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Interdisciplinarity and impact: the effects of the citation time window

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Abstract
The relationship between interdisciplinarity and citation impact is affected by many factors, and the citation time window is a crucial factor. Our study examines the effect of the citation time window on the relationship between interdisciplinarity and scientific impact. All journal articles published in 2006 in Web of Science (WoS) are considered. The relationship between interdisciplinarity and scientific impact is explored by conducting a year-by-year negative binomial regression analysis with different interdisciplinarity indicators. Three diversity single-property indicators (namely variety, balance, and disparity) and three typical composite interdisciplinarity indicators (Rao-Stirling index (RS), Leinster–Cobbold diversity indices (LCDiv), and DIV) are used in this study. The results show that evaluating the scientific impact of interdisciplinarity requires a sufficiently long citation time window. However, the length of the citation time window is different for different interdisciplinarity indicators. A 4-year citation time window is necessary when the variety indicator is used, whereas balance and disparity require at least 11-year and 13-year citation time windows, respectively. The citation time window is the same (at least 5 years) for the three composite interdisciplinarity indicators (RS, LCDiv, and DIV). The recommended length of the citation time window is based only on this study and may be affected by the data set, regression model, and discipline classification system.

Keywords Interdisciplinarity · Citation time window · Indicators · Negative binomial regression

Introduction

Science is becoming more interdisciplinary, and interdisciplinary research has become a vital research mode in modern science (Larivière & Gingras, 2014; Porter & Rafols, 2009). More importantly, interdisciplinary research is regarded as an important source of innovation and effective approaches to solving social problems. Therefore, it has attracted substantial attention in science research and national science policy. Data from the Web of Science (WoS (Science Citation Index (SCI)/Social Sciences Citation Index (SSCI))

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demonstrates that the number of documents with titles including "interdisciplinar* or inter-disciplinar*" has exceeded 10,000 records since 2003. The number of publications related to interdisciplinary research shows an increasing trend, indicating that interdisciplinary research has attracted increasing interest during the past 20 years. Furthermore, interdisciplinarity has been encouraged in science policy by creating multidisciplinary centers and funding interdisciplinary research projects, such as the National Academies Keck Futures Initiative (NAKFI) in the U.S. Recently, the National Natural Science Foundation of China also established an interdisciplinary department dedicated to the funding and development of interdisciplinary research.

Interdisciplinary research is often associated with innovation and breakthroughs. Many researchers have investigated the relationship between interdisciplinarity and scientific impact. Since the number of citations is a frequently used indicator of research quality, one may expect that interdisciplinary research is more highly cited than mono-disciplinary research. However, these studies did not provide universal results. The relationship between interdisciplinarity and citation impact is affected by many factors, such as the data source, discipline classification system, interdisciplinarity indicators, and citation time window (also citation period). Few studies focused on the effect of the citation time window on the scientific impact of interdisciplinarity. The effect of the citation time window on citation impact has been examined by some researchers (Clermont et al., 2021; Dorta-Gonzalez & Dorta-Gonzalez, 2013; Schreiber, 2015; Wang, 2013). Since a citation delay occurs in interdisciplinary research (Ke et al., 2015, Wang et al. 2015), it is suggested that the evaluation of interdisciplinary research needs longer citation time windows than mono-disciplinary research. In general, although these studies have found that the scientific impact of interdisciplinary research was affected by the citation time window, no studies have systematically explored the extent to which the citation time window affects the scientific impact of interdisciplinarity. Thus, our study tries to answer the following two questions:

(1) How long is the required citation time window for evaluating the effect of interdisciplinarity on scientific impact?
(2) Does the required citation time window vary for different interdisciplinary indicators?

Related research

The measurement of interdisciplinarity

Interdisciplinary research is a complex knowledge system, and understanding and measuring interdisciplinarity is challenging. Current interdisciplinary research has focused on two perspectives: knowledge integration and intermediation (National Academies Committee on Facilitating Interdisciplinary Research 2005; Leydesdorff, 2007; Porter et al., 2007; Rafols & Meyer, 2010; Rafols et al., 2012). From the perspective of knowledge integration, interdisciplinarity is regarded as the distribution of components (disciplines or subdisciplines) that have been linked or integrated in a body of research (as shown by a given output, such as the reference list) (Rafols et al., 2012). In this sense, the concept of diversity, which is borrowed chiefly from ecology (biodiversity measures) and economics (concentration measures), is often used to measure interdisciplinarity. Understanding interdisciplinarity in terms of intermediation was first proposed by Leydesdorff (2007). The network structure indicators derived from social network analysis, such as betweenness centrality, can be used to measure this type of interdisciplinarity. Diversity is more widely used for evaluating interdisciplinary research, especially for evaluating the effect of interdisciplinarity on scientific impact. Therefore, our study focuses on diversity as a measurement of interdisciplinarity.

There is consensus that defining interdisciplinarity using diversity encompasses three features: variety, balance, and disparity (Rafols & Meyer, 2010; Stirling, 2007). In interdisciplinary research, variety is the number of disciplines or specialties, balance is the evenness of the distribution of disciplines or specialties, and disparity is the extent to which these disciplines or specialties are different from a cognitive point of view. Earlier attempts to measure interdisciplinarity based on diversity generally included only one or two aspects of diversity, namely variety or balance. These typical indicators include the citation outside category (COC) (Porter & Chubin, 1985), the proportion of interdisciplinary journals (Levitt & Thelwall, 2008; Morillo et al., 2001), the Shannon entropy measure (Adams et al., 2007), and the Simpson diversity measure (Chen et al., 2015). Mugabushaka et al. (2016) mentioned that interdisciplinarity based on diversity could be divided into three generations. The first generation of diversity measures is the distribution-sensitive measure, and typical examples are the Shannon entropy and Simpson index. The second generation includes the distribution and similar sensitive measures, and a common index in this group is the Rao-Stirling index (RS). The third generation of diversity measures can be regarded as "true diversity" measures, also known as the replication principle. In biodiversity research, the replication principle states that if you have two completely distinct communities (i.e., without any overlap in the species), and each community has a diversity measure X, one would expect that combining the two communities would result in a community with a diversity measure 2X (Mugabushaka et al., 2016). The RS does not satisfy the replication principle, whereas the Hill numbers do. Leinster and Cobbold (2012) developed a measure that extended the Hill numbers to include the similarities/differences between species called the Leinster–Cobbold diversity indices (LCDiv). Theoretically, the LCDiv is more suitable for measuring interdisciplinarity than other measures (Zhang et al., 2016). In addition, Leydesdorff (2018) argued that current diversity measure indices do not effectively integrate variety, balance, and disparity. In the event of "dual concept diversity," the common measurement of diversity cannot distinguish between variety and balance. Therefore, Leydesdorff (2018) stated that the Gini coefficient is an ideal indicator for measuring balance. Furthermore, this study defines a new interdisciplinary indicator, DIV, that integrates the original variety, balance, and disparity indicators, (Leydesdorff, 2018; Leydesdorff et al., 2019a, b; Leydesdorff et al., 2019a, b).

In addition, some indicators dedicated to measuring single diversity properties (variety, balance, disparity) were developed. Variety generally measures the number of disciplines involved. The Gini coefficient is considered an ideal indicator for measuring balance (Leydesdorff, 2018; Leydesdorff et al., 2019a, b). The most common indicator of disparity is the average dissimilarity between disciplines. However, other similar disparity measures have been used to evaluate interdisciplinary research. Larivière et al. (2015), and Klavans and Boyack (2012) used the coordinate distance in science mapping to describe disparity. In innovation studies, some studies used journal co-citation combinations in the reference list to define the papers' novelty (Boyack & Klavans, 2014; Uzzi et al., 2013; Wang et al., 2017). The journal co-citation combination is a measure of disparity.

Interdisciplinarity and scientific impact

The relationship between interdisciplinarity and scientific impact is a hot topic in interdisciplinary research. It has led to a large body of literature, but these studies have not reached universal results. Since the citation impact is generally considered a proxy of scientific impact or research quality, most studies focused on the effect of interdisciplinarity on scientific impact by assessing the relationship between interdisciplinarity and citation impact. Some studies show that interdisciplinary research leads to higher citation impact, on average (Chen et al., 2015, 2021; Larivière et al., 2015; Levitt & Thelwall, 2009; Wang et al., 2015). Others show that interdisciplinarity has no significant effect—or even has a negative effect—on citation impact (Lariviere & Gingras, 2010; Levitt & Thelwall, 2008; Rafols et al., 2012; Rinia et al., 2002). Here, we review some typical studies from the perspectives of the interdisciplinarity indicators, diversity, impact, citation time window, and data samples (Table 1).

Table 1 shows that the citation time window is substantially different in these studies, ranging from 3 to 15 years. In these studies, only Wang et al. (2015) used two citation time windows for the papers published in 2001 from WoS. The study implies that the citation time window affects the relationship between interdisciplinarity and scientific impact. However, this study does not systematically verify the extent to which the citation time window affects the scientific impact of interdisciplinarity. Although several other studies also used multiple citation time windows, different citation time windows correspond to publications published in different years (Adams et al., 2007; Larivière et al., 2015; Leahey et al., 2017). In other words, there is only one citation time window for the publications in the same year; thus, these studies could not reflect the effect of the citation time window on the scientific impact of interdisciplinarity.

Furthermore, the choice of the citation time window is also a topic of concern in research evaluation. Adams (2005) mentioned that a short citation time window might be helpful as a forward indicator of the long-term quality of research publications. Clermont et al. (2021) suggested a citation period in which the trend of the citation rate could be detected early, and other extended periods did not necessarily provide any additional informative value. Most studies argue that a citation period of 3 years is suitable to predict long-term citations (Clermont et al., 2021; Glänzel et al., 2008; Wang, 2013). Due to the citation delay in interdisciplinary research, the effect of the length of the citation time window on the scientific impact of interdisciplinarity is worthy of further exploration.

Methodology

Data

The dataset used in this paper consists of journal articles published in 2006 (N = 979,908 papers), including their references and citing papers (papers citing these journal articles published in 2006) (Fig. 1). The year 2006 is chosen because it is considered far enough in the past to serve as an accurate measure of the long-term scientific impact of the papers. These articles, their reference, and citing papers are indexed in the Clarivate Analytics WoS. The number of references is 19,476,103, and the number of citing papers is 10,464,276. In our study, the citation period is 2006 to 2018. These citing papers produced

Table 1 Published studies on the relationship between interdisciplinarity and citation impact

Authors	Interdisciplinarity Indicator	Impact	Aspect of diversity	Citation time window	Sample
Steele and Stier (2000)	Brillouin's diversity index	Positive	Variety and balance	Annual average citation	750 articles in forestry (1985–1994) (Journal of Forest Science)
Wang et al. (2017)	New journal co-citation pair	Positive	Disparity	15 years	All papers published in WoS in 2001
Yegros-Yegros et al. (2015)	Rao-Stirling (RS)	Insignificant	Variety, balance, and disparity	5 years	All papers of four WoS categories published in 2005 (WoS)
	Number of disciplines	Positive	Variety	5 years	
	Normalized Shannon index	Negative	Balance	5 years	
	Average dissimilarity	Negative	Disparity	5 years	
Wang et al. (2015)	Simpson diversity	Positive	Variety and balance	13 years	All papers published in WoS in 2001
	1-Gini	Negative	Balance	13 years	
	Average dissimilarity	Positive	Disparity	13 years	
	Simpson diversity	Negative	Variety and balance	3 years	
	1-Gini	Insignificant	Balance	3 years	
	Average dissimilarity	Negative	Disparity	3 years	
Larivière et al. (2015)	Number of disciplines	Positive	Variety	2–13 years	All papers in WoS (2000–2012)
	Mapping distance	Positive	Disparity	2–13 years	
Chen et al. (2015)	Simpson diversity	Positive	Variety and balance	13 years	All papers published in WoS in 2000
Rinia et al. (2002)	Proportion of papers published in other disciplines	No effect	Balance	uncertain	All academic groups in physics the Netherlands
Uzzi et al. (2013)	Atypical combination	Positive	Disparity	8 years	All papers in WoS (1990–2000)

Table 1 (continued)

Authors	Interdisciplinarity Indicator	Impact	Aspect of diversity	Citation time window	Sample
Adams et al. (2007)	Shannon diversity index and proportion of cited references in other subject categories (SCs)	Inverted u shape	Variety and balance	4–10 years	Articles from two UK universities
Lariviere and Gingras (2010)	% cited references to other SC	Inverted u shape	Balance	13 years	All papers published in WoS in 2000
Leahey et al. (2017)	Integration Index (Porter et al. 2007)	Positive	Variety, balance and disparity	5–8 years	900 scientists and their 32,000 published articles (2003–2005) (WoS)
Levitt and Thelwall (2008)	Number of disciplines assigned to the journal	Insignificant	Variety	More than 10 years	All science and social science articles
Chen et al. (2021)	Rao-Stirling (RS)	Positive	Variety, balance, and disparity	13 years	All papers published in WoS in 2000
	Leinster–Cobbold diversity indices (LCDiv)	Positive	Variety, balance, and disparity	13 years	
	Number of disciplines	Positive	Variety	13 years	
	Normalized Shannon index	Negative	Balance	13 years	
	Average dissimilarity	positive	Disparity	13 years	

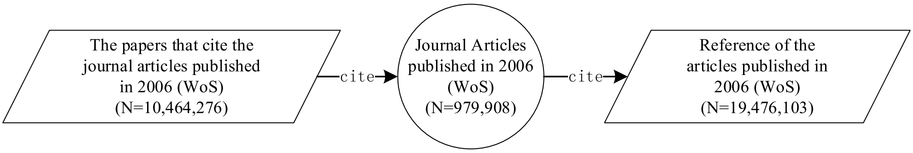

Fig. 1 The articles published in 2006 and their reference and citing papers

24,685,111 citations for papers published in 2006. A total of 877,498 papers in 2006 were cited at least once in the WoS between 2006 and 2018. There are 102,410 papers (10.5%) not cited in the WoS. To identify the disciplinary background of a paper, we use the same approach as Yegros-Yegros et al. (2015), i.e., we used a minimum of four references linked to a specialty or discipline for a paper. The threshold of four is subjectively chosen based on the researcher's experience to remove papers with uncertain disciplinary backgrounds. In addition, the institutions and authors also have to be included in our analysis. Ultimately, 702,545 papers met these conditions, and 27,003 (3.84%) papers in the final data sets were not cited between 2006 and 2018 in the WoS.

The scientific impact is evaluated by the number of citations (citation impact). The disciplinary classification of the journals used in this study is sourced from the U.S. National Science Foundation (NSF) because each journal is only categorized into a single discipline and specialty (i.e., subdiscipline). This classification includes 14 general disciplines that are further refined into 143 specialties. Our study investigates the variety, balance, and disparity at the level of the specialties, following the example of "small interdisciplinarity" used by Rinia (2007).

Interdisciplinarity indicators

Several common interdisciplinarity indicators, including various aspects of interdisciplinarity (diversity) and composite indicators, are used in our analysis to compare the relationship between the citation impact of interdisciplinarity and citation time windows with different interdisciplinarity indicators. The different aspects of interdisciplinarity is measured using diversity single-property indicators, i.e., variety, balance, and disparity. The composite interdisciplinarity indicators in our study include RS (Rafols & Meyer, 2010; Stirling, 2007), LCDiv (Mugabushaka et al., 2016; Zhang et al., 2016), and DIV (Leydesdorff et al., 2019a, b). These indicators are selected because they are commonly used indicators in current interdisciplinarity measurement.

(1) Aspects of diversity: Variety, balance, and disparity

Variety refers to the number of disciplines involved in interdisciplinary research. Balance is typically measured by the Shannon evenness index (Rafols et al., 2012) and the Gini coefficient (Wang et al., 2015). We adopt the Gini index because Nijssen et al. (1998) proved mathematically that the Gini index is an ideal indicator of balance. Since the Gini coefficient is maximally diverse for Gini = 0 and fully homogeneous for Gini=1, we use 1-Gini (reverse Gini index, rGini) to measure balance. In addition, our study uses the average dissimilarity (Rafols et al., 2012; Wang et al., 2015; Yegros-Yegros et al., 2015) between disciplines or specialties to measure disparity. Table 2 lists the calculation formulas of these indicators.

Table 2 Dimensions and indicators of interdisciplinarity (variety, balance, and disparity)

Dimension	Indicators	Description
Variety	Number of referenced disciplines	n
Balance	Reverse Gini Coefficient (rGini)	$1-\frac{\sum(2i-n-1)x_i}{n\sum x_i}$, where *i* is the index, *xi* is the number of references in the *i*-th NSF specialty, and the specialties are sorted by *xi* in nondecreasing order
Disparity	The average dissimilarity between referenced disciplines	$\frac{1}{n(n-1)}\sum_{i\neq j} d_{ij}$, where *dij* is the dissimilarity between the NSF specialty *i* and *j*, specifically, *dij* = *1* − *sij*,, where *sij* is the cosine similarity between the NSF specialty *i* and *j* based on their co-citation matrix

(2) Composite interdisciplinarity indicators: RS, LCDiv, and DIV

The RS is currently the most commonly used interdisciplinary indicator. Compared with LCDiv and DIV, the RS was used earlier and integrates variety, balance, and disparity. It is widely used to measure the interdisciplinarity of articles, authors, and institutions (Leydesdorff et al., 2013, Leydesdorff et al., 2015, Moreno & Danowitz, 2016; Cassi et al., 2017). The RS can be expressed as follows:

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

where p_i is the proportion of references in specialty *i,* and d_{ij} is the dissimilarity between the NSF specialties *i* and *j*.

As mentioned above, some studies indicated that the RS does not meet the "true diversity" and "monotonicity of balance" requirements. The LCDiv, which is derived from biodiversity indicators, meets these two requirements (Leinster & Cobbold, 2012). The studies of Zhang et al. (2016) and Mugabushaka et al. (2016) have shown that LCDiv can measure interdisciplinarity. The 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 s_{ij} is the cosine similarity between specialties *i* and *j,* and the meanings of *i, j*, and p_i are the same as above. The q is a sensitivity parameter that controls the relative emphasis that the user wishes to place on common and rare elements. The LCDiv can easily be converted from the RS or the Gini-Simpson index when q = 2. It is a suitable choice for q = 2 in terms of interdisciplinarity measures. Therefore, we only consider the case q = 2, leading to:

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

The DIV is a new interdisciplinarity indicator proposed by Leydesdorff et al. (2019a, b), which determines the variety, balance, and disparity independently and then combines them. This index has overcome the "dual-concept diversity" problems of previous interdisciplinary indicators. Although Rousseau (2019) and Leydesdorff et al., (2019a, b) proposed the new measure DIV* based on DIV, our study used DIV because it combines variety, balance, and disparity in a clear manner. Variety, balance, and disparity are normalized to a range of 0 to 1. Since DIV tends to become very small because three terms in the range of zero to one are multiplied, we used the geometric mean of DIV ($\overline{\mathrm{DIV}}$) to represent DIV, The formual of $\overline{\mathrm{DIV}}$ is as follows:

$$\overline{\mathrm{DIV}} = \sqrt[3]{(n/N) * (1 - \mathrm{Gini}) * \sum_{i \neq j} d_{ij} / [n * (n-1)]},$$

where n is the number of specialties in the paper's references, N is the total number of classes, Gini is the Gini coefficient, and the meanings of i, j, and d_{ij} are the same as above.

The distribution of NSF specialties in the reference lists is used to compute the above interdisciplinarity indicators for any given paper. The reference lists of the publications reflect the potential integration of knowledge from different disciplines, a focus issue in relation to measuring interdisciplinarity (Wang & Schneider, 2020). References have been extensively used to measure interdisciplinarity (Boyack & Klavans, 2014; Tahamtan & Bornmann, 2018; Wang, 2016; Wang & Schneider, 2020). In addition to the distribution of NSF specialties in the reference list, a specialty similarity index or distance matrix is essential for interdisciplinarity measurement. Our study uses the co-citation relation to represent discipline similarity and construct a co-citation matrix s_{ij} between the NSF specialties according to the citing papers from the WoS in 2006. The cosine similarity is used to normalize the co-citation matrix. The formula is as follows:

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

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

Statistical analysis

Citations are typically not normally distributed but have a skewed distribution (Seglen, 1992). Furthermore, citation counts are integers. Poisson regression and negative binomial regression are for count data (Fleming, 2001; Wang et al., 2017). Researchers often use Poisson models to analyze count data, but Poisson models assume that the mean and variance of the observed distribution are equal. Citation count data, like most count data, exhibit overdispersion, i.e., the variance is greater than the mean. Negative binomial regression can explicitly handle overdispersion by ensuring that the variance is greater than the mean. In addition, the difference in citations between disciplines is mainly caused by the difference in the number of references in the papers between disciplines. Since the number of references is one of the control variables in negative binomial regression analysis, our study uses the original citation instead of the category normalized citation impact (CNCI). The glm.nb() function (generalized linear models) in the R language is used to perform negative binomial regression analysis.

To answer our research questions, we analyze the relationship between interdisciplinarity and citation impact by performing year-by-year negative binomial regression analysis for different interdisciplinarity indicators. Three diversity single-property indicators (variety, balance, and disparity) and three typical composite interdisciplinarity indicators (RS, LCDiv, DIV) are used in our study. A 13-year citation time window and six interdisciplinarity indicators are investigated; thus, we conduct $13 \times 6 = 78$ negative binomial regression analyses.

In addition to interdisciplinarity indicators, studies have shown that the number of citations in publications is affected by many factors, such as the number of authors, the number of institutions, and other factors (Bornmann et al., 2014; Katz & Hicks, 1997; Peters & Vanraan, 1994; Tang, 2013; Vieira & Gomes, 2010). Therefore, we include the number of authors, the number of institutions, the number of countries, and the number of references in the publication as control variables. Some studies have shown that these features are associated with the number of citations in the publications. In order to minimize the skew of the variable distribution, we used a natural logarithm transformation of the control variables.

Results

Correlation between interdisciplinarity indicators, control variables, and citations

Table 3 presents the correlation matrix for the variables used in this study. The table shows that the correlation coefficients between the citations and all other variables are relatively low. Except for balance (rGini) and disparity, the other variables have a positive relationship with the citation count (Y18). There is a negative relationship between balance (rGini) and the citation count (Y18), and there is no significant relationship between disparity and the citation impact. The control variables (the number of authors, institutions, references, and countries) also have a positive relationship with the citation impact. Furthermore, the control variable lnref is strongly correlated with lnVariety; therefore, we need to test for multicollinearity in regression analysis. Figure 2 further presents the correlation between the interdisciplinarity indicators RS, LCDiv, and DIV. It is evident that the three interdisciplinarity indicators are strongly correlated, and the distribution is not normal. Table 4 presents the correlation coefficients between the six interdisciplinarity indicators and 13 citation time windows. Variety always has a positive relationship with the citations, whereas balance is always negatively correlated with the citations. In the beginning, the disparity has a negative correlation with the citations; however, it has an insignificant correlation with the citations after the 11th year. For the three composite interdisciplinarity indicators, RS and LCDiv initially have negative correlations with citations, followed by positive correlations after the 4th year. In contrast, DIV always has a positive correlation with citations. The results indicate that the citation time window influences the scientific impact of interdisciplinarity. Therefore, we analyze the relationship between the citation time window and the scientific impact of interdisciplinarity using regression analysis.

Table 3 Correlation matrix

	lnvariety	rGini	disparity	RS	LCDiv	DIV	lnau	lninst	lnref	lncountry
rGini	0.18***									
disparity	0.23***	0.33***								
RS	0.56***	0.37***	0.69***							
LCDiv	0.48***	0.31***	0.67***	0.97***						
DIV	0.80***	0.51***	0.70***	0.83***	0.75***					
lnau	0.22***	0.04***	− 0.14***	− 0.03***	− 0.05***	0.08***				
lninst	0.08***	0.00	0.01***	0.03***	0.02***	0.06***	0.49***			
lnref	0.64***	− 0.11***	0.05***	0.15***	0.12***	0.38***	0.17***	0.10***		
lncountry	0.01***	− 0.02***	0.04***	0.02***	0.02***	0.02***	0.27***	0.58***	0.07***	
Y18	0.12***	− 0.02***	0.00	0.03***	0.03***	0.07***	0.12***	0.10***	0.17***	0.07***

Notes Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

Y18 is the total citation count in the 13-year period (2006 to 2018). Lnvariety, lnau, lninst, lnref, and lncountry are the natural logarithmic transformations of the number of disciplines, authors, institutions, references, and countries, respectively

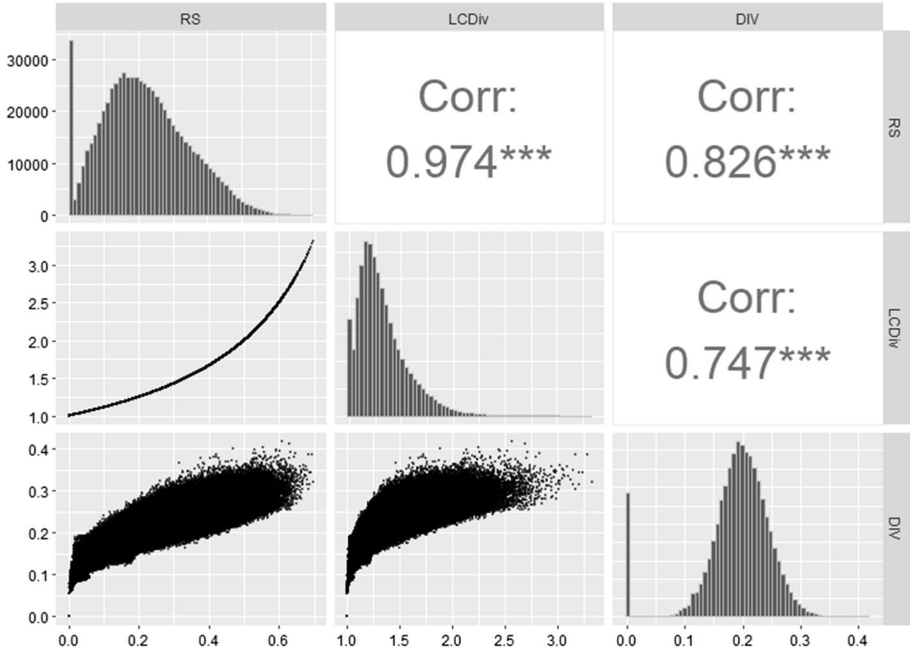

Fig. 2 Correlation between RS, LCDiv, and DIV

Citation time window and the scientific impact of interdisciplinarity

We created 13 citation time windows from 2006 to 2018 for the three diversity single-property indicators and three composite interdisciplinarity indicators. Since the regression analyses use the same data set, it is meaningful to compare the regression coefficients of the same variable in different years. Since the control variable lnref has a strong correlation with lnVariety (Table 3), we randomly select several regression procedures to check the multicollinearity using the variance inflation factor (VIF). The results show that the VIFs of all variables are less than 4, indicating no multicollinearity. Tables 5, 6, 7, and 8 present the negative binomial regression analysis results for various interdisciplinarity indicators. Table 5 shows the relationship between the three aspects of diversity and the citation impact from 2006 to 2018. Variety has a negative effect on citations from 2006 to 2008 but a positive effect starting in 2009. The regression coefficient increases year by year in the second year after the paper was published. Disparity initially has a negative effect on citations. The regression coefficient also increases year by year starting in the second year but does not show a significant positive effect on citations until the 11th year. Unlike disparity and variety, balance (rGini) initially has a positive effect on citations, and the regression coefficient also decreases year by year. It is not until the 13th year that balance (rGini) shows an insignificant effect on citations. The results indicate that the scientific impact of interdisciplinarity is affected by the length of the citation time window. In other words, there is a citation delay in the scientific impact of interdisciplinarity.

Tables 6, 7, and 8 show the relationship between the three composite interdisciplinarity indicators and the scientific impact of interdisciplinarity year by year from 2006 to

Table 4 Correlation matrix between the interdisciplinarity indicators and the citation time window

IDR	Y06	Y07	Y08	Y09	Y10	Y11	Y12	Y13	Y14	Y15	Y16	Y17	Y18
lnVariety	0.06	0.12	0.14	0.15	0.15	0.15	0.14	0.14	0.14	0.13	0.13	0.13	0.12
rGini	− 0.01	− 0.01	− 0.01	− 0.02	− 0.02	− 0.02	− 0.02	− 0.02	− 0.02	− 0.02	− 0.02	− 0.02	− 0.02
disparity	− 0.03	− 0.05	− 0.04	− 0.04	− 0.03	− 0.03	− 0.02	− 0.02	− 0.01	− 0.01	− 0.01	0	0
RS	− 0.02	− 0.02	− 0.01	0	0.01	0.01	0.02	0.02	0.02	0.03	0.03	0.03	0.03
LCDiv	− 0.02	− 0.03	− 0.01	0	0	0.01	0.01	0.02	0.02	0.02	0.03	0.03	0.03
DIV	0.02	0.04	0.05	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07

Notes Y06–Y18 are the citation counts of different citation time windows, ranging from 2006 to 2018. The underlined correlation coefficient indicates that the correlation is insignificant ($p = 0.05$), and the other correlation coefficients are significant ($p = 0.05$)

Table 5 Negative binomial models with variety, balance and disparity

Variable	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Variety	**− 0.19*** (0.01)**	**− 0.07*** (0.004)**	**− 0.01*** (0.00)**	**0.02*** (0.003)**	**0.034*** (0.003)**	**0.048*** (0.003)**	**0.058*** (0.003)**	**0.067*** (0.003)**	**0.074*** (0.003)**	**0.079*** (0.003)**	**0.082*** (0.003)**	**0.084*** (0.003)**	**0.085*** (0.003)**
rgini	**0.61*** (0.02)**	**0.52*** (0.01)**	**0.40*** (0.01)**	**0.313*** (0.009)**	**0.258*** (0.009)**	**0.212*** (0.009)**	**0.171*** (0.009)**	**0.135*** (0.009)**	**0.102*** (0.009)**	**0.074*** (0.009)**	**0.049*** (0.009)**	**0.026** (0.009)**	**0.003 (0.009)**
disparity	**− 0.30*** (0.03)**	**− 0.38*** (0.01)**	**− 0.31*** (0.01)**	**− 0.234*** (0.008)**	**− 0.180*** (0.008)**	**− 0.133*** (0.008)**	**− 0.097*** (0.008)**	**− 0.059*** (0.008)**	**− 0.020** (0.008)**	**0.015. (0.008)**	**0.051*** (0.008)**	**0.082*** (0.008)**	**0.116*** (0.008)**
lnau	0.31*** (0.01)	0.37*** (0.00)	0.35*** (0.00)	0.330*** (0.002)	0.317*** (0.002)	0.307*** (0.002)	0.296*** (0.002)	0.285*** (0.002)	0.274*** (0.002)	0.264*** (0.002)	0.253*** (0.002)	0.242*** (0.002)	0.231*** (0.003)
lninst	0.1*** (0.01)	0.05*** (0.00)	0.05*** (0.00)	0.057*** (0.003)	0.061*** (0.003)	0.063*** (0.003)	0.068*** (0.003)	0.072*** (0.003)	0.075*** (0.003)	0.078*** (0.003)	0.081*** (0.003)	0.085*** (0.003)	0.089*** (0.003)
lnref	0.87*** (0.01)	0.82*** (0.00)	0.76*** (0.003)	0.723*** (0.003)	0.701*** (0.003)	0.684*** (0.003)	0.670*** (0.003)	0.657*** (0.003)	0.646*** (0.003)	0.636*** (0.003)	0.627*** (0.003)	0.618*** (0.003)	0.610*** (0.003)
lncoun-try	0.20*** (0.01)	0.17*** (0.01)	0.14*** (0.01)	0.125 (0.005)	0.118*** (0.004)	0.113*** (0.004)	0.110*** (0.005)	0.108*** (0.005)	0.108*** (0.005)	0.108*** (0.005)	0.109*** (0.005)	0.111*** (0.005)	0.113*** (0.005)
Intercept	− 4.06*** (0.02)	− 2.31*** (0.01)	− 1.37*** (0.01)	− 0.817 (0.010)	− 0.452*** (0.010)	− 0.170*** (0.010)	0.059*** (0.010)	0.254*** (0.010)	0.419*** (0.010)	0.563*** (0.010)	0.690*** (0.010)	0.805*** (0.010)	0.914*** (0.010)

Signif. codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.1$

Standard errors are in parenthesis

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Table 6 Negative binomial models with the Rao-Stirling index (RS)

Variable	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
RS	**− 0.663***** **(0.024)**	**− 0.454***** **(0.013)**	**− 0.220***** **(0.011)**	**− 0.073***** **(0.011)**	**0.031**** **(0.011)**	**0.113***** **(0.011)**	**0.173***** **(0.011)**	**0.233***** **(0.011)**	**0.287***** **(0.011)**	**0.334***** **(0.011)**	**0.378***** **(0.011)**	**0.416***** **(0.011)**	**0.452***** **(0.011)**
lnau	0.316*** (0.005)	0.382*** (0.003)	0.367*** (0.003)	0.350*** (0.002)	0.337*** (0.002)	0.326*** (0.002)	0.315*** (0.002)	0.303*** (0.002)	0.291*** (0.002)	0.280*** (0.002)	0.267*** (0.002)	0.255*** (0.002)	0.242*** (0.002)
lninst	0.097*** (0.007)	0.043*** (0.004)	0.045*** (0.003)	0.051*** (0.003)	0.056*** (0.003)	0.059*** (0.003)	0.063*** (0.003)	0.067*** (0.003)	0.071*** (0.003)	0.074*** (0.003)	0.078*** (0.003)	0.082*** (0.003)	0.086*** (0.003)
lnref	0.738*** (0.005)	0.762*** (0.003)	0.738*** (0.002)	0.719*** (0.002)	0.709*** (0.002)	0.700*** (0.002)	0.694*** (0.002)	0.687*** (0.002)	0.680*** (0.002)	0.673*** (0.002)	0.666*** (0.002)	0.660*** (0.002)	0.652*** (0.002)
lncoun-try	0.213*** (0.010)	0.159*** (0.005)	0.130*** (0.005)	0.116*** (0.005)	0.108*** (0.004)	0.103*** (0.004)	0.100*** (0.004)	0.099*** (0.005)	0.099*** (0.005)	0.100*** (0.005)	0.102*** (0.005)	0.105*** (0.005)	0.107*** (0.005)
(Inter-cept)	− 3.565*** (0.018)	− 2.015*** (0.010)	− 1.200*** (0.008)	− 0.710*** (0.008)	− 0.385*** (0.007)	− 0.134*** (0.007)	0.069*** (0.007)	0.243*** (0.007)	0.393*** (0.007)	0.524*** (0.007)	0.642*** (0.007)	0.749*** (0.008)	0.852*** (0.008)

Signif. codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.1$

Standard errors are in parenthesis

The bold fonts emphasize independent variables (interdisciplinarity) and their statistics, and the normal fonts indicate the control variables and their statistics

Table 7 Negative binomial models with LCDiv

Index	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
lcdiv	**− 0.299***** **(0.013)**	**− 0.209***** **(0.007)**	**− 0.092***** **(0.006)**	**− 0.014*** **(0.006)**	**0.040***** **(0.006)**	**0.083***** **(0.005)**	**0.115***** **(0.005)**	**0.146***** **(0.006)**	**0.175***** **(0.006)**	**0.200***** **(0.006)**	**0.224***** **(0.006)**	**0.244***** **(0.006)**	**0.264***** **(0.006)**
lnau	0.316*** (0.005)	0.382*** (0.003)	0.367*** (0.003)	0.350*** (0.002)	0.338*** (0.002)	0.327*** (0.002)	0.316*** (0.002)	0.305*** (0.002)	0.293*** (0.002)	0.282*** (0.002)	0.269 (0.002) ***	0.257*** (0.002)	0.244*** (0.002)
lninst	0.096*** (0.007)	0.043*** (0.004)	0.045*** (0.003)	0.051*** (0.003)	0.055*** (0.003)	0.058*** (0.003)	0.063*** (0.003)	0.067*** (0.003)	0.071*** (0.003)	0.074*** (0.003)	0.078*** (0.003)	0.082*** (0.003)	0.086*** (0.003)
lnref	0.734*** (0.005)	0.759*** (0.003)	0.736*** (0.002)	0.718*** (0.002)	0.708*** (0.002)	0.700*** (0.002)	0.694*** (0.002)	0.687*** (0.002)	0.681*** (0.002)	0.674*** (0.002)	0.668*** (0.002)	0.661*** (0.002)	0.654*** (0.002)
lncountry	0.214*** (0.010)	0.160*** (0.005)	0.130*** (0.005)	0.116*** (0.005)	0.108*** (0.004)	0.103*** (0.004)	0.100*** (0.004)	0.098*** (0.005)	0.098*** (0.005)	0.099*** (0.005)	0.101*** (0.005)	0.103*** (0.005)	0.106*** (0.005)
(Intercept)	− 3.302*** (0.023)	− 1.829*** (0.013)	− 1.121*** (0.011)	− 0.704*** (0.010)	− 0.430*** (0.010)	− 0.218*** (0.010)	− 0.045*** (0.010)	0.099*** (0.010)	0.221*** (0.010)	0.328*** (0.010)	0.424*** (0.010)	0.512*** (0.010)	0.596*** (0.010)

Signif. codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.1$

Standard errors are in parenthesis

The bold fonts emphasize independent variables (interdisciplinarity) and their statistics, and the normal fonts indicate the control variables and their statistics

Table 8 Negative binomial models with DIV

Index	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
DIV	**− 1.425***** **(0.054)**	**− 0.829***** **(0.030)**	**− 0.369***** **(0.026)**	**− 0.091***** **(0.024)**	**0.101***** **(0.024)**	**0.253***** **(0.024)**	**0.359***** **(0.024)**	**0.463***** **(0.024)**	**0.556***** **(0.024)**	**0.634***** **(0.024)**	**0.707***** **(0.024)**	**0.766***** **(0.024)**	**0.822***** **(0.025)**
lnau	0.327*** (0.005)	0.389*** (0.003)	0.371*** (0.003)	0.351*** (0.002)	0.337*** (0.002)	0.324*** (0.002)	0.312*** (0.002)	0.299*** (0.002)	0.286*** (0.002)	0.274*** (0.002)	0.261*** (0.002)	0.248*** (0.002)	0.234*** (0.002)
lninst	0.094*** (0.007)	0.041*** (0.004)	0.044*** (0.003)	0.051*** (0.003)	0.056*** (0.003)	0.059*** (0.003)	0.064*** (0.003)	0.068*** (0.003)	0.072*** (0.003)	0.076*** (0.003)	0.080*** (0.003)	0.084*** (0.003)	0.088*** (0.003)
lnref	0.769*** (0.005)	0.779*** (0.003)	0.745*** (0.003)	0.721*** (0.002)	0.706*** (0.002)	0.695*** (0.002)	0.686*** (0.002)	0.677*** (0.002)	0.669*** (0.002)	0.660*** (0.002)	0.652*** (0.002)	0.644*** (0.002)	0.636*** (0.003)
lncountry	0.207*** (0.010)	0.156*** (0.005)	0.128*** (0.005)	0.115*** (0.005)	0.109*** (0.004)	0.104*** (0.004)	0.102*** (0.004)	0.101*** (0.005)	0.102*** (0.005)	0.103*** (0.005)	0.105*** (0.005)	0.108*** (0.005)	0.110*** (0.005)
Intercept	− 3.543*** (0.018)	− 2.014*** (0.010)	− 1.202*** (0.008)	− 0.714*** (0.008)	− 0.389*** (0.008)	− 0.138*** (0.007)	0.065*** (0.007)	0.240*** (0.007)	0.390*** (0.007)	0.522*** (0.008)	0.641*** (0.008)	0.748*** (0.008)	0.852*** (0.008)

Signif. codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.1$

Standard errors are in parenthesis

The bold fonts emphasize independent variables (interdisciplinarity) and their statistics, and the normal fonts indicate the control variables and their statistics

2018. The three interdisciplinarity indicators surprisingly show the same development trend. In the first 4 years after the papers were published, the interdisciplinarity shows a significant negative effect on citations. Interdisciplinarity shows a significant positive effect on citations starting in the 5th year. Furthermore, the regression coefficients show increasing trends. Although some studies observed that the RS is not a perfect indicator for measuring interdisciplinarity theoretically, our results indicate that this indicator does not affect the research conclusion in terms of the scientific impact of interdisciplinary research.

The results demonstrate that the relationship between interdisciplinarity and citation impact is affected by the length of the citation time window. In some studies, this effect is called the citation delay. The characteristics of interdisciplinary research likely cause the citation delay. It is well known that interdisciplinary research involves multiple disciplines, and different disciplines have different research paradigms. Most people specializing in a narrow discipline have difficulty understanding interdisciplinary publications; thus, they are less likely to be cited soon after they are published. A few years later, the intellectual value of these interdisciplinary publications is perceived by more and more scholars, and the article is cited more frequently.

The length of the citation time window differs for different interdisciplinarity indicators. For the variety indicator, the effect of interdisciplinarity on the citation impact becomes evident in the 4th year after publication. In contrast, for balance and disparity, the citation delay is more pronounced. For the disparity indicator, the effect of interdisciplinarity on the citation impact is not observed until the 11th year after publication, and for the balance indicator, the effect of interdisciplinarity on citation impact occurs in the 13th year or later. However, the three composite interdisciplinarity indicators show consistent results for the citation delay, i.e., the effect of interdisciplinarity on the citation impact is observed in the 5th year after publication. The results indicate that a sufficiently long citation time window is required to analyze the effect of interdisciplinarity on scientific impact. In addition, different interdisciplinarity indicators, especially variety, balance, and disparity, result in different citation time windows. Furthermore, there are some differences in the correlation analysis and regression analysis results for the six interdisciplinary indicators and citation time windows. Correlation analysis only considers the relationship between any two variables, whereas regression analysis considers the effect of multiple factors and their interrelationships. Therefore, the results of the regression analysis are more meaningful.

Conclusion and discussion

The scientific impact of interdisciplinarity may be affected by multiple factors, such as the data source, classification system, interdisciplinarity indicator, and citation time window. The interdisciplinary indicator and citation time window may be the two most important factors. Therefore, this study considered different interdisciplinarity indicators for evaluating the effect of the citation time window on the scientific impact of interdisciplinarity. Three diversity single-property indicators (variety, balance, and disparity) and three typical composite interdisciplinarity indicators (RS, LCDiv, DIV) were used. The results show that the citation time window substantially affects the scientific impact of interdisciplinary research. It may even change the results, i.e., the effect of interdisciplinarity on scientific impact, explaining the inconsistent conclusions of studies on the effect of interdisciplinarity on scientific impact. Furthermore, the effect of the citation time window on the scientific impact of interdisciplinarity was different for the different diversity indicators (variety, balance, and disparity). The citation delay was much longer for balance and disparity (a citation time window of at least 11 years and 13 years, respectively) than for variety (a citation time window of at least 4 years). For the three composite interdisciplinarity indicators RS, LCDiv, and DIV, the citation time window was the same (at least 5 years). This recommended length of the citation time window is based only on the results of this study. It may also be affected by the data set, regression model, and discipline classification system.

Clermont et al. (2021) found that the validity of citation indicators increased over time. Therefore, it is possible that the longer the citation time window, the stronger the connection between the citation impact and interdisciplinarity is. Our study also shows that the effect of interdisciplinarity on scientific impact becomes more evident and stable over time. Compared to previous studies, our study systematically analyzed the effect of the citation time window on the relationship between interdisciplinarity and scientific impact using negative binomial regression analysis and controlling the influencing factors. More importantly, our study reveals the required length of the citation time window for analyzing the effect of interdisciplinarity on scientific impact and explores whether the length of the citation time windows varies for different interdisciplinary indicators.

The RS is the most commonly used interdisciplinarity indicator among the three composite indicators, but some studies have pointed out that it had some shortcomings. Zhang et al. (2016) and Mugabushaka et al. (2016) observed that the RS did not satisfy the requirement of "true diversity," especially the replication principle. Rousseau (2018) also showed that the RS did not meet the *ceteris paribus* monotonicity requirement, which states that for a given variety and disparity, the diversity increases monotonically with the balance. In addition, Leydesdorff et al., (2019a, b) stated a "dual concept diversity" problem in RS. The LCDiv and DIV are improved indicators to overcome the above shortcomings. Although DIV and LCDiv may be more reasonable than the RS from a mathematical point of view, in general, the RS does not affect the conclusions on the scientific impact of interdisciplinarity. Therefore, for large-scale data, it is not necessary to determine which of the three interdisciplinary indicators is more suitable for interdisciplinary research.

Wang et al. (2015) used 3-year and 13-year citation time windows. Our study also evaluated the 3-year and 13-year citation time windows, allowing us to compare our study with theirs. For the 3-year citation time window, Wang et al. (2015) found that variety and disparity had a negative effect on citation impact, and balance had no insignificant effect on citation impact. Our study showed that variety and disparity had a negative effect on citation impact, and balance had a positive effect on citation impact. Therefore, the results on the effects of balance on citation impact are inconsistent for the two studies. Furthermore, for the 13-year citation time window, Wang et al. (2015) showed that variety and disparity had a positive effect, and balance had a negative effect on citation impact. Our study shows that variety and disparity are positively correlated with citation impact, whereas balance (rGini) is not significantly associated with citation impact. In general, both studies show inconsistencies in the relationship between balance and citation impact for 3-year and 13-year citation time windows. However, in our research, balance has a negative effect on citation impact according to the trend of the annual regression results. In addition, since our study uses different regression models and control variables, it is acceptable that there are slight differences in the conclusions.

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