defined as *TC*, and its formula is as follows:

$$TC = -\sum_{i=1}^{n} w_i \log w_i \tag{4}$$

Where w_i represents the weight of the topic i. In this study, it is believed that the larger the proportionate weight of extracted topics, the greater the influence of the involved fields, disciplines, and other factors, indicating higher TC.

4 Empirical research

4.1 Data processing

We chose the APS database for research analysis due to its extensive and comprehensive dataset, convenient data collection, concise analytical capabilities and each researcher has a unique ID.

Firstly, to reflect the impact of research in different periods, the time range was set from Jan. 2000 to Sep. 2010. Secondly, considering the focus on research teams and the issue of data volume, the size of research teams was limited to 3-9 members. Ultimately, a total of 169,443 articles met the selection criteria, involving 98,992 teams. After excluding non-English data and entries lacking time information or abstracts, a total of 85,934 valid data sets were obtained. As shown in Figure 2, although the number of research teams fluctuated each year, there was a clear overall upward trend.

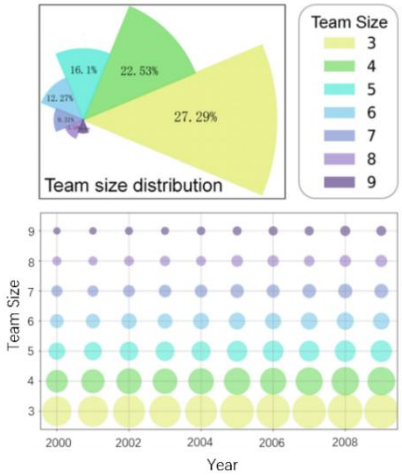

Figure 2 Distribution of team size

4.2 Distribution of IC

Firstly, in this study, we calculated the IC for each person within the research teams and grouped them based on team size and author order. As shown in Figure 3, the IC of authors not only decreases with the increasing of team size but also becomes more concentrated, especially for the first and second authors. It is worth noting that the IC of all team members increases with the authorship order, reaching its peak at the third author with a fixed vale of 0.2, and then steadily decreases, following a normal distribution trend (Appendix Table 2). This indicates that the third author may play a crucial role in facilitating the formation of research teams. Typically, the authorship order is believed to represent the authors' contribution to the academic paper, with the first author often being the primary contributor (Maciejovsky et al., 2009; Marušić et al., 2011). However, this study reveals that the IC of the first author is relatively lower compared with authors with other authorship orders, suggesting that the first author is a newcomer to the research team compared with other team members.

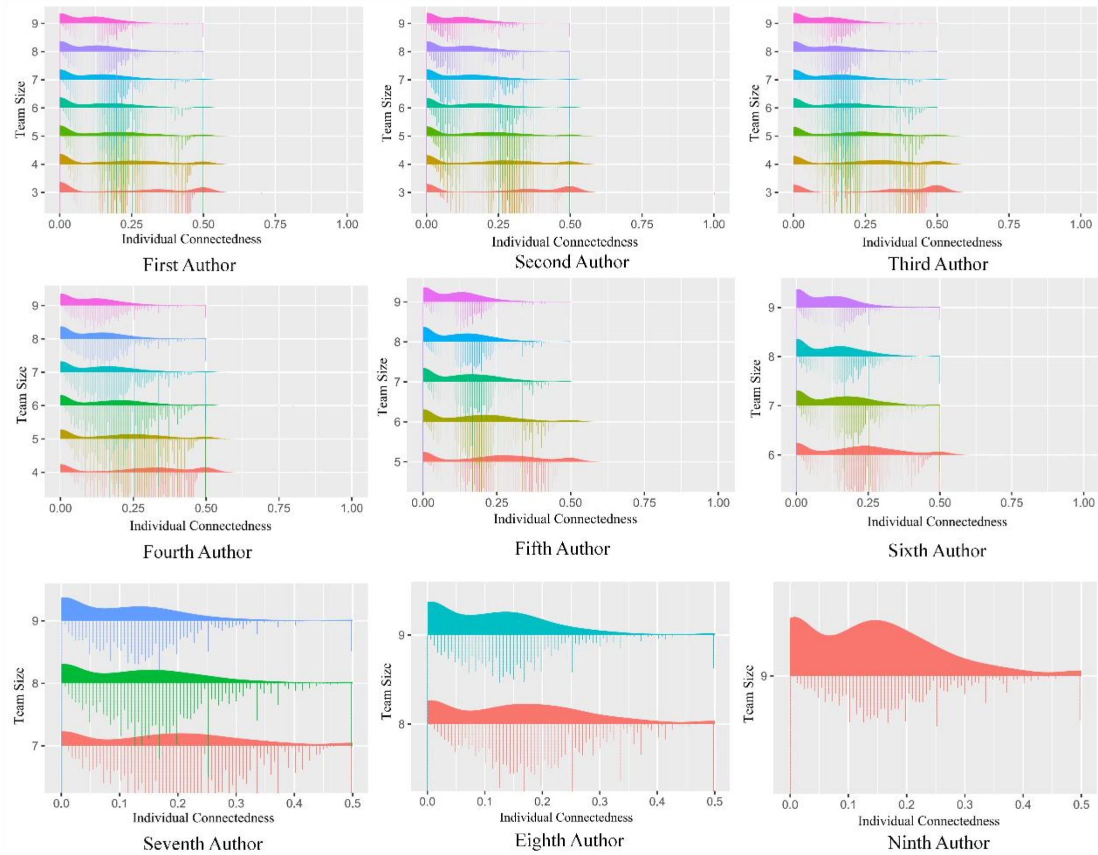

Figure 3 Individual connectedness raincloud plot

Scientific research is not a solitary endeavor, especially for significant research projects or studies in the biomedical field, which often require larger research teams. Leading a team and guiding its research direction are also crucial aspects, and effective team leaders need to possess both academic authority and prestige, as well as strong management skills. Team members make progress through collaboration and division of labor, achieving common learning goals. In this study, we consider the first author as the actual executor of the research paper and typically a newcomer to the academic field, while the role of the third author within the team is that of the team leader. For the development of young researchers, such as graduate students and young faculty, academic output is essential, which is why the first author is often a newcomer to the research team. Despite not being listed as the first author, the team leader plays an irreplaceable role in driving the team and the overall research forward.

4.3 Team familiarity distribution

According to the IC, we calculated the team familiarity ($\boldsymbol{H_f}$) and performed descriptive statistics (Table 1 and Appendix Table 3). For $\boldsymbol{H_f}$, as the team size increases, the number of cases gradually decreases, and the mean and standard deviation increase. The standard error also increases, indicating that the variability among individuals within the group increases with the group size. The values of $\boldsymbol{H_f}$ show a wide range, indicating a right-skewed distribution (skewness > 0) with a peak (kurtosis > 0). The 95% confidence interval of the mean widens with the increase in group size. This means that the confidence interval is more likely to include the true population mean as the group size increases.

Table 1 The descriptive statistics for H_f

Number	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis
89,534	0	6.053	0.620,79	0.631,262	1.599	3.635

From Figure 4, it can be observed that the maximum value of team familiarity increases with the team size. Smaller teams are more likely to have lower team familiarity, while the distribution of team familiarity in larger teams is more dispersed. This observation aligns with our understanding, as smaller teams are more likely to have members who are collaborating for the first time or have fewer previous collaborations. On the other hand, larger teams tend to be built around a few core scientists, and the members are less likely to have very low familiarity, as it could pose challenges in managing a large team.

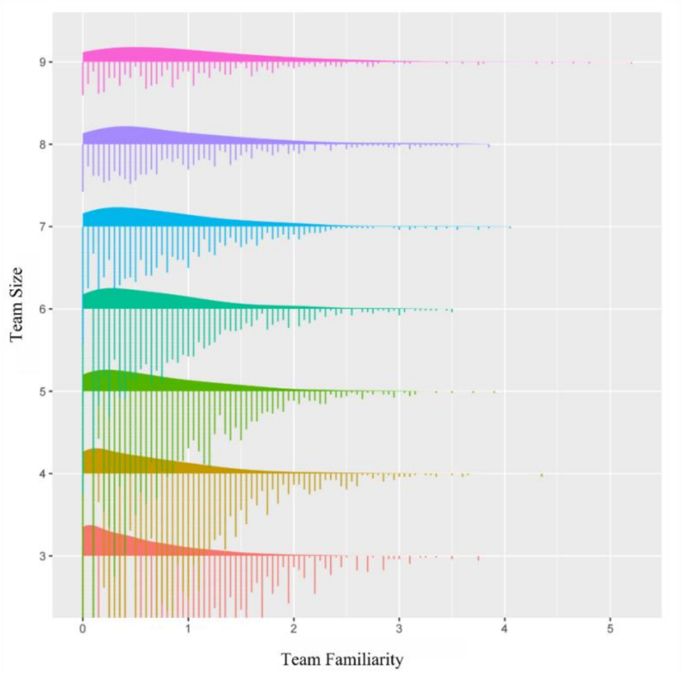

Figure 4 Team familiarity raincloud plot

In order to observe the dynamic changes in team familiarity over the past ten years, this study calculated the mean team familiarity for all teams each year. Additionally, the mean team familiarity was compared based on the categorization of team size to explore any differences. As shown in Figure 5, the dashed line represents the annual changes in team familiarity for all teams. Overall, team familiarity increases over time. The six-member teams show a specific trend that closely aligns with the overall trend. In terms of fluctuation amplitude, the nine-member teams exhibit the largest fluctuations. In terms of numerical values, the team familiarity of three-member teams and four-member teams starts at a lower value and remains consistently lower than that of medium to large-sized teams. In terms of time characteristics, since 2008, the team familiarity of three-member teams, four-member teams, five-member team, and nine-member teams has experienced a decline, while the overall team familiarity has shown a slowing growth trend since 2005.

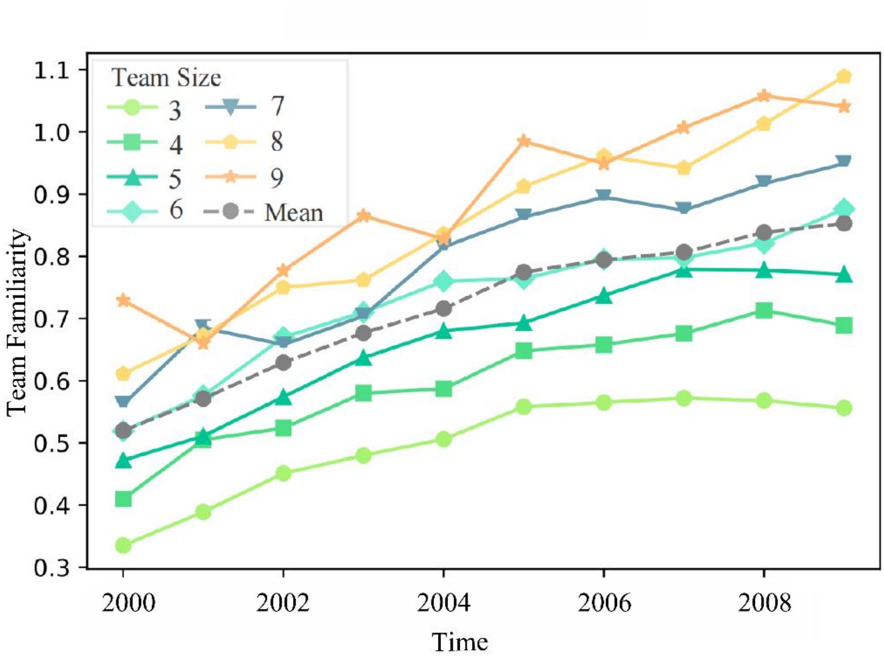

Figure 5 Team familiarity time plot

4.4 TC distribution

Next, we calculate the probabilities of each article on the topics, and obtained the research TC of each team and conducted a descriptive statistical analysis (Table 2). The overall distribution of TC showed a right-skewed (skewness > 0) and peaked (kurtosis > 0) trend, but the values were relatively small. For different team sizes, the number of cases gradually decreased with an increase in the number of members, and the mean gradually decreased. The standard deviation and standard error increased with an increase in team size. The 95% confidence interval of the mean widened with an increase in team size. The minimum and maximum values gradually decreased with an increase in team size(Appendix Table 4).

Table 2 Descriptive statistics of topic complexity

Number	Minimum	Maximum	Mean	Standard Deviation	Variance	Skewness	Kurtosis
85,934	0	0.76	0.253,1	0.086,84	0.008	1.037	1.817

5 Feature analysis

Through the aforementioned study, we observed that team size exerts a certain influence on both team familiarity and research complexity. Next we employ the methods of analysis of variance (ANOVA) and quantile regression analysis to estimate the association between team familiarity and research complexity. ANOVA is utilized to explore whether significant differences exist in the mean values among different groups. And we also employs quantile regression analysis, incorporating team size as a control variable to mitigate potential biases and uncover varying patterns of association that team familiarity ($\boldsymbol{H_f}$) might exhibit at different levels of TC. Due to the non-normal distribution of the samples, we log-transformed the data prior to analysis.

5.1 ANOVA for team familiarity and team size

According to ANOVA results, for the factor $\boldsymbol{H_f}$, the between-groups mean square is much larger than the within-groups mean square, resulting in a large *F* statistic and a very small p-value (less than 0.05), which indicates that there is a significant difference in means among the different $\boldsymbol{H_f}$ groups (Table 3). Honestly significant difference was further used for post-hoc comparison to determine whether there are significant differences among the means of multiple groups. The post-hoc comparison results show that there is a significant difference in the values of team familiarity across different team sizes (Appendix Table 5).

Table 3 ANOVA for team familiarity among different team size

Team familiarity	Sum of Squares	Degrees of Freedom	Mean Square	*F*	Significance
Between groups	6,729.858	6	1,121.643	2,689.849	0
Within groups	163,637.7	392,425	0.417		
Total	170,367.6	392,431			

Figure 6 shows the average $\boldsymbol{H_f}$ values for teams of different sizes. Team familiarity increases with the growth of team size. One threat that impedes team development is the differences among team members. Different members coming from various organizations may have distinct working methods and styles that are entrenched and difficult to bridge in the short term. Wiersema & Bantel (1992) found that heterogeneity can lead to higher team conflicts and lower levels of interactive communication, triggering self-defensive awareness and behavior among team members. Additionally, as the team size increases, the opportunities and possibilities for interaction between team members decrease, making it challenging to build cohesion. Compared with smaller teams, larger teams have more complex structures and a greater number of members. If not intervened or guided properly, conflicts and mutual distrust can easily arise within large teams. Therefore, larger teams often prefer selecting members with whom they have previously cooperated, potentially to reduce risks that could impact team collaboration, so team familiarity in larger team usually higher than that in smaller team.

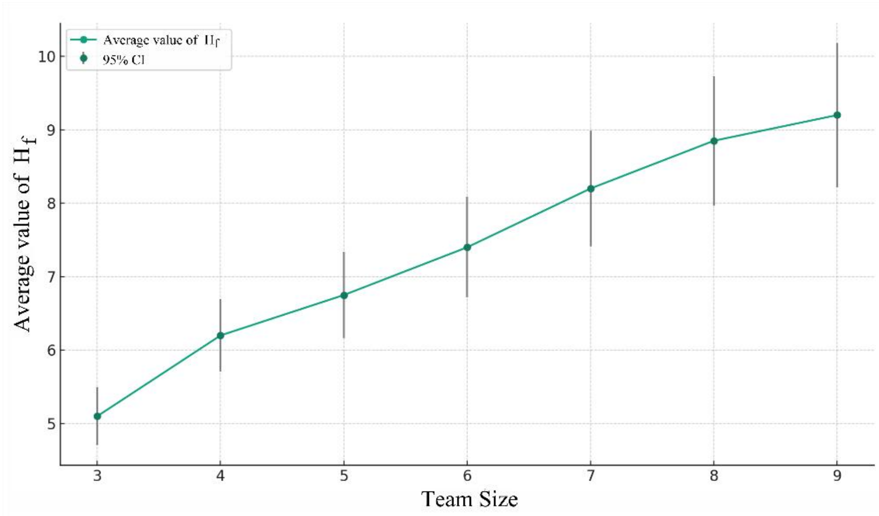

Figure 6 Average team familiarity (H_f) values for different team sizes

5.2 ANOVA for TC and team size

Table 4 shows the ANOVA results for TC and team size. For TC, the between-group mean square is larger than the within-group mean square, and the F-statistic is also large, with a small p-value, indicating significant differences in means among different groups. To further investigate the specific significant differences, post-hoc comparisons were conducted. The results are shown in Appendix Table 6.

Table 4 ANOVA for topic complexity among different team size

Topic complexity	Sum of Squares	Degrees of Freedom	Mean Square	F	Significance
Between groups	13.182	6	2.197	297.367	0.000
Within groups	662.661	89,690	0.007		
Total	675.843	89,696			

Next, we plotted the mean line chart between TC and team size and scatter density plot of TC and team familiarity. As shown in Figure 7, TC increases with the increase of team size. This indicates that as the team size grows and team collaboration strengthens, the team needs to handle more information and perspectives, and requires more collaboration and communication, which may lead to the increase in TC. Additionally, we categorized the teams based on their size and generated a scatter density plot illustrating the relationship between team familiarity and TC. As depicted in Figure 8, for teams with 1 to 3 members, TC primarily falls within the range of 0.1 to 0.3, while team familiarity is predominantly below 0.5. In contrast, for teams with 4 to 5 members, the values are generally higher, with TC concentrated between 0.15 and 0.4, and team familiarity ranging from 0.3 to 0.8.

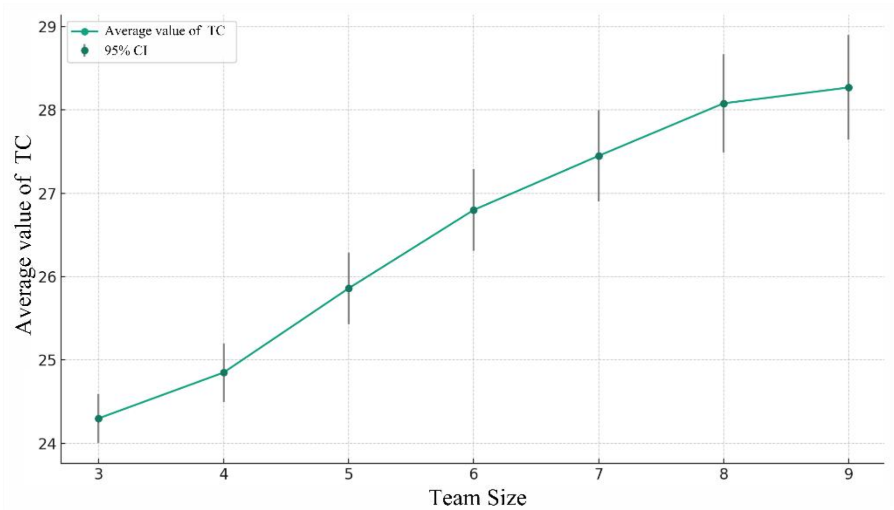

Figure 7 Average topic complexity (TC) values for different team sizes

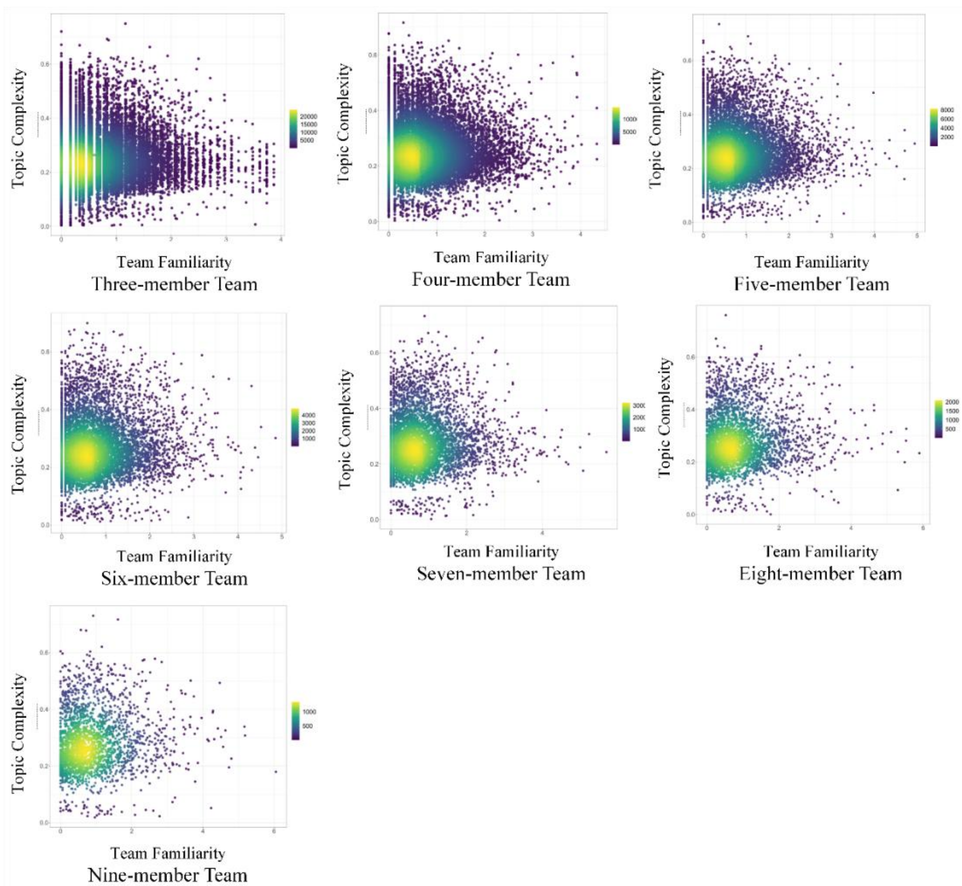

Figure 8 Scatter density plot of team familiarity and topic complexity

Therefore, in team collaboration and task allocation, team size should be considered to facilitate task handling and foster team innovation. Research indicates that small teams are more likely to produce groundbreaking outcomes. For instance, Wu et al. (2019) found that small research teams tend to achieve disruptive results, driving new trends in technology development across various fields. The lower complexity of topics in small teams may be linked to their ability to focus on specific research areas and generate innovative and transformative outcomes. However, the exact relationship between TC and innovation remains to be explored.

5.3 Quantile regression analysis of team familiarity and TC

In this study, we conducted quantile regression analysis using SPSS software and selected quantiles of 10%, 25%, 50%, 75%, and 90%. Similar to traditional linear regression R-squared, values closer to 1 indicate better model fit.

The results are shown in Appendix Table 7. When $\boldsymbol{H_f}$ is at the 10th quantile of TC values, the relationship between $\boldsymbol{H_f}$ and TC is significant, but the coefficient value is relatively small. As $\boldsymbol{H_f}$ approaches higher quantiles of TC values, the relationship between $\boldsymbol{H_f}$ and TC becomes more significant. In addition, the R-squared values are relatively small for each quantile. This may be partly due to the fact that this study only explores the relationship between two variables. In the fields of political science and sociology, statisticians began to reject the use of R-squared in models, starting in the mid-1980s. Seeking high R-squared values encouraged the inclusion of many independent variables, which could be problematic for various reasons. In publications with high levels of significance, the R-squared can be as low as 0.10. Evaluating whether a regression is "optimal" is not based on having a high R-squared level but rather on academic innovation, that is, whether the regression explores previously unknown and important explanatory factors (Dong et al., 2018). Therefore, this study does not consider the R-squared value as the primary indicator for assessing the quality of the results.

Figure 9-total represents the predicted lines between team familiarity and TC across different team sizes. It can be observed that the regression coefficients and slopes increase with higher quantiles of the dependent variable. This indicates that the impact of team familiarity on TC varies under different distributions of TC. Overall, as team familiarity increases, TC also gradually increases. However, the rate of increase in team familiarity varies across different quantiles of TC; higher quantiles are associated with a faster rate of increase in team familiarity. Subsequent images in Figure 9 displays the predicted lines between $\boldsymbol{H_f}$ and TC for different team sizes. As the quantiles of the dependent variable increase, the regression coefficient values and slopes also increase. This indicates that the impact of team familiarity on TC varies under different distributions of TC. Overall, with the growth of team familiarity, TC gradually increases. However, the rate of team familiarity growth differs across different quantiles of TC, with higher quantiles showing a faster rate of team familiarity growth.

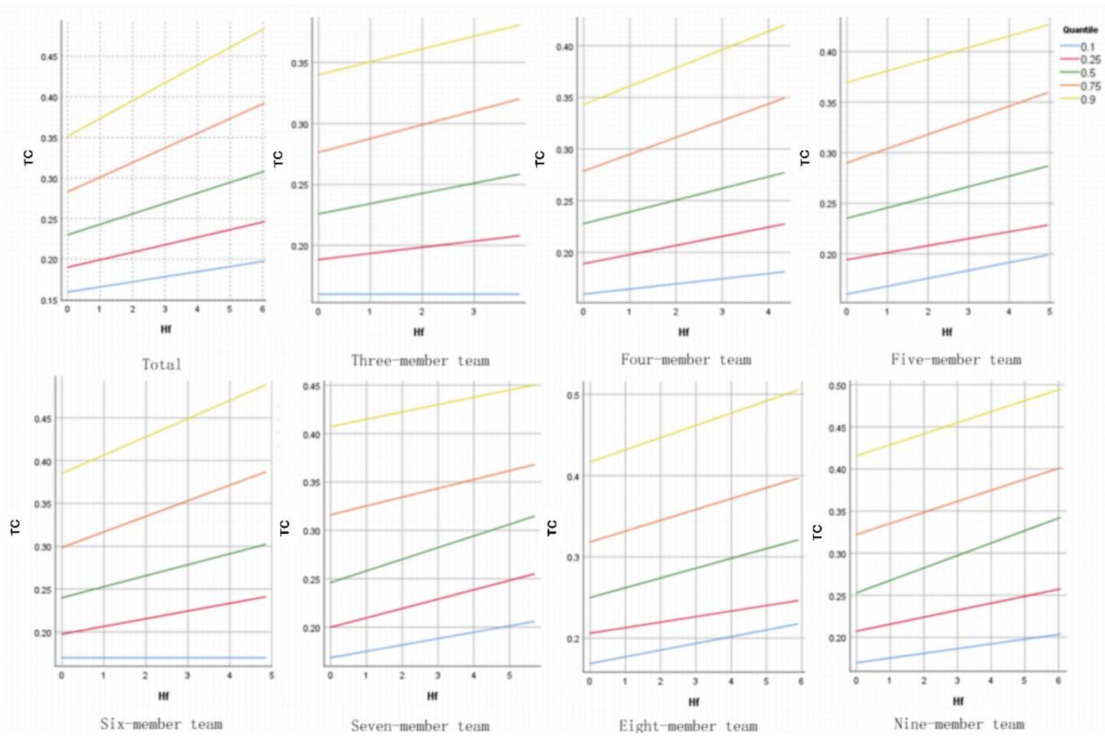

Figure 9 The predictive line between team familiarity and topic complexity

The association between team familiarity and TC exhibits variations under different distributions of TC. Firstly, the process of reaching consensus is an iterative and dynamic one, often requiring multiple rounds of discussion and revisions to achieve group consensus. In social networks, consensus is usually achieved through trust connections within the collaboration network (Dong et al., 2018). Research has shown that many teams fail to fully tap into the knowledge possessed by individual members due to the lack of awareness of each other's expertise. The more frequently scientific teams collaborate, the faster they can reach consensus, reducing the organization's exposure to risks. Scientific teams comprised of unfamiliar experts from different fields often face challenges in performing well. Familiarity helps teams overcome this barrier, allowing them to quickly apply communication techniques and strategies from one project to the next.

Secondly, innovation typically arises from the recombination of existing knowledge (Liu et al., 2022). Scientific team members must not only share specific knowledge with each other but also integrate isolated pieces of information. Knowledge sharing among members can enhance team innovation and performance. Familiarity facilitates effective information sharing and communication among team members, enabling them to integrate knowledge and propose appropriate innovative solutions. Team capability is a crucial factor for organizational competitiveness. High-familiarity teams are generally more efficient, innovative, and capable of reaching consensus than low-familiarity teams. These teams excel because the trust and understanding among team members foster collaboration and knowledge sharing. Members of highly familiar teams better comprehend each other's work methods and habits, making coordination easier.

Finally, high-familiarity teams possess a distinct advantage that competitors struggle to reproduce. Competitors are unable to replicate the entirety of the team's capabilities merely by copying individual members. Instead, the interdependence and collaboration among members of high-familiarity teams foster a cohesive unity that proves difficult to fragment and imitate.

To conclude, high-familiarity teams constitute a crucial element in enhancing organizational competitiveness. The trust, mutual understanding, and collaborative dynamics among team members enhance the team's capabilities, resulting in advantages that are challenging to emulate. These benefits empower scientific teams to focus their endeavors on research involving greater levels of TC.

6 Conclusion

This study explores the association between team familiarity and research TC within a framework of teamwork and complex systems science. We introduce a novel 'personal connectedness' metric to assess team familiarity. Research topics are identified using BERTopic, which facilitates the creation of a topic matrix to evaluate research complexity. Rigorous statistical analyses validate the research methodology's effectiveness. Moreover, this study innovatively employs information entropy to measure team familiarity in scientific collaboration, laying the foundation for subsequent investigations by specialized researchers. By introducing an innovative 'IC' metric to measure team familiarity, it helps to more precisely understand and analyze the interactions and connections between team members. Using BERTopic to extract research topics and create a topic matrix to determine the complexity of the research, this method not only provides a new perspective to observe research topics but also helps us better understand how TC is formed. The main research findings and implications include:

(1) Third authors play a pivotal role in team collaboration by coordinating and communicating within the team. Their central position relates to increased team familiarity and enhanced performance. The team should value the role of the third author to better facilitate communication and cooperation among team members.

(2) Team familiarity progressively improves over time, fostering mutual understanding and collaborative experience among members. This aids effective problem-solving in complex tasks.

(3) Team familiarity significantly impacts TC. As team familiarity increases, so does TC. However, the impact of team familiarity on TC varies under different TC distributions. Under conditions of lower TC, the growth rate of team familiarity is slower; conversely, it is faster under conditions of higher TC. To optimize team collaboration, managing team growth, enhancing member capabilities, and strategically increasing TC are necessary. This is because, under conditions of higher TC, team members require more communication and cooperation to better understand and address problems.

Additionally, this study has the following areas for improvement. Firstly, scientific team collaboration is complex and multi-dimensional. This paper specifically focuses on the impact of team familiarity on research TC. This focus is due to the consideration that these two indicators can, to a certain extent, assist team leaders and managers in better understanding and optimizing their team's performance and outcomes. However, reliance solely on these indicators is somewhat limited. In future research, a broader range of variables could be employed to explore the mechanisms of team cooperation more comprehensively. Secondly, this study exclusively utilized the APS dataset, limiting its scope to teams within the field of physics. Future research could apply this framework across different disciplines to investigate whether the relationship between team familiarity and TC is universal. Thirdly, due to various constraints, this research only analyzed teams ranging from 3 to 9 members, thus lacking consideration for much larger teams typically found in complex scientific research.

In summary, the findings of this study indicate a complex interrelationship between team familiarity, team size, and TC. The results highlight the pivotal role of the third author within teams, offering guidance to team leaders and managers in allocating team roles and responsibilities. Understanding the relationship between team familiarity and TC aids team leaders in designing more effective team collaboration strategies. In terms of strategy formulation and resource allocation, teams should control the complexity of the research topics appropriately based on their capabilities and resources, ensuring efficient use of resources and maximization of team performance, thereby enhancing their ability to solve complex problems and improve overall team effectiveness.

Appendices

Appendix Table 1 Keywords of the an topics

Topics	Keywords
Topic #1	mass; model; quark; energy; neutrino; section; cross; decay; data; nucleon
Topic #2	mathrm; ex; phantom; em; rule; ensuremath; mn; fi; ifmmode; else
Topic #3	sub; sup; yield; approx; pi; gamma; alpha; state; sigma; decay
Topic #4	spin; magnetic; field; electron; magnetization; current; ferromagnetic; exchange; orbit; polarization
Topic #5	surface; structure; energy; band; film; si; layer; electronic; calculation; electron
Topic #6	phase; transition; temperature; pressure; order; critical; diagram; low; liquid; lattice
Topic #7	ensuremath; text; ifmmode; else; fi; rightarrow; gamma; pi; delta; alpha
Topic #8	laser; pulse; mode; frequency; optical; electron; wave; beam; atom; field
Topic #9	quantum; state; dot; entanglement; system; qubit; photon; ground; entangled; scheme
Topic#10	system; model; time; equation; particle; dynamic; function; simulation; solution; method

Appendix Table 2 Individual connectivity for different team sizes

Team size	Authorship type	*N*	Minimum	Maximum	Mean	Standard deviation
3-member team	first author	35,700	0	1	0.207,634	0.205,649
	second author	35,700	0	0.922,337	0.249,068	0.212,906
	third author	35,700	0	1	0.272,068	0.214,713
4-member team	first author	22,107	0	1	0.174,572	0.175,429
	second author	22,107	0	0.922,337	0.193,895	0.179,877
	third author	22,107	0	1	0.210,639	0.183,458
	fourth author	22,107	0	0.857,143	0.242,383	0.189,013
5-member team	first author	12,657	0	1	0.146,285	0.153,519
	second author	12,657	0	0.75	0.156,895	0.156,878
	third author	12,657	0	1	0.165,603	0.158,541
	fourth author	12,657	0	0.922,337	0.179,826	0.163,442
	fifth author	12,657	0	0.922,337	0.215,329	0.172,332
6-member team	first author	8,024	0	0.75	0.130,200	0.136,823
	second author	8,024	0	0.75	0.135,465	0.138,333
	third author	8,024	0	0.5	0.138,615	0.138,325
	fourth author	8,024	0	0.922,337	0.146,768	0.142,197

	fifth author	8,024	0	0.8	0.156,577	0.145,894
	sixth author	8,024	0	0.922,337	0.192,01	0.156,863
7-member team	first author	5,221	0	1	0.119,257	0.123,779
	second author	5,221	0	0.922,337	0.117,904	0.125,269
	third author	5,221	0	1	0.120,25	0.124,987
	fourth author	5,221	0	0.566,667	0.125,739	0.125,285
	fifth author	5,221	0	0.5	0.129,399	0.127,008
	sixth author	5,221	0	0.5	0.139,477	0.131,347
	seventh author	5,221	0	0.5	0.176,407	0.143,599
8-member team	first author	3,497	0	0.5	0.107,393	0.109,285
	second author	3,497	0	0.5	0.109,172	0.114,135
	third author	3,497	0	0.5	0.109,583	0.113,502
	fourth author	3,497	0	0.5	0.104,214	0.112,425
	fifth author	3,497	0	0.5	0.111,935	0.112,948
	sixth author	3,497	0	0.5	0.116,464	0.116,856
	seventh author	3,497	0	0.5	0.128,953	0.121,422
	eighth author	3,497	0	0.5	0.155,7	0.132,69
9-member team	first author	2,328	0	0.5	0.102,352	0.105,203
	second author	2,328	0	0.5	0.097,501	0.104,132
	third author	2,328	0	0.5	0.098,063	0.104,157
	fourth author	2,328	0	0.5	0.100,078	0.104,609
	fifth author	2,328	0	0.5	0.102,568	0.104,615
	sixth author	2,328	0	0.5	0.101,527	0.104,192
	seventh author	2,328	0	0.5	0.102,387	0.106,652
	eighth author	2,328	0	0.5	0.109,756	0.109,841
	ninth author	2,328	0	0.5	0.138,755	0.121,107

Appendix Table 3 Descriptive statistics of H_f for different team sizes

Team size	Sample size	Mean	Standard deviation	Standard error	95% confidence interval of mean		Minimum	Maximum
					Lower limit	Upper limit		
3-member team	35,700	5.057,7	5.594,48	0.029,61	4.999,7	5.115,7	0.00	3.869
4-member team	22,107	6.114,9	5.994,91	0.040,32	6.035,8	6.193,9	0.00	4.338
5-member team	12,657	6.779,8	6.385,14	0.056,76	6.668,6	6.891,1	0.00	4.943
6-member team	8,024	7.430,6	6.727,61	0.075,10	7.283,4	7.577,8	0.00	4.854
7-member team	5,221	8.124,4	7.263,82	0.100,53	7.927,3	8.321,5	0.00	5.694
8-member team	3,497	8.823,3	7.952,89	0.134,49	8.559,6	9.087,0	0.00	5.894
9-member team	2,328	9.180,7	8.112,70	0.168,14	8.851,0	9.510,4	0.00	6.053

Appendix Table 4 Descriptive statistics of topic complexity for different team sizes

Team size	Sample size	Mean	Standard deviation	Standard error	95% confidence interval of mean Lower limit	95% confidence interval of mean Upper limit	Minimum	Maximum
3-member team	35,700	0.243,2	0.079,25	0.000,42	0.242,4	0.244,0	0	0.75
4-member team	22,107	0.248,5	0.082,33	0.000,55	0.247,4	0.249,5	0	0.72
5-member team	12,657	0.258,2	0.089,35	0.000,79	0.256,5	0.259,7	0	0.73
6-member team	8,024	0.267,4	0.096,88	0.001,08	0.265,2	0.269,4	0.1	0.70
7-member team	5,221	0.274,8	0.098,51	0.001,36	0.272,1	0.277,4	0	0.73
8-member team	3,497	0.280,6	0.102,67	0.001,73	0.277,1	0.284,0	0	0.76
9-member team	2,328	0.283,0	0.101,82	0.002,11	0.278,9	0.287,2	0.02	0.73

Appendix Table 5 Post hoc comparison results for team familiarity and team size

(I)Classification	(J)Classification	Mean Difference (I-J)	Standard error	Significance	95% Confidence Interval Lower limit	95% Confidence Interval Upper limit
3-member team	4-member team	-1.057,16*	0.053,06	0.000	-1.213,6	-0.900,7
	5-member team	-1.722,11*	0.064,13	0.000	-1.911,2	-1.533,0
	6-member team	-2.372,89*	0.076,59	0.000	-2.598,7	-2.147,1
	7-member team	-3.066,69*	0.091,85	0.000	-3.337,5	-2.795,9
	8-member team	-3.765,60*	0.109,85	0.000	-4.089,5	-3.441,7
	9-member team	-4.122,97*	0.132,61	0.000	-4.513,9	-3.732,0
4-member team	3-member team	1.05716*	0.053,06	0.000	0.900,7	1.213,6
	5-member team	-0.664,95*	0.069,10	0.000	-0.868,7	-0.461,2
	6-member team	-1.315,73*	0.080,80	0.000	-1.553,9	-1.077,5
	7-member team	-2.009,53*	0.095,39	0.000	-2.290,8	-1.728,3
	8-member team	-2.708,44*	0.112,82	0.000	-3.041,1	-2.375,8
	9-member team	-3.065,81*	0.135,08	0.000	-3.464,1	-2.667,5
5-member team	3-member team	1.722,11*	0.064,13	0.000	1.533,0	1.911,2
	4-member team	0.664,95*	0.069,10	0.000	0.461,2	0.868,7
	6-member team	-0.650,78*	0.088,46	0.000	-0.911,6	-0.390,0
	7-member team	-1.344,58*	0.101,97	0.000	-1.645,2	-1.043,9
	8-member team	-2.043,49*	0.118,43	0.000	-2.392,7	-1.694,3
	9-member team	-2.400,86*	0.139,80	0.000	-2.813,0	-1.988,7
6-member team	3-member team	2.372,89*	0.076,59	0.000	2.147,1	2.598,7
	4-member team	1.315,73*	0.080,80	0.000	1.077,5	1.553,9
	5-member team	0.650,78*	0.088,46	0.000	0.390,0	0.911,6
	7-member team	-0.693,80*	0.110,23	0.000	-1.018,8	-0.368,8
	8-member team	-1.392,71*	0.125,61	0.000	-1.763,1	-1.022,3
	9-member team	-1.750,08*	0.145,94	0.000	-2.180,4	-1.319,8
7-member team	3-member team	3.066,69*	0.091,85	0.000	2.795,9	3.337,5
	4-member team	2.009,53*	0.095,39	0.000	1.728,3	2.290,8
	5-member team	1.344,58*	0.101,97	0.000	1.043,9	1.645,2

	6-member team	0.693,80*	0.110,23	0.000	0.368,8	1.018,8
	8-member team	-0.698,91*	0.135,46	0.000	-1.098,3	-0.299,5
	9-member team	-1.056,28*	0.154,50	0.000	-1.511,8	-0.600,8
8-member team	3-member team	3.765,60*	0.109,85	0.000	3.441,7	4.089,5
	4-member team	2.708,44*	0.112,82	0.000	2.375,8	3.041,1
	5-member team	2.043,49*	0.118,43	0.000	1.694,3	2.392,7
	6-member team	1.392,71*	0.125,61	0.000	1.022,3	1.763,1
	7-member team	0.698,91*	0.135,46	0.000	0.299,5	1.098,3
	9-member team	-0.357,37	0.165,82	0.320	-0.846,3	0.131,5
9-member team	3-member team	4.122,97*	0.132,61	0.000	3.732,0	4.513,9
	4-member team	3.065,81*	0.135,08	0.000	2.667,5	3.464,1
	5-member team	2.400,86*	0.139,80	0.000	1.988,7	2.813,0
	6-member team	1.750,08*	0.145,94	0.000	1.319,8	2.180,4
	7-member team	1.056,28*	0.154,50	0.000	0.600,8	1.511,8
	8-member team	0.357,37	0.165,82	0.320	-0.131,5	0.846,3

*significant differences at the significance level α = 0.05.

Appendix Table 6 Post hoc comparison results for topic complexity and team size

Dependent variable	(I) Classification	(J) Classification	Mean Difference (I-J)	Standard error	Significance Lower limit	95% Confidence Interval Upper limit
3-member team	4-member team	-0.005,28*	0.000,74	0.000	-0.007,4	-0.003,1
	5-member team	-0.014,98*	0.000,89	0.000	-0.017,6	-0.012,4
	6-member team	-0.024,19*	0.001,06	0.000	-0.027,3	-0.021,1
	7-member team	-0.031,66*	0.001,27	0.000	-0.035,4	-0.027,9
	8-member team	-0.037,42*	0.001,52	0.000	-0.041,9	-0.032,9
	9-member team	-0.039,91*	0.001,84	0.000	-0.045,3	-0.034,5
4-member team	3-member team	0.005,28*	0.000,74	0.000	0.003,1	0.007,4
	5-member team	-0.009,71*	0.000,96	0.000	-0.012,5	-0.006,9
	6-member team	-0.018,92*	0.001,12	0.000	-0.022,2	-0.015,6
	7-member team	-0.026,38*	0.001,32	0.000	-0.030,3	-0.022,5
	8-member team	-0.032,14*	0.001,56	0.000	-0.036,7	-0.027,5
	9-member team	-0.034,63*	0.001,87	0.000	-0.040,1	-0.029,1
5-member team	3-member team	0.014,98*	0.000,89	0.000	0.012,4	0.017,6
	4-member team	0.009,71*	0.000,96	0.000	0.006,9	0.012,5
	6-member team	-0.009,21*	0.001,22	0.000	-0.012,8	-0.005,6
	7-member team	-0.016,68*	0.001,41	0.000	-0.020,8	-0.012,5
	8-member team	-0.022,44*	0.001,64	0.000	-0.027,3	-0.017,6

	9-member team	-0.024,93*	0.001,94	0.000	-0.030,6	-0.019,2
6-member team	3-member team	0.024,19*	0.001,06	0.000	0.021,1	0.027,3
	4-member team	0.018,92*	0.001,12	0.000	0.015,6	0.022,2
	5-member team	0.009,21*	0.001,22	0.000	0.005,6	0.012,8
	7-member team	-0.007,47*	0.001,53	0.000	-0.012	-0.003
	8-member team	-0.013,23*	0.001,74	0.000	-0.018,4	-0.008,1
	9-member team	-0.015,72*	0.002,02	0.000	-0.021,7	-0.009,8
7-member team	3-member team	0.031,66*	0.001,27	0.000	0.027,9	0.035,4
	4-member team	0.026,38*	0.001,32	0.000	0.022,5	0.030,3
	5-member team	0.016,68*	0.001,41	0.000	0.012,5	0.020,8
	6-member team	0.007,47*	0.001,53	0.000	0.003	0.012
	8-member team	-0.005,76*	0.001,88	0.035	-0.011,3	-0.000,2
	9-member team	-0.008,25*	0.002,14	0.002	-0.014,6	-0.001,9
8-member team	3-member team	0.037,42*	0.001,52	0.000	0.032,9	0.041,9
	4-member team	0.032,14*	0.001,56	0.000	0.027,5	0.036,7
	5-member team	0.022,44*	0.001,64	0.000	0.017,6	0.027,3
	6-member team	0.013,23*	0.001,74	0.000	0.008,1	0.018,4
	7-member team	0.005,76*	0.001,88	0.035	0.000,2	0.011,3
	9-member team	-0.002,49	0.002,3	0.933	-0.009,3	0.004,3
9-member team	3-member team	0.039,91*	0.001,84	0.000	0.034,5	0.045,3
	4-member team	0.034,63*	0.001,87	0.000	0.029,1	0.040,1
	5-member team	0.024,93*	0.001,94	0.000	0.019,2	0.030,6
	6-member team	0.015,72*	0.002,02	0.000	0.009,8	0.021,7
	7-member team	0.008,25*	0.002,14	0.002	0.001,9	0.014,6
	8-member team	0.002,49	0.002,3	0.933	-0.004,3	0.009,3

*significant differences at the significance level α = 0.05.

Appendix Table 7 Quantile regression coefficients between team familiarity and topic complexity

Quantiles and R-squared	Parameters	Regression Coefficients	Standard Error	t	Degrees of Freedom	Significance	95% Confidence Interval	
							Lower limit	Upper limit
Quantiles=0.1 R2=0.002	intercept	0.159	0.000,4	386.576	89,695	0.000	0.159	0.160
	$\boldsymbol{H_f}$	0.006	0.000,5	13.502	89,695	0.000	0.005	0.007
Quantiles=0.25 R2=0.006	intercept	0.190	0.000,4	481.428	89,695	0.000	0.189	0.191
	$\boldsymbol{H_f}$	0.009	0.000,4	20.781	89,695	0.000	0.008	0.010
Quantiles=0.5	intercept	0.230	0.000,4	570.761	89,695	0.000	0.229	0.231
R2=0.006	$\boldsymbol{H_f}$	0.013	0.000,5	28.362	89,695	0.000	0.012	0.014
Quantiles=0.75	intercept	0.283	0.000,7	428.276	89,695	0.000	0.282	0.284
R2=0.007	$\boldsymbol{H_f}$	0.018	0.000,7	24.154	89,695	0.000	0.017	0.019
Quantiles=0.9	intercept	0.351	0.001,1	306.967	89,695	0.000	0.349	0.354
R2=0.005	$\boldsymbol{H_f}$	0.022	0.001,3	16.940	89,695	0.000	0.019	0.024

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