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Is interdisciplinarity more likely to produce novel or disruptive research?

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Abstract

Although many studies suggest that interdisciplinary research fosters creativity and breakthroughs, there has been no quantitative study to confirm this belief. In recent years, several indicators have been developed to measure novelty or disruption in research. Compared with the citation impact, this type of indicator can more directly characterize research quality and contribution. Based on the F1000 Prime database and Scopus datasets accessed via ICSR Lab, F1000 novelty tags and two disruption indices (DI_1 and DI_5) were used in this study for the assessment of research quality and contribution, and it was explored whether interdisciplinarity is more likely to produce novel or disruptive research. Interestingly, DI_1 and DI_5 exhibit different relationships with F1000 novelty tags; the reason for this may be that DI_5 highlights disruptive research within a given discipline and amplifies the disruptive signal within that discipline. Furthermore, it is found that interdisciplinarity (RS and LCDiv) is positively associated with F1000 novelty tags and the disruption indices (DI_1 and DI_5). As a result, it is demonstrated that interdisciplinarity helps to produce novel or disruptive research.

Keywords Interdisciplinarity · Novelty · Disruption index · Interdisciplinarity indicators

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Introduction

Studies show that science is becoming more interdisciplinary (Porter & Rafols, 2009; Van Noorden, 2015), and interdisciplinary research has become a vital research mode in modern science (Gibbons et al., 1994; Larivière & Gingras, 2014). The increasing number of interdisciplinary research programs and centers also demonstrates that interdisciplinary research is becoming increasingly important in science. The development of interdisciplinary research has also received widespread attention in scientific research and policy. Related studies are devoted to exploring interdisciplinarity measurement, interdisciplinary knowledge exchange, the scientific impact of interdisciplinarity, the evaluation of interdisciplinary research, interdisciplinary evolution, and the detection of emerging interdisciplinary research, among others (Bordons et al., 2005; Wagner et al., 2011).

A multitude of studies have been orchestrated to validate the effect of interdisciplinary research on science, primarily by examining the relationship between interdisciplinarity and the citation impact(Gooch et al., 2017; Lariviere & Gingras, 2010; Larivière et al., 2015; Levitt & Thelwall, 2008, 2009; Wang et al., 2015; Yegros-Yegros et al., 2015). Nevertheless, it is worth noting that citation counts in isolation fail to encapsulate the divergent forms of scholarly contributions, especially when confronted with papers that exhibit similar citation counts but diverge in their respective contributions. In recent years, several alternative indicators have surfaced, with an emphasis on novelty or disruption, thereby contributing to a more nuanced evaluation of research output. Novelty is generally defined as the atypical combination of previously existing knowledge, while disruptive research disrupts traditional theories and introduces new ideas. (Uzzi et al., 2013; Wang et al., 2017; Wu et al., 2019). In addition, the post-review database system F1000Prime (now Faculty Opinions) also provides expert judgment on novelty. Compared with the citation counts, this type of indicator can more directly characterize research quality or contribution. Although there have been studies exploring the link between interdisciplinarity and novelty (primarily through the lens of atypical combinations of knowledge), it has been observed that atypical combinations of knowledge strongly overlap with the interdisciplinarity indicators based on proximity, this type of novelty measurement captures interdisciplinarity rather than novelty (Fontana et al., 2020). As a result, there is currently a lack of research that fully explores the relationship between interdisciplinary research and novelty or disruption from a quantitative perspective. This study holds significance in addressing this gap and aims to enhance our understanding of the importance of interdisciplinary research in modern science. Moreover, it seeks to promote the development of interdisciplinary research and facilitate the formulation of science and technology policies that support and foster interdisciplinary endeavors.

In this paper, the F1000 classification tags expressing novelty are used to characterize novelty, and the disruption indices are also used to denote disruptive characteristics. The two types of measure represent two different types of indicators and they can capture the research contribution beyond citation counts. The F1000 classification tags are expressed as experts rating data. Although F1000 classification tags do not strictly adhere to the traditional peer review, they still represent a peer evaluation mechanism. Accordingly, the disruptive indices are bibliometrics indicators. As such, our research can reveal the relationship between interdisciplinarity and disruptive or novel studies, going beyond mere citation impact. It is intriguing to confirm the significance of interdisciplinarity in science.

Interdisciplinarity, novelty, and disruption

Interdisciplinarity

According to the National Academies report (National Academy of Sciences, 2005), interdisciplinary research is a mode of research by teams or individuals that integrates.

- Perspectives/concepts/theories and/or
- Tools/techniques and/or
- Information/data

from two or more disciplines or bodies of specialized knowledge. The disciplines or bodies of specialized knowledge can be those listed in the Subject Categories of the Web of Science, the Scopus subject classification system, etc. According to this definition, knowledge integration is the essence of interdisciplinary research. Interdisciplinarity can be understood as the degree of knowledge integration involved in interdisciplinary research and can be measured from the perspectives of diversity and coherence (Rafols & Meyer, 2010; Rafols et al., 2012). Compared with diversity, coherence has been less considered in interdisciplinary research.

The concept of diversity has three aspects: variety, balance, and disparity (Rafols & Meyer, 2010; Stirling, 2007). Variety is the number of disciplines, balance is the evenness of the distribution of the disciplines, and the disparity is the extent to which these disciplines are different from a cognitive perspective. Earlier interdisciplinarity indicators were dedicated to measuring singular diversity properties, such as the citation outside category (COC) (Porter & Chubin, 1985), the Shannon entropy (Adams et al., 2007), and the Simpson diversity (Chen et al., 2015). However, more recent studies have tended to develop composite indicators integrating variety, balance, and disparity. At present, the commonly used composite indicators are the Rao-Stirling diversity (RS) (Rafols & Meyer, 2010; Stirling, 2007), the Leinster–Cobbold diversity indices (LCDiv) (Mugabushaka et al., 2016; Zhang et al., 2016), and DIV (Leydesdorff et al., 2019a, 2019b). RS is a widely used indicator for the assessment of the interdisciplinarity of an article, author, or institution (Leydesdorff et al., 2013, Leydesdorff et al., 2015, Moreno and Danowitz 2016, Cassi et al., 2017), but there is evidence to suggest that RS does not satisfy the criteria of "true diversity" and the "monotonicity of balance." LCDiv, which is derived from biodiversity indicators, can compensate for the deficiencies of RS (Leinster & Cobbold, 2012; Mugabushaka et al., 2016). Some studies have demonstrated that LCDiv can be used as a measure of interdisciplinarity (Mugabushaka et al., 2016; Zhang et al., 2016). In addition, a new interdisciplinary indicator (DIV) has been developed by Leydesdorff (2018); it independently operationalizes diversity, balance, and disparity, and then combines them ex-post (Leydesdorff, 2018; Leydesdorff et al., 2019a, 2019b; Leydesdorff et al., 2019a, 2019b). Recently, with recourse to Shannon's probabilistically-based entropy concept, Mutz (2022) reconceptualized variety, balance, and disparity as entropy masses that add up to an overall diversity indicator div_e.

Novelty and disruption

Novelty and disruption are key characteristics of the scientific enterprise. Novelty in research refers to the introduction of a new idea or a unique perspective that adds to the existing knowledge in a particular field of study. Disruption in research refers to a fundamental transformation that can radically alter existing knowledge or practice, particularly when such research may change or disrupt existing scientific paradigms (Kuhn, 1962). Novelty brings new perspectives and approaches to a specific field, but it does not necessarily imply disruptive or revolutionary changes. As such, novelty is also considered to be an essential element of disruptive research (Lee et al., 2015). According to Leahey et al. (2023), different types of novelty can have different impacts on science. As expected, new methods tend to be disruptive, while new theories tend to be less disruptive. It is surprising to find that new results do not have a robust effect on the nature of scientific influence.

In scientometrics, novelty is characterized as the recombination of existing knowledge (Schumpeter, 1939; Uzzi et al., 2013). Discoveries do not appear out of thin air but are derived from what is already known (Arthur, 2009). In recent years, significant progress has been made regarding the indicators with which to quantitatively measure novelty. These indicators define novelty as atypical combinations of keywords or cited references. Uzzi et al. (2013) proposed a novel indicator (NoveltyU) based on unusual combinations of cited references (cited journals) in articles, and Wang et al. (2017) assessed novelty by examining whether a published article makes first-time-ever combinations of referenced journals. Furthermore, Lee et al. (2015) proposed a revised version of the novelty indicator developed by Uzzi et al. (2013). Fontana et al. (2020) and Bornmann et al. (2019) compared the novelty measurements of Uzzi et al. (2013) and Wang et al. (2017). The two studies demonstrated that the novelty indicator proposed by Uzzi et al. (2013) is more suitable for measuring novelty. Furthermore, some other studies have used unusual keyword combinations to identify knowledge novelty and the introduction of new concepts (Carayol et al., 2016; Uddin & Khan, 2016; Warman et al., 2013; Yan et al., 2020). In addition to bibliometric indicators, novelty evaluation based on peer review has also been developed. The F1000 Prime database provides one or more ratings and classification tags by experts for each recommended article. These F1000 classification tags include several typical tags expressing novelty.

Recently, Wu et al. (2019) presented a disruption index for the measurement of how disruptive a publication is to the field of science. The disruption is the degree to which each work disrupts the field of science or technology to which it belongs by introducing something new that eclipses attention to the previous work upon which it has been built (Wu et al., 2019). Such disruptive influences are characterized by citations to a focal article but not references. This measure was previously designed to identify destabilization and consolidation in patented inventions (Funk & Owen-Smith, 2017). The disruption index provides a new quantitative measurement for disruption, and the type of measurement is considered a realization of Kuhn's scientific revolutions theory (Kuhn, 1962). Subsequently, Shibayama and Wang (2020) proposed a similar measure. Bu et al. (2021) introduced several similar variant disruption indices from the multidimensional perspective of impact measurement. In these studies, the disruption index proposed by Wu et al. was regarded as the original disruption index, i.e., DI_1. Furthermore, Bornmann et al. (2020) and Bornmann and Tekles (2021) investigated the convergent validity of the disruption index proposed by Wu et al. (2019) and some other variant disruption indicators. They also proposed a new variant disruption index, DI_5, and revealed that this index performs slightly better than the original disruption index (DI_1) and other variants.

Studies have shown that there is a strong relationship between interdisciplinarity and novelty. According to Fontana et al. (2020), atypical knowledge combinations strongly overlap with proximity-based interdisciplinarity indicators, and this type of novelty measurement captures interdisciplinarity rather than novelty. The study reveals a strong correlation between novelty as proposed by Uzzi et al. (2013) and disparity. Furthermore, research has demonstrated that variety across fields bolsters scientific creativity (Rafols & Meyer, 2010; Yong et al., 2014). It has been argued by Hollingsworth (2009) organizations making breakthrough discoveries in biomedical research tend to be interdisciplinarity and have organizational structures that facilitate communication across fields. However, the atypical combination of reference as a measurement of novelty has been scrutinized in some studies. For instance, Tahamtan and Bornmann (2018) identified landmark papers in Scientometrics and interviewed the corresponding authors to pinpoint the sources of ideas and the contribution of cited publications. According to their findings, prior publications do not necessarily act as the inspiration for creative ideas. In contrast, these creative ideas often originate from practical problem-solving, collaborations with colleagues, and the benefits derived from interdisciplinary dialogues. As well, although some studies also examined the relationship between interdisciplinarity and breakthroughs, these studies generally identified breakthroughs based on citation counts, such as highly cited papers(Ponomarev et al., 2014a, 2014b; Ponomarev et al., 2014a, 2014b; Winnink & Tijssen, 2015). As mentioned earlier, citation counts alone do not provide a precise reflection of a paper's research contribution (Lyu et al., 2021; Wu et al., 2019), underscoring the need for more comprehensive evaluative metrics.

Methods

Each article in the F1000 Prime database has one or more ratings and classification tags assigned by an expert. These F1000 classification tags include several tags expressing novelty (Bornmann et al., 2020), which are defined as F1000 novelty tags. Furthermore, the disruption index (DI_1) proposed by Wu et al. (2019) and its variant index, DI_5, are also used. DI_5 can be considered a field-specific variant disruption index that highlights disruptive research within a given discipline (Bornmann et al., 2020; Leydesdorff & Bornmann, 2021). The two disruption indices can complement each other to capture disruption. According to related studies, novelty is assumed to be a defining feature of disruption (Bornmann et al., 2020; Lee et al., 2015). Then, the F1000 novelty tags and two disruption indices (DI_1 and DI_5) are taken as measurements of disruption. Atypical combinations of knowledge strongly overlap with the interdisciplinarity indicators based on proximity, and this type of indicator captures interdisciplinarity rather than novelty (Fontana et al., 2020). As a result, no atypical combination measurements were chosen for this study to identify the novelty.

The F1000 novelty tags and disruption index represent two different criteria. F1000 faculty members assign F1000 novelty tags, and this evaluation method falls under the peer review system. The disruption index is a typical bibliometric indicator used by the publication citation network. The two types of methods aim to represent the novelty and disruption deposited in the publications. Furthermore, to compute the interdisciplinarity and the disruption index, the detailed bibliometric information of F1000 articles is obtained by matching F1000 articles and Scopus datasets accessed via ICSR Lab from Elsevier.

Classification tags provided by F1000

F1000Prime selects important articles and trends in biology and medicine based on the post-published expert peer review of PubMed articles (see https://F1000.com/prime/home). More than 10,000 basic research scholars and clinical experts (namely faculty members) nominated by peers classify and evaluate the biomedical articles included in PubMed and explain why it is necessary to read their recommended articles. Each article that receives an F1000 recommendation gets a rating to indicate "how important" the faculty member perceives the work to be. Each article is scored on a scale of one to three stars (respectively indicating "Good," "Very Good," and "Exceptional").

A classification(s) provides an "at-a-glance" guide for a reason(s) the article is being recommended. The classification tags are as follows (https://facultyopinions.com/prime/my/about/evaluating).

- Confirmation: validates previously published data or hypotheses
- Controversial: challenges established dogma
- Good for teaching: key article in the field and/or well-written
- *Interesting hypothesis*: presents a new model
- Negative/null results: the article has null or negative findings
- *New finding*: presents original data, models, or hypotheses
- *Novel drug target*: suggests new targets for drug discovery
- Refutation: disproves previously published data or hypotheses
- *Technical advance*: introduces a new practical/theoretical technique or the novel use of an existing technique

The tags in bold reflect aspects of novelty in research (Bornmann et al., 2020), and the four tags are defined as F1000 novelty tags in this study. The importance of the tags lies in their assignment by an expert. Considering that disruptive research should include elements of novelty, the tags are expected to be positively related to the disruption index values.

Formation of the dataset to which bibliometric data are attached

As of March 2021, the F1000Prime database included 184,910 records and 289,062 assessments, including all recommendations (and classifications) made and the bibliographic information of the corresponding articles in the systems. The dataset contains a total of 179,144 different DOIs, among which all are individual articles with very few exceptions. It was found that some records have the same DOI, and a few (three) records were found to have an incorrect DOI. These records were omitted from the analysis. To obtain detailed bibliometrics data about the F1000 articles, the F1000 articles and publications from the Scopus database were matched by the DOI. The Elsevier ICSR Lab platform was used to match the F1000 articles and Scopus records. ICSR Lab is a cloud-based computational platform that enables the analysis of large structured datasets, including those that power Elsevier solutions such as Scopus and PlumX. Through

ICSR Lab, 176,334 F1000 articles were searched from the Scopus dataset. This dataset includes F1000 tags, recommendations, references, citing publications, discipline, etc.

The interdisciplinarity of articles was computed by their references. The references of some publications could not be retrieved from the Scopus dataset, so these articles could not be used to calculate interdisciplinarity via the corresponding references list. In addition, the study of Wu et al. (2019) indicated that disruptive research is affected by team size. The team size or the number of authors was therefore also included in the analysis. However, the records of some articles in the Scopus dataset had missing author and institutional information. Moreover, considering that the disruption index is affected by the citation time window, only articles with a citation time window of at least three years were selected. Therefore, only documents published in F1000Prime before 2018 were included. Finally, 146,004 articles with complete bibliometric information were retained for analysis.

There are two types of journal classification systems used in the Scopus dataset, namely the Elsevier journal classification system and the Science-Metrix classification system. The Elsevier journal classification system includes 330 specialties and 27 disciplines, and some journals are classified into multiple specialties or disciplines. This classification system primarily serves information retrieval. The Science-Metrix classification system is recommended by Science-Metrix, Inc. Its goal is bibliometric study, and individual journals are assigned to single, mutually exclusive categories via an approach combining algorithmic methods and expert judgment. This classification system includes 6 domains, 22 fields, and 176 subfields. The Science-Metrix classification developed the journal-based classification into article-level and hybrid versions. A scientific publication is attributed to a domain, field, and subfield for the article-level classification using a deep neural network (an artificial intelligence technique). In the hybrid version, most articles are still classified at the journal level, except for those published in multidisciplinary journals (e.g., *Science*, *Nature*, *PNAS*, and *PLOS One*), which are classified at the article level (Archambault et al., 2011). In this study, the hybrid version of the Science-Metrix classification system was used. Interdisciplinarity was calculated at the level of subfields (specialties), which corresponds to Rinia's (2007) "small interdisciplinarity."

Indicators: interdisciplinarity and the disruption indices

Interdisciplinarity

Two interdisciplinarity indicators were used to evaluate the relationship between interdisciplinarity, and novelty or disruption, namely RS (Rafols & Meyer, 2010; Stirling, 2007) and LCDiv (Mugabushaka et al., 2016; Zhang et al., 2016). The formula for RS is as follows:

$$RS = \sum_{ij}^{n} p_i p_j d_{ij},$$

where p_i is the proportion of references in discipline i, and d_{ij} is the dissimilarity between Science-Metrix disciplines i and j.

LCDiv can be expressed as follows:

$$\left(\sum_{i}^{n} p_i \left(\sum_{j}^{n} s_{ij} p_j\right)^{q-1}\right)^{\frac{1}{1-q}} (q \neq 1, \infty),$$

where i, j, and p_i are the same as previously defined, and s_{ij} is the cosine similarity between specialties i and j. Furthermore, the parameter q controls the relative emphasis placed on common or rare elements according to the user. When $q=2$, it is easy to convert LCDiv from RS or the Gini-Simpson index, making it a suitable choice as an interdisciplinarity measure. Consequently, in this study, only $q=2$ is considered, and the following conclusion holds.

$$\frac{1}{\sum_{ij}^{n} s_{ij} p_i p_j}$$

For any given article, interdisciplinarity indicators are determined by the distribution of the Science-Metrix subfield (specialty) in the reference lists. It is common to use references as a measure of interdisciplinarity (Boyack & Klavans, 2014; Tahamtan & Bornmann, 2018; Wang, 2016; Wang & Schneider, 2020). In addition to the specialty distribution in the reference list, an index of similarity or a distance matrix is essential for interdisciplinarity. Based on the citing articles from Scopus in 2016 and 2017, a co-citation matrix s_{ij} between the Science-Metrix subfields is compiled, which is used to represent the similarity of Science-Metrix subfields (specialties). The cosine similarity is used to normalize the co-citation matrix (Ahlgren et al., 2003). The formula is as follows:

$$s_{i,j} = \frac{\sum_{k=1}^{N} cc_{ik} cc_{jk}}{\sqrt{(\sum_{k=1}^{N} cc_{ik}^2)(\sum_{k=1}^{N} cc_{jk}^2)}},$$

where c_{ik} is the number of co-citations between specialties i and k.

Disruption index

The original disruption index proposed by Wu et al. (2019), namely DI_1, and its variant indicator, DI_5, are used in this study. According to the disruption index and its related research (Bornmann & Tekles, 2021; Bornmann et al., 2020; Bu et al., 2021; Leydesdorff & Bornmann, 2021; Wu et al., 2019), the definition of the disruption index for a focal article is as follows:

$$DI_l = \frac{n_i - n_j^l}{n_i + n_j^l + n_k},$$

where n_i is the number of articles citing the focal article exclusively without referencing any of its references, n_j^l is the number of articles that cite both the focal article and at least l of its references, and n_k is the number of articles citing the references of the focal article, but not the focal article itself. When $l=1$, this formula is the original disruption index (DI_1) and n_j^1 the number of publications that cite both the focal paper and at least one of its cited references. However, a highly cited reference of the focal paper is more likely to be cited in a citing paper of the focal paper than a less frequently cited reference. This citation behavior may affect the measure of paper disruptiveness. Bornmann et al. (2020) suggested that the problem can be mitigated by taking into account citing papers that cite at least a certain number of the focal paper's references (namely $l > 1$). They proposed the disruption index variant DI_5, which has a threshold of $l = 5$. Given that only citing papers with a minimum of five citation links to the focal paper's cited references are considered for counting the bibliographic couplings between the focal paper and its references, the citing papers of the focal paper inevitably exhibit a certain degree of topic similarity with the focal paper itself. Therefore, DI_5 can be considered a field-specific variant disruption index that highlights disruptive research within a given discipline (Bornmann et al., 2020; Leydesdorff & Bornmann, 2021). In an empirical analysis by Bornmann et al. (2020), DI_5 produced comparably good results.

Statistical analysis

The F1000 novelty tags include "New Finding," "Hypothesis," "Novel drug target," and "Technical advance." An article in F1000Prime does not have to be assigned only one novelty tag, which means that one publication may have several novelty tags. Thus, there is an overlap between publications in different categories if grouped by F1000 novelty tags. To separately analyze the relationship between these four novelty tags and interdisciplinarity, four datasets for the four F1000 novelty tags were respectively constructed. First, the articles without any F1000 novelty tags were classified into a single category, and this category is regarded as the reference category.

Second, the articles were grouped into four novelty tag categories according to the F1000 novelty tags. Of course, the articles with multiple types of F1000 novelty tags were

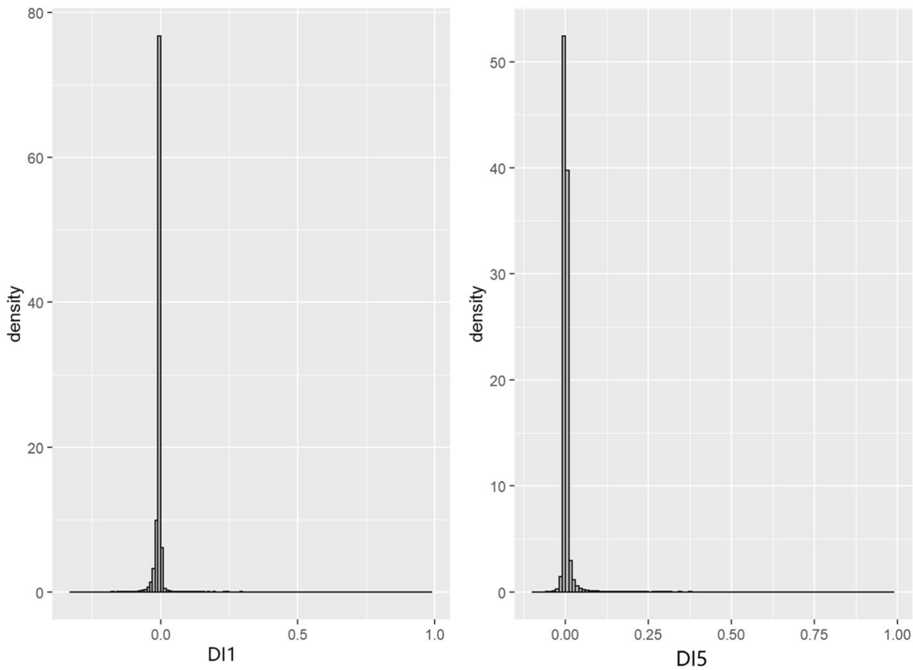

Fig. 1 The distribution of the two disruption indices

grouped into multiple novelty tag categories. Finally, five categories were obtained, including four novelty tag categories and a reference category.

The relationship between F1000 novelty tags and the disruption index was first explored. As mentioned previously, novelty is necessary for disruption. The F1000 novelty tags may be more related to the identification of the novelty of articles; the disruption index was set as the dependent variable, and the F1000 novelty tag was set as the independent variable. These tags are count variables and include the sum of the tag assignments from the F1000Prime faculty members (F1000 members) for a single article. In addition, the disruption indices DI_1 and DI_5 exhibit a skewed distribution, not a normal distribution. Figure 1 presents the distributions of DI_1 and DI_5. Due to a large number of articles, multiple linear regression can still be used to explore the relationships between the F1000 novelty tags and the disruption index. Because many articles are assigned multiple F1000 novelty tags, respective linear regression models are constructed for the four F1000 novelty tags.

Second, the effect of interdisciplinarity on novel and disruption was explored, and the effects of interdisciplinarity on the F1000 novelty tags and disruption indices are respectively disclosed. The F1000 novelty tags or the disruption index was the dependent variable, and interdisciplinarity was the independent variable. As research has confirmed that disruption is affected by the team size (Hu et al., 2021; Lariviere et al., 2015; Lee et al., 2015; Weiss & Hoegl, 2016; Wu et al., 2019), the team size was used as the control variable. The team size was set as an ordered categorical variable from 1 to 15, and the articles with 15 or more authors were aggregated into a single variable, namely 15+. In addition, discipline also be regarded as a factor in disruption. Furthermore, as per the findings of Wu et al. (2019), the association between disruption and team size remains consistent across 90% of disciplines, with the exceptions being computer science and engineering. Despite the F1000 database is mainly focused on medicine and life science, it also encompasses topics from computer science and engineering. As such, the discipline is also taken as a control variable in our study. In our analysis, discipline is represented by the "Field" in the Science Metrix classification system.

The F1000 novelty tags are count variables and include the sum of the tag assignments from the F1000Prime faculty members for a single article. Therefore, a robust Poisson regression was used to analyze the relationship between interdisciplinarity and the F1000 novelty tags. The Poisson model is recommended for use in cases in which count data are the dependent variable. Robust methods are recommended when the distributional assumptions for the model are not completely met. In this study, the glmRob() function from the robust package in the R language was used to perform a robust Poisson regression analysis. On the other hand, because the disruption indices and interdisciplinarity are continuous variables, multiple linear regression was used to explore the relationships between them. The lm() function in the R language was used to perform the linear regression analysis.

Results

F1000 novelty tags and the disruption indices

Table 1 presents the distribution of the publications with F1000 novelty tags. Over 56% of the articles have two or more F1000 novelty tags. Among them, publications with "New Findings" tags account for the vast majority, and the proportion of these articles reaches 71.97%. This is followed by publications with "Interesting Hypothesis" and "Technical

Table 1 The tags allocated by faculty members ($n = 146{,}004$ records, $n = 228{,}318$ tag mentions)

Tag	Absolute number	Percent of tag mentions	Percent of records
New finding	105,081	46.02%	71.97%
Interesting hypothesis	32,006	14.02%	21.92%
Confirmation	28,143	12.33%	19.28%
Technical advance	22,807	9.99%	15.62%
Good for teaching	15,363	6.73%	10.52%
Controversial	10,685	4.68%	7.32%
Novel drug target	8162	3.57%	5.59%
Refutation	1790	0.78%	1.23%
Clinical trial: RCT	1449	0.63%	0.99%
Changes clinical practice	1394	0.61%	0.95%
Negative/null results	654	0.29%	0.45%
Systematic review/meta-analysis	530	0.23%	0.36%
Clinical trial: non-RCT	252	0.11%	0.17%
Review/commentary	2	0.001%	0.001%
	228,318	100.00%	156.38%

Table 2 The disruption indices (DI_1) and F1000 novelty tags

	New finding	Interesting hypothesis	Technical advance	Novel drug target
DI_1	− 0.0012*** 0.0001	− 0.0002 0.0001	0.0000 0.0001	− 0.0002 0.0002
Team Size	− 1.095e-05*** 0.0000	2.632e-05*** 0.0000	− 2.486e-05*** 0.0000	2.401e-05*** 0.0000
Field	0.0002*** 0.0000	0.0003*** 0.0000	0.0003*** 0.0000	0.0003 *** 0.0000
Intercept	− 0.0051*** 0.0001	− 0.0062*** 0.0002	− 0.0061*** 0.0002	− 0.0064*** 0.0003

***$p < 0.000$; **$p < 0.001$; *$p < 0.01$, $p < 0.05$

Advance" tags, the proportions of which are 21.92% and 15.62%, respectively. Finally, the fewest publications have the "Novel Drug Target" tag, and the proportion reaches only 5.59%. The number of publications without any novelty tags is 21,587. The publications and reference categories of each novelty tag were combined, and four analysis datasets were formed.

Table 2 presents the regression analysis results for the four F1000 novelty tags and two disruption indices (DI_1 and DI_5). The "New Findings" and "Interesting Hypothesis" show a significant negative effect on DI_1 ($p < 0.001$), and the other two tags show an insignificant effect on DI_1. These results are contrary to the expectations. The F1000 novelty tags are more likely to represent the novelty of the study, while the disruption index aims to characterize disruption. The effect of the F1000 novelty tags on DI_1 means that most studies with novelty tags do not exhibit a corresponding disruption, and disruption does not increase with novelty. Compared with DI_1, DI_5

Table 3 The disruption indices (DI_5) and F1000 novelty tags

	New finding	Interesting hypothesis	Technical advance	Novel drug target
DI_5	0.0015*** 0.0001	0.0006*** 0.0001	0.0016*** 0.0001	0.0001 0.0002
Team Size	1.369e-05*** 0.0000	1.232e-05*** 0.0000	1.706e-05*** 0.0000	1.138e-05** 0.0000
Field	0.0003*** 0.0000	0.0003*** 0.0000	0.0003*** 0.0000	0.0003*** 0.0001
Intercept	– 0.0013*** 0.0001	0.0006** 0.0002	0.0002 0.0003	0.0008* 0.0003

Table 4 The Poisson regression of the F1000 novelty tags and interdisciplinarity (RS)

	New findings	Interesting hypothesis	Technical advance	Novel drug target
RS	0.1121*** 0.0550	1.3201*** 0.0932	3.4909*** 0.0935	– 1.6610*** 0.2486
Team Size	0.0105*** 0.0004	0.0119*** 0.0007	0.0164*** 0.0008	0.0656*** 0.0009
Field	– 0.0610*** 0.0015	– 0.1259*** 0.0029	– 0.1099*** 0.0030	– 0.2384*** 0.0070
Intercept	0.2703*** 0.0088	0.0655*** 0.0172	– 0.3811*** 0.0193	– 0.4047*** 0.0431

***$p<0.000$; **$p<0.001$; *$p<0.01$, $p<0.05$

has a different relationship with F1000 novelty tags. The "Novel Drug Target" show an insignificant effect on DI_5, and the other three F1000 novelty tags have significant positive effects on DI_5. Therefore, from the perspective of DI_5, most papers with F1000 novelty tags tend to have highly disruptive, and this conclusion is more in line with the expectations.

The discrepancy between DI_1 and DI_5 implies that the two disruption indices may exhibit an inconsistent relationship with F1000 novelty tags. As noted earlier, in the case of the DI_1 index, a highly cited reference of the focal paper is more likely to be cited in a citing paper of the focal paper than a less frequently cited reference. Consequently, some citing papers that cite both the focal paper and its highly cited references may not exhibit a thematic similarity to the focal paper. This scenario may lead to some disruptive research with a low DI_1 value. The variant disruption index, DI_5, serves to mitigate this issue.

There may also be additional factors influencing the relationship between F1000 novelty tags and disruption. As is known, novelty may be necessary for disruption, but it is not necessarily sufficient to make something disruptive. In addition, F1000 novelty tags are allocated by F1000 faculty members. Judgments of novelty are subjective and may be influenced by the expertise and experience of experts. In some cases, radically disruptive research may not be recognized within a short time frame. The citation delay and Sleeping Beauty phenomena in science also support this possibility (Ho & Hartley, 2017; Ke et al., 2015; Lachance & Lariviere, 2014; Min et al., 2016; Rinia et al., 2001).

Table 5 The Poisson regression of the F1000 novelty tags and LCDiv

	New findings	Interesting hypothesis	Technical advance	Novel drug target
LCDiv	0.1177*** 0.0430	1.0649*** 0.0699	2.6579*** 0.0665	− 1.4784*** 0.2039
Team Size	0.0105*** 0.0004	0.0117*** 0.0007	0.0161*** 0.0008	0.0647*** 0.0009
Field	− 0.0622*** 0.0015	− 0.1286*** 0.0029	− 0.1122*** 0.0030	− 0.2402*** 0.0071
Intercept	0.1566*** 0.0470	− 0.9776*** 0.0783	− 2.9849*** 0.0758	1.0893*** 0.2282

***$p < 0.000$; **$p < 0.001$; *$p < 0.01$, $p < 0.05$

Table 6 The regression of disruptive indices and interdisciplinarity

	DI_1		DI5	
	RS	LCDiv	RS	LCDiv
IDR	0.0209*** 0.0006	0.0141*** 0.0005	0.0028*** 0.0007	0.0024*** 0.0005
Team Size	− 7.950e-06*** 0.0000	− 7.978e-06*** 0.0000	1.164e-05*** 0.0000	1.168e-05*** 0.0000
Field	0.0001*** 0.0000	0.0001*** 0.0000	0.0002*** 0.0000	0.0002*** 0.0000
Intercept	− 0.0069*** 0.0001	− 0.0206*** 0.0005	0.0006*** 0.0001	− 0.0018** 0.0006

***$p < 0.000$; **$p < 0.001$; *$p < 0.01$, $p < 0.05$

Interdisciplinarity and F1000 novelty tags

The effect of interdisciplinarity on the F1000 novelty tags was also explored. As mentioned previously, the team size and Science-Metrix field were used as control variable. The robust Poisson regression model was used in this study. Tables 3 and 4 respectively present the relationship between the two common interdisciplinarity indicators, namely RS and LCDiv, and the F1000 novelty tags. The tags “New Findings,” “Interesting Hypothesis,” and “Technical Advance” were found to have a positive relationship with interdisciplinarity ($p < 0.00$), but the “Novel Drug Target” tag has a negative relationship with interdisciplinarity, both for the RS and LCDiv indicators ($p < 0.00$). It should be noted that the proportion of articles with the “Novel Drug Target” tag is relatively low. These results mean that, in most cases, interdisciplinarity is more likely to produce innovative research from the perspective of F1000 peer reviews. In addition, the team size also has a positive effect on F1000 novelty tags, which indicates that a large team also helps facilitate the emergence of novel research.

The effect of interdisciplinarity on the "Novel Drug Target" behaves differently than it does on the other three F1000 novelty tags, and the underlying mechanism of this phenomenon is challenging to discern. The research dataset for this study consists of papers recommended by F1000 experts, indicating an inherently high quality of research. As a whole, F1000 recommended papers tend to exhibit a higher degree of interdisciplinarity. Although "Novel Drug Target" is designated as a novelty by F1000 novelty tags, its level of interdisciplinarity may not necessarily surpass that of other papers not labeled with such tags.

Interdisciplinarity and the disruption indices

Tables 5 and 6 present the linear regression results of the disruption indices (DI_1 and DI_5) and interdisciplinarity. The team size and Science-Metrix Field were also used as the control variables. The two disruption indices (DI_1 and DI_5) show positive relationships with interdisciplinarity (RS and LCDiv). Consequently, interdisciplinarity would improve the emergence of disruptive research. In addition, the team size was found to have a negative effect on DI_1 ($p < 0.001$). This also means that small teams are more likely to produce disruptive research. This conclusion is consistent with that of the study by Wu et al. (2019). Regarding DI_5, the team size was found to have a positive effect on disruptive research. Although DI_1 and DI_5 are both used to measure disruption, there are still some differences between them.

Conclusion and discussion

This study investigated whether interdisciplinarity is more likely to produce novel or disruptive research from the perspective of quantitative analysis. Although many studies have indicated that interdisciplinary research is often associated with novelty and breakthroughs, no research has systematically confirmed the relationship between them. Two measurements of research quality and contribution, namely the F1000 novelty tags and disruption indices, were used in this study. First, the two disruption indices were found to have different relationships with the F1000 novelty tags. F1000 novelty tags have a negative association with DI_1, but three of the four F1000 novelty tags have a positive relationship with DI_5. Second, the relationship between interdisciplinarity and the F1000 novelty tags is clear. Interdisciplinarity has a positive effect on novelty, which indicates that interdisciplinarity helps to produce novel research. Furthermore, the disruption indices (DI_1 and DI_5) have positive relationships with interdisciplinarity. Consequently, interdisciplinarity can help to produce disruptive research. In summary, it can be concluded that interdisciplinarity is more likely to produce novel or disruptive research.

DI_5 is a variant indicator of DI_1, the calculation of which considers only the citing articles of the focal article that cite at least five of the references of the focal article. In this practice, citation links in a specific field are closely linked to the focal article, and the citing articles are more closely related on a thematic level. As such, DI_5 is a field-specific disruption index that identifies disruptive articles within a given discipline and amplifies a disruptive signal within that discipline. Regarding the disruption index, positive values should tend to indicate disruptive research, while negative values should tend to reflect developmental research. In the dataset used in this study, the ratio of articles with $DI_1 > 0$ accounted for 7.3%, while the ratio of articles with $DI_5 > 0$ accounted for 47.5%. Therefore, DI_5 amplifies the original disruption index and thus may lead to partially different conclusions in the analysis of the relationship between the disruption index and F1000 novelty tags or interdisciplinarity.

This study also indicates that novelty and disruption are two different concepts. While novelty may be necessary for disruption, it is not necessarily sufficient to make something disruptive. Additionally, the F1000 novelty tags also do not necessarily accurately characterize novelty. The findings of this study show that some disruptive research also does not exhibit evident novelty from the perspective of F1000 novelty tags. It is possible that some of the most novel research may not be recognized in a short period. In addition, it is worth noting that novel or disruptive research does not necessarily lead to high citations. Some novel or disruptive research is likely to be characterized by citation delay (Wu et al., 2019). Similarly, some highly cited articles may just be developmental research to advance current science and technology, and may not indicate disruption or breakthroughs. This study was characterized by several other limitations. F1000 Faculty Opinions are mainly related to medicine and biomedicine, not all disciplines. Therefore, the research conclusions may have a certain disciplinary orientation. In the future, the authors hope to conduct a similar study using datasets from subjects other than biology and medicine, as well as other periods and databases. Another limitation of this study may be possible biases in the F1000Prime data. Several studies have demonstrated that there can exist biases in peer-review assessments (of journals and grants) (Bornmann and Daniel, 2009).

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Declarations

Conflict of interest The authors declare no conflicts of interest.

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