Expertise diversity of teams predicts originality and long-term impact in science and technology

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Despite the growing importance of teams in producing innovative and high-impact science and technology, it remains unclear how expertise diversity among team members relates to the originality and impact of the work they produce. Here, we develop a new method to quantify the expertise distance of researchers based on their prior career histories and apply it to 23 million scientific publications and 4 million patents. We find that across science and technology, expertise-diverse teams tend to produce work with greater originality. Teams with more diverse expertise have no significant impact advantage in the short- (2 years) or mid-term (5 years). Instead, they exhibit substan-
tially higher long-term impact (10 years), increasingly attracting larger cross-
disciplinary influence. This impact premium of expertise diversity among
team members becomes especially pronounced when other dimensions of team
diversity are missing, as teams within the same institution or country appear
to disproportionately reap the benefits of expertise diversity. While gender-
diverse teams have relatively higher impact on average, teams with varied lev-
els of gender diversity all seem to benefit from increased expertise diversity.
Given the growing knowledge demands on individual researchers, implemen-
tation of incentives for original research, and the tradeoffs between short-term
and long-term impacts, these results may have implications for funding, as-
sembling, and retaining teams with originality and long-lasting impacts.

Teams play an increasingly important role in producing high-impact work across a wide
range of creative domains (1–7). The growing burden of knowledge (8) and the specialization
of individual researchers (9, 10) promote the need to form teams that span traditional disci-
plinary boundaries to solve complex problems, as narrow expertise from a single field becomes
increasingly inadequate to address many of the key challenges facing society (11–15). A bet-
ter understanding of how to assemble teams with disparate expertise is therefore essential for
coordinating collective actions, fostering interdisciplinary thinking, and integrating existing ex-
pertise to tackle new challenges across scientific and technological domains (16–21).

However, it remains unclear about how prior expertise diversity among team members is re-
lated to the originality and the impact of work the team produces. Some indicators have focused
on quantifying the diversity of the prior expertise among individuals, by calculating for example
the Pearson correlation of the distribution across technological classes distributions (22), a Z-
score based proximity metric for research areas (23), a frequency-inverse document frequency
(TF-IDF) method for research content similarity (24), and a distance metric based on the Jac-
card dissimilarity of researchers’ references (25). Although these methods can be used to approximate expertise diversity among team members, an effective measure should also explicitly account for the relatedness of research disciplines (26, 27). For instance, ecology has more interactions with environmental science and evolutionary biology than condensed matter physics. Similarly, artificial intelligence is more deeply influenced by mathematics and computer science compared to organic chemistry. Therefore, ecologists should on average have higher expertise similarity to environmental scientists and evolutionary biologists than condensed matter physicists, and the knowledge possessed by artificial intelligence researchers may be more related to the knowledge of mathematicians and computer scientists than that of organic chemists.

In part to tackle these challenges, researchers have developed several methods to infer expertise diversity from the product the team has developed, by using a paper’s references or citations, using measurements such as the distinction of fields, entropy, Gini coefficient, and the Rao-Stirling (RS) index, to quantify interdisciplinarity of the work and its association with impact (26, 28–32). While these measures allow researchers to quantify interdisciplinarity of the work and its association with impact, as proxies for expertise diversity, they depend upon the paper that a team has produced, by analyzing its references or citations, which are only available after the fact, i.e., after the paper has been published. Understanding the association between the expertise diversity among team members and the outcome the team produces is crucial for funding and investment decisions, and highlights the importance of developing measures to estimate ex ante knowledge diversity to inform fruitful collaboration strategies.

To address these challenges, in this paper we propose a new metric to identify and quantify the diversity of prior expertise among team members that extends beyond single disciplines. Our expertise distance metric explicitly takes into account the relatedness of scientific fields and draws on the disciplinary distributions of prior career histories among collaborators. The expertise diversity of a team is then obtained as the average distance of all possible pairwise
coauthorships, which correlates with a broad range of indicators of scholarly diversity in terms of the combination of past knowledge, and other dimensions of diversity among team members regarding their affiliations, nationality and gender.

A large body of work has focused on understanding the interplay between team composition and outcomes, probing dimensions of team diversity around affiliations (2), ethnicity (33), gender (34), expertise (12), technical background (35), problem-solving ability (36), intelligence (37), and more. In the technology sector, inventors from distinct social groups tend to generate patents with greater collaborative creativity (38). In the online knowledge sharing community, polarized teams composed of a balanced proportion of ideologically diverse Wikipedia editors produce articles of higher quality than homogeneous teams (39). Overall, studies from diverse domains consistently demonstrate that the impact of team outcomes improves with team diversity. Thus, creative output in science and technology may be heavily rooted in the composition of team members’ expertise and background, which is largely determined during the team assembly process.

Although studies have suggested that high multidisciplinarity is associated with high impact, we find that scientific teams with multidisciplinary approaches do not appear to be correlated with originality, quantified by the disruption score, and has negative correlations with originality in technology. Expertise-diverse teams, in contrast, have positive correlations with originality in both science and technology. Therefore, despite its close correlation with multidisciplinarity, expertise diversity of teams provides new perspectives in terms of the originality of teams’ produced work.

Moreover, contrary to the common belief that team diversity consistently promotes team impact, we find that research teams with high expertise diversity exhibit no significant impact advantage in the short- (2 years) or mid-term (5 years). This pattern persists for teams spanning both scientific and technological domains. We find that, instead, teams with high expertise
diversity enjoy a substantive impact premium of their work in the long-term (10 years), increasingly attracting cross-disciplinary influence in the longer-run. This long-term effect of expertise diversity becomes more prominent as team size and citation time window grow. In particular, when other dimensions of diversity are missing, teams formed in the same institution or country disproportionately harness the benefit of expertise diversity. These results may have implications for fostering and retaining innovative and high-impact teams with more diverse knowledge composition among team members.

Results

We propose a new metric to measure the expertise distance between two researchers based on their prior career histories, which we illustrate in a concise example (Fig. 1). The publication vector $\mathbf{p}_i$ records the crude number of papers written by author $i$ distributed across all research fields at the time of collaboration. We define $\mathbf{p}_1 = (3, 4, 1)$ and $\mathbf{p}_2 = (2, 1, 4)$ in the illustrative model for the selected authors 1 and 2, respectively (Fig. 1A). The prior expertise vectors $\mathbf{q}_1$ and $\mathbf{q}_2$ with unit length are shown in the geometric space of research fields $(e_1, e_2, e_3)$, obtained by normalizing the raw publication vectors $\mathbf{p}_1$ and $\mathbf{p}_2$. The field vectors in this space are usually not orthogonal to each other, due to large heterogeneity across fields. Both the vector normalization and the distance estimation take into account the field interaction matrix $\mathbf{M}$, where each element $m_{ij}$ is calculated as the dot product of the corresponding field vectors $e_i$ and $e_j$ of field $i$ and $j$ (see Methods). The final analytical form of author expertise distance is given as

$$d_{12} = \sqrt{2 - 2\mathbf{q}_1^T \mathbf{M} \mathbf{q}_2^T}.$$  \hspace{1cm} (1)

As such, the derived distance metric varies between 0 and $\sqrt{2}$, and a higher distance value corresponds to greater prior career diversity between two authors. The expertise diversity of a team is therefore defined as the average expertise distance among all possible pairs of coauthors.
Figure 1: **Illustrating the estimation of expertise distance among team members and its correlation with multidisciplinarity.** (A) We first indicate the prior career histories of two authors 1 and 2, distributed across three research fields 1, 2, and 3. Then we display the expertise vectors \( q_1 \) and \( q_2 \) and their prior expertise distance \( d_{12} \) in the geometric space of research fields, in which the field vectors \( e_j \) are usually non-orthogonal to each other due to the heterogeneity of interactions among fields, where \( j \in \{1, 2, 3\} \). To estimate the expertise distance, we obtain the expertise vectors \( \overline{q}_i \) of unit length by normalizing the publication vectors \( \overline{p}_i \) of authors, where \( i \in \{1, 2\} \). The expertise vector \( \overline{q}_i \) shown in the space of fields can be related to the expertise vector \( \overline{q}_i \) as \( \overline{q}_i = \overline{q}_i^T (e_1, e_2, e_3) \). We then compute the coauthor expertise distance \( d_{12} \) by taking into account the interaction matrix \( M \) that explicitly embeds in the relatedness of fields. Definitions of variables, normalization of expertise vectors and mathematical derivations of the distance metric can be found in the Methods section. (B) The distribution of the average expertise distance among team members for over 11 million research papers published in 1970-2019. Then we mark the skin cancer classification paper using neural networks \( (d = 1.00, \text{top } 2\%) \) that is more interdisciplinary in terms of both the composition of team expertise and the produced work, and the image recognition paper \( (d = 0.08, \text{bottom } 5\%) \) that is conducted by a team with members focusing primarily on a specific research area. Both papers are highly cited. (C) We show the contemporary trends of teams’ expertise diversity for papers and patents, from 1970 to 2019. Shaded areas represent 95% confidence intervals. (D) To validate the efficacy of the distance metric, we show the interplay between teams’ expertise distance percentile and the multidisciplinary inspiration (solid lines) and impact (dashed lines) of for papers and patents.
Empirical evidence suggests that teams of either high or low expertise diversity may possess the potential to develop original and high-impact research. But the level of interdisciplinarity in the approaches implemented by high-originality or high-impact teams varies substantively, which can be predicted by the team members’ expertise diversity estimated using the proposed metric. For instance, a team that applied a deep neural network method to classify skin cancer involves researchers from departments of electrical engineering, dermatology, microbiology & immunology, and computer science, spanning a wide range of research areas (Fig. 1B) (40). Correspondingly, they proposed a highly interdisciplinary approach by creatively adapting artificial intelligence technologies to life science problems in the paper. In another example, a group of researchers from the same institution who focus primarily on computer vision produced a well-cited paper that trains deep residual learning networks for image recognition (41). Their paper presents a new framework within a particular research topic of computer vision. The distance metric accurately captures the two teams’ propensity of conducting interdisciplinary research based on the prior career histories of team members.

In the following analyses, we aggregate groups of research papers according to the sizes of teams, defined by the number of authors of a paper. Previous studies show that a team’s preference in research agenda, originality and expected impact are strongly associated with its size. Large teams tend to build their work on more recent developments and have higher impact, whereas small teams are more likely to disrupt science and technology (1, 42). Aggregating teams by their sizes mitigates this confounding effect and controls for the structural variations of the coauthorship network of teams with varying sizes. As such, we categorize teams with the same size into five uniform percentile bins based on the team members’ average expertise distance in our analyses.

We extract and refine 23 million original research articles and over 4 million patents from the Microsoft Academic Graph (MAG) dataset in the period of 1950 to 2019. At the level of
Figure 2: Originality and its correlation with expertise diversity of teams and multidisciplinarity of the teams’ work. We present the interplay between expertise diversity of teams and disruption of the teams’ work, and find that high expertise diversity is correlated with high disruption score for both papers (A) and patents (B). In contrast, we show the interplay between multidisciplinary inspiration and disruption of the teams’ work. We find that multidisciplinary inspiration has no consistent correlation with disruption for papers (C), and appears to be negatively correlated with disruption for patents (D). This demonstrates the unique property of teams’ expertise diversity in predicting the originality of teams’ work.
coauthor pairs, expertise distance follows a log-normal distribution for both papers and patents (fig. S1), and declines as the duration of collaboration extends (fig. S3). The expertise diversity of scientific research teams has been continually increasing over time since the 1970s, suggesting that teams have become more diverse in the distribution of knowledge composition among the members (Fig. [C]). The contemporary trend of teams’ expertise diversity also varies across disciplines. Research teams in natural and social sciences have become substantially more diverse over time, whereas the historical level of expertise diversity for engineering & mathematics teams has been fairly stable in the past decades (fig. S5).

To validate whether our distance metric accurately captures the diversity of knowledge composition among team members, we measure the diversity of field distributions in the references or citations of papers and patents using the Rao-Stirling index and see how it relates to team expertise diversity (26). A RS index of zero means the work’s references or citations concentrate mostly on one particular field, while an RS index close to one means the work’s references or citations distribute broadly across many fields. The multidisciplinary inspiration of papers quantified by the RS index using references increases as the teams’ expertise diversity grows, suggesting that high-distance teams tend to reference a wider range of disciplines than low-distance teams (Fig. [D]) (15). Similarly, the multidisciplinary impact of papers measured by the RS index using citations is also positively correlated with the teams’ expertise diversity, suggesting that works of high-distance teams tend to have broader cross-disciplinary influence.

Applying our metric to patenting, we find that the expertise diversity of teams grows modestly over time over the past decades. A team’s expertise diversity is positively correlated with the multidisciplinary inspiration and multidisciplinary impact of the patent it produced. These results exhibits the close coupling between expertise diversity and multidisciplinarity, which validates the efficacy of the expertise distance metric for both science and technology.

Disruption is a metric used to gauge the level of originality of research, ranging from $-1$
to 1 (25, 42). A paper is regarded as more disruptive and original if a high proportion of citations it receives do not cite its references, indicating that these follow-up studies appear to be primarily inspired by this particular research rather than the body of work it builds on. We find that expertise diverse teams are more likely to perform disruptive research in science (Fig. 2A), especially for small teams. High expertise distance teams are also associated with high disruption in technology (Fig. 2B), and the effect is particularly prominent for large teams with more than 5 authors. These results suggest that expertise diversity among team members is positively correlated with disruption of teams’ work for both science and technology.

In contrast, multidisciplinary inspiration of a paper reflects the disciplinary diversity of its references and approaches utilized in the study. This indicator can only be calculated when the work is finished, lagging the availability of expertise diversity among team members which is available when the team is assembled. However, we observe no consistent pattern between multidisciplinary inspiration and its association with disruption in science (Fig. 2C). Conversely, multidisciplinary inspiration of patents are negatively associated with disruption, suggesting that highly disruptive patents are rather likely to focus on narrow research areas (Fig. 2D). These results demonstrate the unique power of team expertise diversity for predicting originality, compared to other known measures of research diversity.

We then proceed to explore other perspectives of team performance related to the expertise diversity among team members. High-distance teams, composed of researchers with a broad spectrum of expertise, exhibit greater potential to apply more novel combinations of past knowledge, draw from more diverse fields, and produce more innovative results. Recent studies suggest that interdisciplinarity in scientific research may withstand underestimated short-term impact, but is usually rewarded with high impact in the longer run (30). We identify and examine three widely existing citation patterns across science and technology to quantify different types of impact. The first is the most commonly used impact measure of research papers, which
Figure 3: **Distance metric and impact in science and technology.** We show the interplay between research impact and the teams’ expertise diversity divided into five uniform distance percentile bins. We consider three different lengths of citation time windows of two years, five years and ten years after publication. We identify three existing citation patterns among science and technology: (A-D), paper-to-paper citations; (E-H), patent-to-paper citations; and (I-L), patent-to-patent citations. For each pattern, results are presented in separate panels categorized by the teams’ size. Shaded areas represent 95% confidence intervals.
we refer to as the paper-to-paper citations (Fig. 3A-D). Moreover, studies have shown that successful scientific publications are more likely to inspire future technological innovations, which we use the number of patent-to-paper citations as an indicator to reflect the influence of scientific research on patenting (Fig. 3E-H) (43). Lastly, we measure the impact of patents using the number of patent-to-patent citations (Fig. 3I-L).

For both papers and patents, we find that a team’s expertise diversity has no significant correlation with short-term (2 years) impact of their work, quantified by the number of citations received two years after publication, regardless of its size and type of impact (Fig. 3). For teams with relatively large sizes of four or more authors, high-distance teams have moderately larger mid-term (5 years) impact than low-distance teams in all three citation patterns, and the effect is less significant for small sized teams of two or three authors. Teams of all sizes exhibit substantively greater long-term (10 years) impact in all citation patterns as the teams’ expertise diversity increases, and this effect becomes more prominent for large teams. In particular, papers published by teams with five or more authors in the highest distance percentile bin garner on average 31.0 paper-to-paper citations in 10 years, 40.9% more than the citations of papers produced by teams from the lowest distance percentile bin (Fig. 3D). The effects persist when we remove all self-citations (fig. S7). The long-term impact premium for expertise diverse teams still exists when we use a dichotomous variable of highly-cited papers and patents to indicate whether they received the upper 5th percentile of citations for a given year and field (fig. S8).

We further validate the results in two extended citation time windows of 20 and 30 years for papers and patents published in the 1980s, and find that the impact premium of high-distance teams becomes even more pronounced (fig. S9).

We further test the robustness of the above findings according to the publication period and research discipline of papers and patents. For all three types of impact, greater team expertise diversity is consistently associated with higher long-term impact across decades, when we inde-
pendently examine papers and patents published in the 1980s, 1990s, and 2000s (fig. S10-12). With respect to research disciplines, however, more fluctuations exist across these patterns of impact. For all three types of impact in natural sciences, larger expertise distance of teams is consistently associated with higher long-term impact, while such correlation is not significant and sometimes negative for engineering & mathematics (fig. S13-15). For large social science teams, greater expertise diversity is related to higher long-term paper-to-paper and patent-to-paper citations, but no identifiable pattern in patent-to-patent citations as relatively fewer patents are issued in social sciences.

To investigate the mechanisms underlying why high-distance teams outperform low-distance teams in the long-term but not in the short run, we probe into the disciplinary origins of citations. Because knowledge-diverse teams are more likely to draw attention and influence research beyond the constraints of disciplines, we expect that high-distance teams may have higher cross-disciplinary impact. We distinguish two citation patterns according to the origins, namely the number of citations a paper received from papers in the same field and the number of citations from papers in other fields. We find that teams of different levels of expertise diversity have similar scientific impact within the field (Fig. 4A-D), an effect that is persistent for both the short- (2 years) and long-term (10 years). While high-distance teams do not exhibit a strong impact advantage on different fields in the short-term, they attract significantly more citations from other fields in the long-term, which becomes more prominent as team size grows. This suggests that while disciplinary impact consistently exhibits little variance for scientific teams, works of diverse teams attract more cross-disciplinary citations, resembling rippling dynamics that accelerate gradually over time.

The long-term boosting effect of cross-disciplinary influence associated with teams’ expertise diversity appears to extend beyond science and persists in the technology sector. Papers produced by high-distance teams have higher cross-disciplinary impact on patented inventions
Figure 4: Teams’ expertise diversity and origins of citations in science and technology. We decompose the citation origins of fields for scientific and technological research according to the teams’ expertise diversity. We compare the number of citations coming from the same field or from different fields, accrued within two different time windows of 2 years and 10 years after publication, respectively. Consistent with previous results, we use three citation patterns among science and technology: (A-D), paper-to-paper citations; (E-H), patent-to-paper citations; and (I-L), patent-to-patent citations. For each pattern, results are presented in separate panels categorized by the team’s size. Shaded areas represent 95% confidence intervals.
in the long-term, but less so in the short-run (Fig. 4E-H). For patents, the cross-disciplinary impact advantage for high-distance teams is relatively weak compared to that of papers, but still with similar boosting effect in the long-term (Fig. 4I-L). These results show that the long-term impact premium of high-distance teams in science and technology is largely driven by the cross-disciplinary attention progressively garnered over time.

We further disaggregate team expertise diversity based on the background diversity of team members in terms of affiliations, nationality and gender (44). Given that the vast majority (over 99%) of patents are registered by single-institutional teams, here we focus on research papers only in our analyses. Scientists tend to collaborate more with people in their own groups (45), and are less inclined to form cross-disciplinary teams with people from more remote positions (46). Therefore, the expertise distance of teams may be associated with the geographical proximity of researchers’ affiliations and locations (2). Teams involving between-school or international collaborations are likely to encompass a more diverse composition of knowledge, expertise, and skills than teams assembled within the same institution or country. We find that the a team’s expertise diversity is positively correlated with the propensity of having collaborators from external or international institutions (fig. S16). Over time, teams with between-school collaborations consistently have greater expertise diversity than those formed within the same institution (Fig. 5A), and, similarly, international teams exhibit greater expertise diversity than domestic teams (Fig. 5B).

We find that for all three dimensions of external diversity regarding institutions, international collaborations, and gender, expertise diverse teams produce more disruptive work than teams with narrow expertise among coauthors (Fig. 5D-F). This effect is stronger for small teams. In particular, work of teams that lack other dimensions of diversity tends to be more disruptive. Papers written by teams from the same institute have higher disruption score than between-school teams. Similarly, domestic teams produce more disruptive science than those with international
Figure 5: The synthesized effects of teams’ expertise diversity and other dimensions of team diversity on long-term impact. We present the temporal trends of team expertise diversity and its correlation with disruption and two types of impact in the long run, conditional upon other dimensions of diversity among team members including affiliations, nationality and gender. (A-C) Temporal trends of team expertise diversity based on the diversity of team members’ affiliations, nationality and gender. The effect of team diversity and expertise diversity on (D-F) disruption, (G-I) paper-to-paper citations and (J-L) patent-to-paper citations. In particular, we consider three types of diversity among team members. Left column, whether it is a single-institutional or between-school team. Middle column, whether the team involves international collaborators. Right column, whether the team is gender-diverse or gender-homogeneous. Teams with diverse background collaborators, i.e., having between-school collaborations, having international collaborations, or having female researchers on board, are indicated by solid lines. Teams with simple background collaborators are shown in dotted lines. Shaded areas represent 95% confidence intervals.
collaborations, and gender-homogeneous teams conduct more disruptive research than gender-diverse teams. For teams that have other dimensions of external diversity and may therefore produce less disruptive work, increasing expertise diversity among team members appear to be particularly beneficial to enhancing the originality of research output.

Past studies suggest that between-school collaborations may facilitate knowledge production and encapsulate more external specializations, which promote high-impact research (2). We find that between-school teams have greater long-term paper-to-paper impact than teams formed within the same institution, for each specific team size and expertise distance percentile bin (Fig. 5G). For large between-school teams with four or more authors, long-term impact increases as the teams’ expertise diversity augments, but the effect is not obvious for small teams of two or three authors. For teams of all sizes that are assembled in the same institution, long-term impact shows a remarkable boost as the team’s expertise diversity increases, which becomes more pronounced as the team size grows. In particular, for paper-to-paper citations, the long-term impact advantage of single-institutional teams in the highest distance percentile bin over those in the lowest distance percentile bin is 17.1% for two-author teams, which rises to 49.0% for teams of five or more authors. For small teams of two to three authors, papers written by single-institutional teams have even higher impact on patents than those written by between-school teams (Fig. 5J). Overall, while between-school teams garner more paper-to-paper citations than teams from the same institution, the impact upticks substantially faster for single-institutional teams as the teams’ expertise diversity increases.

Previous research has also demonstrated that international collaborations promote impact, which we next investigate with respect to the team’s size and expertise diversity (Fig. 5H) (47–49). We find that small or medium sized teams of two to four authors that have foreign collaborators do not exhibit a significant impact shift as expertise diversity increases, while large teams of five or more authors enjoyed greater long-term impact if the team members’
prior career histories are more diverse. For papers written by single-country teams, however, bolstering the teams’ expertise diversity is strongly associated with rising long-term impact, which becomes more pronounced as the teams’ sizes grow. The impact premium of single-country teams in the highest distance percentile bin over those in the lowest distance percentile bin is 16.0% for two-author teams, and 43.5% for five or more author teams. For small teams of two to three authors, domestic teams have even higher impact on patents than international teams (Fig. 5K). Similar to the effect of between-school collaborations, an international team configuration obviously attracts more paper-to-paper citations, but domestic teams of all sizes enjoy greater boost of long-term impact as the teams’ expertise diversity increases.

The above analyses regarding between-school and international collaborations suggest that the scientific and technological impact premium of teams with large expertise diversity is particularly pronounced for those formed within the constraints of geographical boundaries. These findings are further validated in temporal time periods (fig. S17-18). Collaborating with researchers specializing in more remote areas appear to facilitate production of high-impact work, especially for teams localized in their institutional or geographical spheres. These findings thus suggest a plausible enhancement for teams that have limited alternatives of diversification and are restrained to mostly departmental colleagues or domestic collaborators. For such teams, integrating the available expertise from a broad knowledge scope may predict higher-impact outputs.

Previous studies show that women are more inclined to step outside the disciplinary boundaries (50), more engaged in interdisciplinary collaborations (16), more likely to make scientific discoveries that lead to women-related health patents (51), and have a slightly higher propensity to collaborate with topically distant colleagues (20, 52). In the pre-2010 period, gender-diverse teams that include both men and women have greater expertise diversity than gender-homogeneous teams which are composed of men or women only, but gender-diverse teams has
been on pair with gender-homogeneous teams since the past decade (Fig. 5C). We find less variation in the proportion of gender-diverse teams as a function of the team’s expertise diversity after controlling for team size, compared to the previous institutional factors (fig. S16). The propensity of having female collaborators increases slightly as the expertise distance of teams rises up to a moderate level, but declines in the highest distance percentile bin.

Gender-diverse teams perform equally well as gender-homogeneous teams in terms of long-term paper-to-paper citation impact when there are up to four authors, and significantly outperform gender-homogeneous teams when there are five or more authors (Fig. 5I). Gender-diverse teams have higher long-term impact as their expertise diversity increases, and similar results hold for gender-homogeneous teams. Promoting gender diversity in the team assembly process not only improves gender equality in science and provides more collaborative opportunities for women, but also enhances teams’ performance in terms of high-impact research production (53). With respect to patent-to-paper citations, for both types of teams, increasing team expertise diversity is associated with greater impact on patenting, especially when the team has four or more authors. However, gender-homogeneous teams still have moderately higher patenting impact than gender-diverse teams, especially when the team sizes are small (Fig. 5L). Investigating the inherent causes for this gendered gap in patenting would facilitate the participation of women in industrial research, and make technology more diverse and vibrant in the knowledge creating processes.

**Discussion**

We propose a new method to quantify the expertise distance between two researchers based on the disciplinary distributions of their prior career histories. The method encapsulates several key aspects of expertise diversity, especially the intrinsic heterogeneity of interactions and relatedness among research fields. The expertise diversity of teams is strongly correlated with the
teams’ tendency of drawing on broad combinations of past knowledge, disruption of produced work, long-term impact on research in other fields, and the spectrum of diversity among team members’ affiliations and nationality.

Although multidisciplinarity and team expertise diversity tend to reflect similar features of scientific diversity and both appear to be correlated with long-term impact, their correlation with disruption appear to be substantively divergent. Expertise diverse teams produce more disruptive work in science and technology, while high multidisciplinary inspiration exhibits no consistent association with disruption for papers and has negative correlations with disruption for patents. More future research is needed to probe into the causes and implications of the disparity between expertise diversity and multidisciplinarity in predicting the originality of team outcomes.

While a team’s expertise diversity has surprisingly little correlation with short-term or mid-term impact, teams with greater expertise diversity tend to garner substantially higher impact in the longer run. This trend becomes more prominent as the citation time window expands and the team size increases. Since most funding agencies assess research performance when funding ends (typically three to five years), these results raise the question of how best to evaluate works of expertise diverse teams to capture their true potential to inspire future research.

Our distance measure sheds new light on the composition of prior expertise among team members, and offers predictive insights about key features of work the teams may produce, which may assist universities and funding agencies to identify and support highly diverse teams among the candidates (54). Although teams with members from more diverse backgrounds, such as having between-school or international collaborators, usually outperform less diverse teams that are assembled within the same institution or country, our results suggest that pulling together a cohort of experts from a more diverse knowledge scope within the geographical constraints may be particularly powerful when external collaborators are unavailable. It therefore
raises the possibility that, for teams that are restricted to only internal or domestic collaborators, preferentially recruiting more expertise diverse researchers might promote the long-term impact of the teams’ work.

Note that the findings regarding expertise diversity of teams and their long-term impact are correlational, which do not provide causal interpretations. Combining methods in computational social science with tools from other areas, in particular, scientometrics, network science, and machine learning, could result in statistical and generative models that probe expertise diversity from broader perspectives. Efforts to explore underlying mechanisms that drive the formation of diverse teams, and factors that facilitate or hinder teams’ long-term impact, are essential for researchers and policy makers to better understand the integration and production of knowledge in science and technology.

The need to measure the similarity and diversity at the individual or system level is prevalent in many scientific, technological, and social systems (26, 55). Our method provides a general framework of distance metric that accounts for the relatedness of sub-categories within the system. As such, this approach may have applicability in other settings, including but not limited to ecology diversity, innovation, research policy, and portfolio management, suggesting the potential for a more systematic exploration of similarity and diversity across broad domains.

1 Methods

1.1 Data

We use the publication and citation data in the period of 1950-2019 from the Microsoft Academic Graph (MAG) dataset. The original dataset contains over 200 million different types of documents, including journal articles, conference proceedings, patents, pre-prints, et al. We select papers published in journals for science, technology, and social sciences, namely biology, business, chemistry, computer science, economics, engineering, environmental science, geog-
raphy, geology, materials science, mathematics, medicine, physics, political science, sociology, and papers published in conferences for computer science. As our study requires information such as institutions and geographical locations of authors, we retain papers in MAG that record the affiliations of authors and drop those that do not provide affiliation information (56). Also, as the team size grows, for a randomly chosen pair of authors, they are less likely to know each other and lack substantial interactions during the collaboration, especially in mega teams where most coauthorship connections do not necessarily represent effective communications between authors in reality. Therefore, we limit our scope of analysis of coauthor expertise distance for papers with no more than 10 authors.

The MAG dataset collects many types of documents, including regular research papers, review papers, editorial materials, comments, and more. We expect team assembly mechanisms to vary significantly for different document types, as they serve unique purposes and convey different messages to the science community. For instance, research papers usually provide new results on a concurrent scientific topic and advance the frontier of a specific area in science. Other types of papers indirectly contribute to knowledge production, are usually not peer-reviewed, and have dissimilar team assembly mechanisms (49). Review papers provide an overview of recent progress on a relatively broad research theme, and editorial materials or comments aim to advocate opinions of the editors or researchers. Unfortunately, MAG does not provide such essential information for article types. Instead, we use the number of references made in a paper to approximately infer whether the paper itself is more likely to be an original research paper or other document types. We note the common practice in scientific publishing is that editorial materials and comments often make very few citations, while review papers tend to reference more literature. Thus, we refine papers that have at least 10 references and up to 100 references as research papers, which amount to a total number of 22.8 million papers, and 354 million citations from papers to papers.
The MAG dataset collects 4.4 million patents that contain affiliation information of authors. These patents make 29.9 million citations among themselves, and 5.6 million citations to the selected subset of research articles.

1.2 Definition of author expertise distance

Suppose for field $f$, the cumulative reference vector $v_f = (v^1_f, ..., v^n_f)$ records the numbers of references of papers from field $f$ made to all fields, where $n$ is the number of fields $(15,26)$. We then define the unit vector of field $f$ as $e_f = v_f/ ||v_f||$, where $||v_f|| = \sqrt{\sum_{m} (v^m_f)^2}$.

For an author $i$, let the publication vector $p_i$ record the number of publications author $i$ had in each field up to year $t$. The goal is to introduce a definition of expertise distance between a pair of authors that accounts for the relatedness between fields. An explicit form of $p_i$ is $p_i = a^1_i e_1 + ... + a^f_i e_f + ... + a^n_i e_n$, where $a^f_i$ is the number of papers author $i$ published in field $f$. We want to first normalize $p_i$ and obtain expertise vector $q_i$ of unit length $q_i = p_i/ ||p_i|| = q^1_i e_1 + ... + q^f_i e_f + ... + q^n_i e_n$ and $q_i = (q_1^i, ..., q_f^i, ..., q_n^i)$. Note that different from the definition of field vector length, here we explicitly account for the heterogeneous relatedness between fields and define

$$||p_i||^2 = (a^1_i e_1 + ... + a^f_i e_f + ... + a^n_i e_n)^2 = \sum_{j,k} a^j_i a^k_i (e_j \cdot e_k).$$  

(2)

Similarly, the cosine distance between expertise vectors of authors $i$ and $j$ can be calculated as $q_i \cdot q_j = \bar{q}_i M \bar{q}_j^T$, and the distance metric can be obtained as

$$d_{ij} = \sqrt{||q_i - q_j||^2} = \sqrt{2 - 2q_i \cdot q_j} = \sqrt{2 - 2\bar{q}_i M \bar{q}_j^T},$$  

(3)

where $M = (e_i e_j)_{i,j}$ is the matrix indicating the closeness between fields using cosine distance. Analogously, if we let $\bar{p}_i = (p_i^1, ..., p_i^f, ..., p_i^n)$, the length of publication vector of author $i$ can be obtained as

$$||p_i|| = \sqrt{\bar{p}_i M \bar{p}_i^T}.$$  

(4)
1.3 Estimating coauthor distance

To estimate the prior expertise distance of a pair of authors \((i, j)\) that coauthored a paper \(s\) at year \(t\), we first build their respective publication vectors using all papers up to year \(t\). We use the level 1 field classification in the MAG dataset, where each article is assigned to at least one scientific field. For the crude publication vector \(p_i(t)\) of author \(i\), \(a_i^f\) denotes the number of papers \(i\) published in field \(f\) up to \(t\). To account for authors with a reasonably long publishing career, we include only productive authors who have published at least 5 papers up to \(t\). The mean expertise distance of the paper \(\langle d_s \rangle\) is the average distance of all possible coauthor pairs \((i, j)\) among selected productive authors.

Papers with at least two productive authors are eligible to obtain a measure of team expertise distance, and those written by solitary authors are not considered in this study. To allow for a meaningfully long prior publication record of individual researchers, we consider only authors who have published at least 5 papers by the time of collaboration when estimating the expertise distance of the team. Thus, a proportion of less productive or early-career researchers are dropped and we obtain a subset of team-authored papers eligible for a distance metric. The numbers of papers and patents that ultimately receive a score of average expertise distance among coauthors are 11.0 million and 1.0 million, respectively, out of 22.8 million papers and 4.4 million patents in the refined dataset used for this study.

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References

1. S. Wuchty, B. F. Jones, B. Uzzi, The increasing dominance of teams in production of knowledge. *Science* **316**, 1036–1039 (2007).

2. B. F. Jones, S. Wuchty, B. Uzzi, Multi-university research teams: Shifting impact, geography, and stratification in science. *Science* **322**, 1259–1262 (2008).

3. D. Stokols, K. L. Hall, B. K. Taylor, R. P. Moser, The science of team science: overview of the field and introduction to the supplement. *American Journal of Preventive Medicine* **35**, S77–S89 (2008).

4. S. Fortunato, C. T. Bergstrom, K. Börner, J. A. Evans, D. Helbing, S. Milojević, A. M. Petersen, F. Radicchi, R. Sinatra, B. Uzzi, *et al.*, Science of science. *Science* **359** (2018).

5. A. Clauset, D. B. Larremore, R. Sinatra, Data-driven predictions in the science of science. *Science* **355**, 477–480 (2017).

6. D. Wang, A.-L. Barabási, *The science of science* (Cambridge University Press, 2021).

7. L. A. DeChurch, J. R. Mesmer-Magnus, The cognitive underpinnings of effective teamwork: a meta-analysis. *Journal of Applied Psychology* **95**, 32 (2010).

8. B. F. Jones, The burden of knowledge and the “death of the renaissance man”: Is innovation getting harder? *The Review of Economic Studies* **76**, 283–317 (2009).

9. F. Teodoridis, M. Bikard, K. Vakili, Creativity at the knowledge frontier: The impact of specialization in fast-and slow-paced domains. *Administrative Science Quarterly* **64**, 894–927 (2019).
10. S. Schweitzer, J. Brendel, A burden of knowledge creation in academic research: evidence from publication data. *Industry and Innovation* **28**, 283–306 (2021).

11. R. Guimera, B. Uzzi, J. Spiro, L. A. N. Amaral, Team assembly mechanisms determine collaboration network structure and team performance. *Science* **308**, 697–702 (2005).

12. G. S. Van Der Vegt, J. S. Bunderson, Learning and performance in multidisciplinary teams: The importance of collective team identification. *Academy of Management Journal* **48**, 532–547 (2005).

13. V. Larivière, Y. Gingras, On the relationship between interdisciplinarity and scientific impact. *Journal of the American Society for Information Science and Technology* **61**, 126–131 (2010).

14. J. Wang, B. Thijs, W. Glänzel, Interdisciplinarity and impact: Distinct effects of variety, balance, and disparity. *PloS One* **10**, e0127298 (2015).

15. A. J. Gates, Q. Ke, O. Varol, A.-L. Barabási, Nature’s reach: narrow work has broad impact. *Nature* pp. 32–34 (2019).

16. F. J. Van Rijnsoever, L. K. Hessels, Factors associated with disciplinary and interdisciplinary research collaboration. *Research Policy* **40**, 463–472 (2011).

17. A. Lungeanu, Y. Huang, N. S. Contractor, Understanding the assembly of interdisciplinary teams and its impact on performance. *Journal of Informetrics* **8**, 59–70 (2014).

18. I. Mayrose, S. Freilich, The interplay between scientific overlap and cooperation and the resulting gain in co-authorship interactions. *PloS one* **10**, e0137856 (2015).
19. K. L. Hall, A. L. Vogel, G. C. Huang, K. J. Serrano, E. L. Rice, S. P. Tsakraklides, S. M. Fiore, The science of team science: A review of the empirical evidence and research gaps on collaboration in science. *American Psychologist* **73**, 532 (2018).

20. T. B. Smith, R. Vacca, T. Krenz, C. McCarty, Great minds think alike, or do they often differ? research topic overlap and the formation of scientific teams. *Journal of Informetrics* **15**, 101104 (2021).

21. A. Zeng, Y. Fan, Z. Di, Y. Wang, S. Havlin, Impactful scientists have higher tendency to involve collaborators in new topics. *Proceedings of the National Academy of Sciences* **119**, e2207436119 (2022).

22. B. Nooteboom, W. Van Haverbeke, G. Duysters, V. Gilsing, A. Van den Oord, Optimal cognitive distance and absorptive capacity. *Research Policy* **36**, 1016–1034 (2007).

23. X. Shi, L. A. Adamic, B. L. Tseng, G. S. Clarkson, The impact of boundary spanning scholarly publications and patents. *PloS one* **4**, e6547 (2009).

24. M. Araki, M. Katsurai, I. Ohmukai, H. Takeda, Interdisciplinary collaborator recommendation based on research content similarity. *IEICE Transactions on Information and Systems* **100**, 785–792 (2017).

25. A. Zeng, Y. Fan, Z. Di, Y. Wang, S. Havlin, Fresh teams are associated with original and multidisciplinary research. *Nature Human Behaviour* pp. 1–9 (2021).

26. A. Stirling, A general framework for analysing diversity in science, technology and society. *Journal of the Royal Society Interface* **4**, 707–719 (2007).

27. V. Larivière, S. Haustein, K. Börner, Long-distance interdisciplinarity leads to higher scientific impact. *Plos One* **10**, e0122565 (2015).
28. A. Yegros-Yegros, I. Rafols, P. D’este, Does interdisciplinary research lead to higher citation impact? the different effect of proximal and distal interdisciplinarity. *PloS one* **10**, e0135095 (2015).

29. L. Waltman, N. J. van Eck, Field-normalized citation impact indicators and the choice of an appropriate counting method. *Journal of Informetrics* **9**, 872–894 (2015).

30. J. Wang, R. Veugelers, P. Stephan, Bias against novelty in science: A cautionary tale for users of bibliometric indicators. *Research Policy* **46**, 1416–1436 (2017).

31. L. Leydesdorff, C. S. Wagner, L. Bornmann, Interdisciplinarity as diversity in citation patterns among journals: Rao-stirling diversity, relative variety, and the gini coefficient. *Journal of Informetrics* **13**, 255–269 (2019).

32. X. Yu, B. K. Szymanski, T. Jia, Become a better you: Correlation between the change of research direction and the change of scientific performance. *Journal of Informetrics* **15**, 101193 (2021).

33. B. K. AlShebli, T. Rahwan, W. L. Woon, The preeminence of ethnic diversity in scientific collaboration. *Nature Communications* **9**, 1–10 (2018).

34. M. W. Nielsen, S. Alegria, L. Börjeson, H. Etzkowitz, H. J. Falk-Krzesinski, A. Joshi, E. Leahey, L. Smith-Doerr, A. W. Woolley, L. Schiebinger, Opinion: Gender diversity leads to better science. *Proceedings of the National Academy of Sciences* **114**, 1740–1742 (2017).

35. S. E. Jackson, The consequences of diversity in multidisciplinary work teams. *Handbook of work group psychology* pp. 53–75 (1996).
36. L. Hong, S. E. Page, Groups of diverse problem solvers can outperform groups of high-
ability problem solvers. *Proceedings of the National Academy of Sciences* **101**, 16385–
16389 (2004).

37. A. W. Woolley, C. F. Chabris, A. Pentland, N. Hashmi, T. W. Malone, Evidence for a
collective intelligence factor in the performance of human groups. *Science* **330**, 686–688
(2010).

38. L. Fleming, S. Mingo, D. Chen, Collaborative brokerage, generative creativity, and creative
success. *Administrative Science Quarterly* **52**, 443–475 (2007).

39. F. Shi, M. Teplitskiy, E. Duede, J. A. Evans, The wisdom of polarized crowds. *Nature
Human Behaviour* **3**, 329–336 (2019).

40. A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, S. Thrun,
Dermatologist-level classification of skin cancer with deep neural networks. *Nature* **542**, 
115–118 (2017).

41. K. He, X. Zhang, S. Ren, J. Sun, *Proceedings of the IEEE Conference on Computer Vision
and Pattern Recognition* (2016), pp. 770–778.

42. L. Wu, D. Wang, J. A. Evans, Large teams develop and small teams disrupt science and
technology. *Nature* **566**, 378–382 (2019).

43. M. Ahmadpoor, B. F. Jones, The dual frontier: Patented inventions and prior scientific
advance. *Science* **357**, 583–587 (2017).

44. S. E. Page, *The Difference: How the Power of Diversity Creates Better Groups, Firms,
Schools, and Societies*. (Princeton University Press, 2008).
45. B. Bozeman, E. Corley, Scientists’ collaboration strategies: implications for scientific and technical human capital. *Research Policy* **33**, 599–616 (2004).

46. R. Vacca, C. McCarty, M. Conlon, D. R. Nelson, Designing a ctta-based social network intervention to foster cross-disciplinary team science. *Clinical and Translational Science* **8**, 281–289 (2015).

47. A. Inzelt, A. Schubert, M. Schubert, Incremental citation impact due to international co-authorship in hungarian higher education institutions. *Scientometrics* **78**, 37–43 (2009).

48. B. S. Lanco-Barrantes, V. P. Guerrero-Bote, F. de Moya-Anegón, Citation increments between collaborating countries. *Scientometrics* **94**, 817–831 (2013).

49. D. Hsiehchen, M. Espinoza, A. Hsieh, Multinational teams and diseconomies of scale in collaborative research. *Science Advances* **1**, e1500211 (2015).

50. D. Rhoten, S. Pfirman, Women in interdisciplinary science: Exploring preferences and consequences. *Research Policy* **36**, 56–75 (2007).

51. R. Koning, S. Samila, J.-P. Ferguson, Who do we invent for? patents by women focus more on women’s health, but few women get to invent. *Science* **372**, 1345–1348 (2021).

52. G. Abramo, C. A. D’Angelo, G. Murgia, Gender differences in research collaboration. *Journal of Informetrics* **7**, 811–822 (2013).

53. Y. Yang, T. Y. Tian, T. K. Woodruff, B. F. Jones, B. Uzzi, Gender-diverse teams produce more novel and higher-impact scientific ideas. *Proceedings of the National Academy of Sciences* **119**, e2200841119 (2022).

54. J. S. Chu, J. A. Evans, Slowed canonical progress in large fields of science. *Proceedings of the National Academy of Sciences* **118** (2021).
55. C. A. Hidalgo, B. Klinger, A.-L. Barabási, R. Hausmann, The product space conditions the development of nations. *Science* **317**, 482–487 (2007).

56. C.-K. Huang, C. Neylon, C. Brookes-Kenworthy, R. Hosking, L. Montgomery, K. Wilson, A. Ozaygen, Comparison of bibliographic data sources: Implications for the robustness of university rankings. *Quantitative Science Studies* **1**, 445–478 (2020).