

The measurement of “interdisciplinarity” and “synergy” in scientific and extra-scientific collaborations

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Abstract

Problem solving often requires crossing boundaries, such as those between disciplines. When policy-makers call for “interdisciplinarity,” however, they often mean “synergy.” Synergy is generated when the whole offers more possibilities than the sum of its parts. An increase in the number of options above the sum of the options in subsets can be measured as redundancy; that is, the number of not-yet-realized options. The number of options available to an innovation system for realization can be as decisive for the system's survival as the historically already-realized innovations. Unlike “interdisciplinarity,” “synergy” can also be generated in sectorial or geographical collaborations. The measurement of “synergy,” however, requires a methodology different from the measurement of “interdisciplinarity.” In this study, we discuss recent advances in the operationalization and measurement of “interdisciplinarity,” and propose a methodology for measuring “synergy” based on information theory. The sharing of meanings attributed to information from different perspectives can increase redundancy. Increasing redundancy reduces the relative uncertainty, for example, in niches. The operationalization of the two concepts—“interdisciplinarity” and “synergy”—as different and partly overlapping indicators allows for distinguishing between the effects and the effectiveness of science-policy interventions in research priorities.

1 | INTRODUCTION

The faculties and disciplines have been organized since the Middle Ages, first as structures of higher education (notably: theology, medicine, and law), but since the 19th century increasingly also as frameworks for academic research (Stichweh, 1990). After WW II, the NSF was created (Bush, 1945) and the disciplines became increasingly important for the distribution of funding, peer review, and editorial control (Langford, Burch, & Langford, 1997; Zuckerman & Merton, 1971). In this context, the call for “interdisciplinary” problem-solving from the policy side

meets an institutional dynamics of the disciplines which shields the sciences against external steering (Mulkay, 1976). Government priorities and social demands have to be adapted to the imperatives of the disciplines before they can be implemented successfully at the specialty level (Studer & Chubin, 1980).

How can the gaps between disciplinary organization and social relevance be bridged to the benefit of both science and society? Gibbons et al. (1994) suggested the emergence of a “Mode-2” type of scientific knowledge production in which the context of application would serve a “Third Mission” in interactions together with the

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internal contexts of discovery and justification distinguished by Popper ([1935], 1959; cf. Lakatos & Musgrave, 1970). Different disciplines and specialties may be in different stages of paradigmatic closure (Kuhn, 1977; van den Daele & Weingart, 1975).

In the context of the Triple Helix of University-Industry-Government relations (Etzkowitz & Leydesdorff, 2000), the emphasis has been on “synergy” as an objective different from “interdisciplinarity.” The third mission of the university is not necessarily to challenge the disciplinary or interdisciplinary frameworks of research. The crucial question is whether and how social and scientific relevance can be integrated and generate additional value (Bunders & Leydesdorff, 1987).

Discussions about “interdisciplinarity” can easily be confusing, because the concept itself is composite (Centre for Educational Research and Innovation, 1972; Klein, 1990; Organisation for Economic Co-operation and Development, 1971; cf. Q. Wang & Schneider, 2020). Furthermore, the distinction of inter-disciplinarity from multi-disciplinarity, or trans-disciplinarity tends to be fluid. In bibliometrics, however, “interdisciplinarity” has been further operationalized and made amenable to measurement (Rakas & Hain, 2019). In this communication, we report on these recent advances in the operationalizations of “interdisciplinarity” and “synergy.”

We limit the discussion to “interdisciplinarity” and “synergy” as two most policy-relevant evaluation criteria among a multitude of further refined indicators, such as “heterogeneity” in networks (Hu, Leydesdorff, & Rousseau, 2017), “novelty” measured in terms of atypical combinations of references (Klavans & Boyack, 2017; Uzzi, Mukherjee, Stringer, & Jones, 2013; J. Wang, Veugelers, & Stephan, 2017), “breakthroughs” (Ponomarev et al., 2012), and “disruption” (Azoulay, Bower & Christensen, 1995; Wu, Wang, & Evans, 2019). However, we deliberately keep the analysis of “interdisciplinarity” and “synergy” together in order to clarify the difference.

2 | THEORETICAL SPECIFICATIONS

2.1 | Interdisciplinarity

In a paper entitled “A general framework for analysing diversity in science, technology and society,” Stirling (2007) distinguished between (a) variety, (b) balance, and (c) disparity as three aspects of interdisciplinarity. Based on an extensive literature review, Stirling (1998) had translated diversity measures used in ecology, economics, and information theory into a framework for the measurement of “interdisciplinarity” in science policy

and research evaluation. In ecology, for example, variety and balance are often combined into a so-called “dual-concept” indicator (Junge, 1994) such as the Simpson index: $[\sum_{i,j}(p_i p_j)]$ —or, equivalently, the Hirschman–Herfindahl index $[\sum_i (p_i)^2]$ as a measure of concentration in economics.¹ If there is no variety, but complete concentration into a single variant, the index is equal to one. In empirical cases, these indexes vary between zero and one. Note that factors bounded between zero and one can always be multiplied and the product can be used as another indicator between zero and one.²

Rao (1982) added “disparity” as a third dimension to “diversity.” *Ceteris paribus*, grouping into different clusters can be expected to modify diversity. In an ecology, parts of the variety may be “related variety” in potentially different niches (Frenken, Van Oort, & Verburg, 2007). For example, a biochemist and a sociologist are more distanced in terms of their disciplines—as a grouping variable—than a biochemist and a physicist. One can measure disparity in terms of the distances between elements. However, the measurement of disparity is sensitive to the choice of the unit distance or proximity. Bromham et al. (2016, p. 6841), for example, developed an interdisciplinary distance metrics, which contains a disparity value based on co-classifications. For technical reasons, one often uses $(1 - \cosine_{ij})$ as the distance measure instead of Euclidean distances or Pearson correlations (Ahlgren, Jarneving, & Rousseau, 2003).³ Network analysts can also use shortest distances (geodesics) in terms of the links in between two nodes.

Elaborating on Rao (1982; cf. Ricotta & Szeidl, 2006), Stirling (2007) proposed the following measure of diversity as a composed indicator of interdisciplinarity:

$$\Delta = \sum_{i,j} (p_i p_j)^\alpha d_{ij}^\beta \quad (1)$$

For the least complex case of $\alpha = \beta = 1$,⁴ this measure $\Delta (= \sum_{i,j} p_i p_j d_{ij})$ is often called Rao–Stirling (RS) diversity. RS is identical to the “integration score” developed and used by Porter, Roessner, Cohen, and Perreault (2006) and Porter, Cohen, David Roessner, and Perreault (2007), cf. Porter & Chubin (1985).

Rafols and Meyer (2010, p. 266) provided Figure 1, which has become iconographic for visualizing the distinctions among the three components of “interdisciplinarity.” Rafols and Meyer (2010, pp. 268 ff.) added the distinction between diversity and coherence (cf. Rafols, 2014; Rafols, Leydesdorff, O’Hare, Nightingale, & Stirling, 2012, p. 1268).⁵

Based on recent literature in ecology (Jost, 2006; Leinster & Cobbold, 2012; cf. Mugabushaka et al., 2016), Zhang, Rousseau, and Glänzel (2016) have distinguished

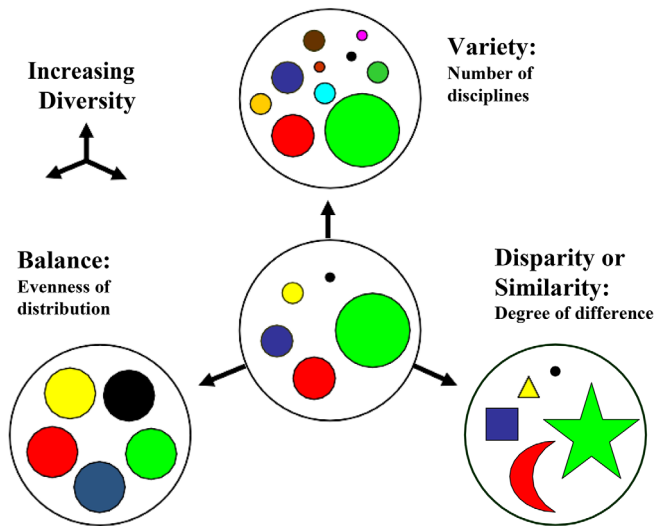


FIGURE 1 Schematic representation of the attributes of diversity, based on Stirling (1998, p. 41). Source: Rafols & Meyer (2010, p. 266) [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Four column vectors in a toy model

v1	v2	v3	v4	Sum
0	0	3	0	3
0	6	0	4	10
9	0	0	3	12
4	4	0	5	13
0	3	4	0	7
13	13	7	12	45

between Rao-Stirling diversity (Δ) and “true” diversity ($^2D^3$). As against RS, one can calculate with “true” diversity as a metric: a “true” diversity of two, for example, is precisely twice as diverse as a “true” diversity of one. Furthermore, Zhang et al. (2016, eq. 6 at p. 1260; cf. Mugabushaka et al., 2016, p. 602, Table 1) derived that RS diversity (Δ) can be converted into the “true” diversity index $^2D^3$ using:

$$^2D^3 = 1/(1-\Delta) \quad (2)$$

A major advantage of “true” diversity is that one can express one diversity as a percentage of another and thus define a measure for above- and below-expected values in the evaluation. Note that “true” diversity is not bounded between zero and one.

Furthermore, Stirling (1998, p. 48) stated that “any integration of variety and balance into dual-concept diversity must necessarily involve the implicit or explicit

prioritization of the subordinate properties.” In the meantime, however, Nijssen, Rousseau, and Hecke (1998) had shown that the Gini Index can be considered a measure of balance, but *not* of variety. One can thus operationalize the three components independently of each other, by using the Gini-coefficient as an indicator of (un)balance (Zhang, Sun, Chinchilla-Rodríguez, Chen, & Huang, 2018). Variety can be defined independently as (n_c/N) , with N being the total number of classes available and n_c the number of classes with values larger than zero. Using this decomposition, Leydesdorff, Wagner, and Bornmann (2019) proposed *DIV* as a diversity indicator combining the three components as follows:

$$DIV_c = [n_c/N] \cdot [1 - \text{Gini}] \cdot \left[\sum_{i=1, j=1, i \neq j}^{i=n_c} d_{ij} \{n_c * (n_c - 1)\} \right] \quad (3)$$

The three components are indicated in Equation (3) with brackets. The right-most factor in this equation is similar to the disparity measure used in RS diversity (Equation (1)), albeit normalized differently. The other two factors represent relative variety as (n_c/N) and balance measured as $(1 - \text{Gini})$.

Unlike RS, *DIV* meets Rousseau's (2018) requirement that diversity increases for each of the three components when the other two remain the same. Rousseau (2019) further improved *DIV* into a “true” diversity measure as follows:

$$DIV^* = (N * DIV) \quad (4)$$

As a “true” diversity measure, *DIV** is not bounded between zero and one, but again one can calculate with it. In our opinion, *DIV** is the current state of the art.

2.2 | Synergy

The term *synergy* originates from the Greek word *συνεργία* which means “working together.” By working together, a whole is sometimes created that is greater than the sum of its parts. In science, for example, synergy may mean that new options have become available because of the collaboration across (e.g., disciplinary, sectorial, or geographic) boundaries. In other words, the

number of options in the system under study can be increased by making further distinctions.

Newly emerging options are vital to innovative systems, even more than past performances. A system may run out of steam and be deadlocked if new options are no longer generated. Future performance of a region or nation is dependent on both entrepreneurial and structural dynamics such as interactions among selection environments (markets, sciences, endowments, etc).

Technically, a larger number of options add to the maximum capacity of a system. Unlike biological systems, the maximum capacity of a cultural system—he H_{max} in information theory—is not a given but can be reconstructed (Figure 2). New options can be invented as alternative possibilities (Leydesdorff, Johnson, & Ivanova, 2018, Leydesdorff, Wagner, & Bornmann, 2018, p. 1184). For example, new means of transport can be invented. This adds capacity to the system(s) under study.

The maximum capacity of a system H_{max} is equal to the (logarithm of the) number of options ($\log(N)$). H_{max} is composed of the number of realized states ($H_{observed}$ or H_{obs} in Figure 2) and the number of possible, but not realized states ($H_{max} - H_{obs}$). Shannon (1948) defined the proportion of non-realized but possible options [$(H_{max} - H_{obs})/H_{max}$] as redundancy (colored green in Figure 2), and the proportion of realized options as relative uncertainty. If redundancy increases, the *relative* uncertainty decreases.

For example, when a child asks permission from one of its parents, the other parent is latently present in the

response. Uncertainty can be reduced when a latent relation is expected to operate in the background, like in this case the relation between the parents (Abramson, 1963, pp. 130f.). In a triad, the correlation in the relations between each two sets can spuriously be co-determined by a third with a plus or a minus sign. In other words, a latent dimension is operating as a selection environment.

The same information can be appreciated differently by other stakeholders, for example, in university-industry-government relations. The appreciations from different perspectives (“the meanings of the information”) can be shared and thus generate redundancy; the same information can be involved more than once. Whereas information can be communicated in relations and measured (using Shannon’s formulas), meanings can be provided and shared from different perspectives. Sharing can generate an “overlay” among perspectives with a dynamic of redundancy different from that of information processing (Etzkowitz & Leydesdorff, 2000).

First, there is variation in historical events at the bottom as part of the (probabilistic) entropy flow. Unlike this variation, the dynamic among perspectives operates reflexively—as an “overlay”—upon changes in the network of relations. The perspectives operate as selection environments on the variation and the interactions among these selections can feedback as redundancy on the variation. The feedback has an opposite sign.

Shannon (1948) defined information H as the statistical term in Gibbs’ formula for thermodynamic entropy $S = k_B * H$. In this formula $H = -\sum_i p_i * \log_2 p_i$ and k_B is

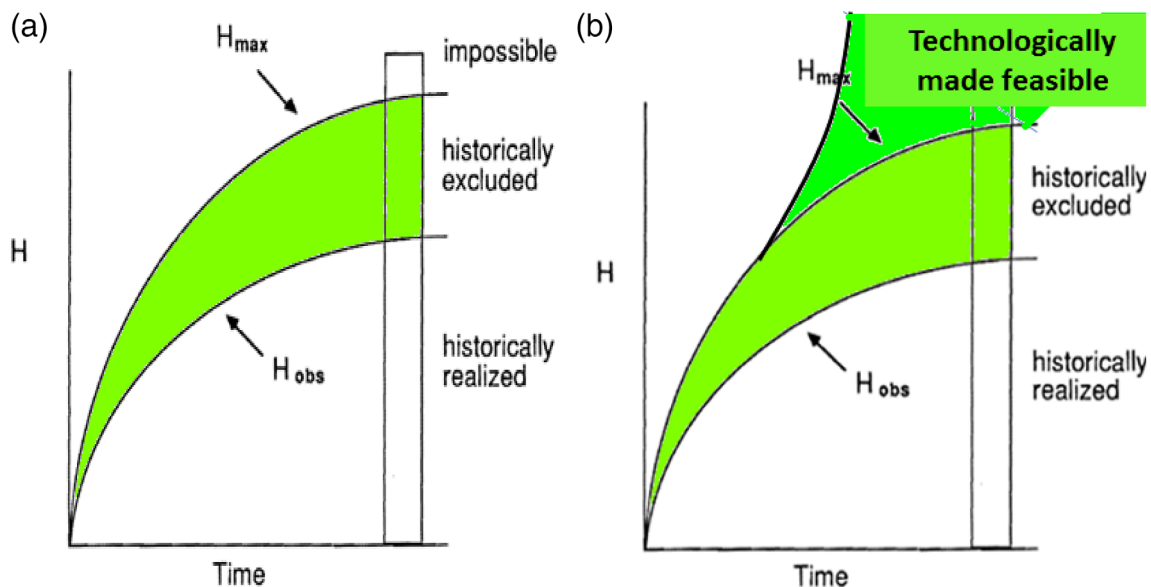


FIGURE 2 (a) The development of entropy (H_{obs}), maximum entropy (H_{max}), and redundancy ($H_{max} - H_{obs}$). Source: Brooks & Wiley (1986, at p. 43). (b) Hitherto impossible options are made possible because of technological developments. Source: Leydesdorff, Johnson, and Ivanova (2018, Leydesdorff, Wagner, & Bornmann, 2018, p. 1184) [Color figure can be viewed at wileyonlinelibrary.com]

the Boltzmann constant. Like entropy, the Boltzmann constant has the dimensionality Joule/Kelvin so that H is a dimensionless statistic, sometimes called “probabilistic entropy.” If the logarithm is two-based, H is measured in bits of information. Note that the second law of thermodynamics is equally valid for H , because k_B is a constant. Shannon-type information is therefore necessarily positive and adds to the uncertainty (Krippendorff, 2009).

Figure 3 shows two overlapping sets of options with the respective information contents H_1 and H_2 . One can consider the overlap as mutual information or transmission (T_{12}). However, counting the information in the overlap twice would be redundant, and thus:

$$H_{12} = H_1 + H_2 - T_{12} \quad (5)$$

The redundancy R_{12} is equal in absolute value to T_{12} but with the opposite sign. Whereas mutual information T_{12} is Shannon-type information and thus necessarily positive, mutual redundancy R_{12} is a measure of reduction of uncertainty, and cannot be Shannon-type information because of the (potentially) negative sign (Krippendorff, 2009). The potential sign switch indicates that a receiving system can appreciate (Shannon-type) information and consider the empty “boxes” as

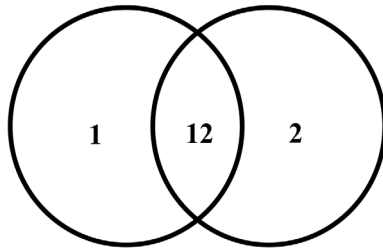


FIGURE 3 Set-theoretical representation of two sets of overlapping options

redundancy; that is, the opposite of information in terms of positive or negative contributions to the uncertainty. Shannon's co-author Weaver (1949) already envisaged a calculus of redundancy as a supplement to Shannon's theory of information (cf. Bateson, 1972; Leydesdorff, Johnson, & Ivanova, 2018).

Figure 3 is extended to three sets in Figure 4. Three configurations are depicted in Figure 4 metaphorically indicating that T_{123} (the overlap among the three in the centre) can be positive (A), absent (C), or zero (B). Redundancy is a measure of these absent options, which can nevertheless be declared (Bateson, 1972; Deacon, 2012). Different from the empty spaces outside the three circles, the size of the delineated gap among them in Figure 4C can be measured.

The formula for the combined set H_{123} follows— analogously to H_{12} above—using summations and subtractions of the numbers of elements in overlaps among sets, as follows:

$$H_{123} = H_1 + H_2 + H_3 - T_{12} - T_{13} - T_{23} + T_{123} \quad (6)$$

In Equation (6), the tri-lateral overlap in the center (T_{123} in the left pane of Figure 4) is included three times in the summation ($H_1 + H_2 + H_3$) and then subtracted three times by $(-T_{12} - T_{13} - T_{23})$. It follows that T_{123} has to be *added* once more after the subtractions in order to capture H_{123} .

Equation (6) can be reorganized as follows:

$$\begin{aligned} H_{123} &= H_1 + H_2 + H_3 - [H_1 + H_2 - H_{12}] - [H_2 + H_3 - H_{23}] \\ &\quad - [H_1 + H_3 - H_{13}] + T_{123} \quad T_{123} = H_{123} - H_1 - H_2 - H_3 \\ &\quad + [H_1 + H_2 - H_{12}] + [H_2 + H_3 - H_{23}] \\ &\quad + [H_1 + H_3 - H_{13}] \quad T_{123} = H_1 + H_2 + H_3 - H_{12} \\ &\quad - H_{23} - H_{13} + H_{123} \end{aligned} \quad (7)$$

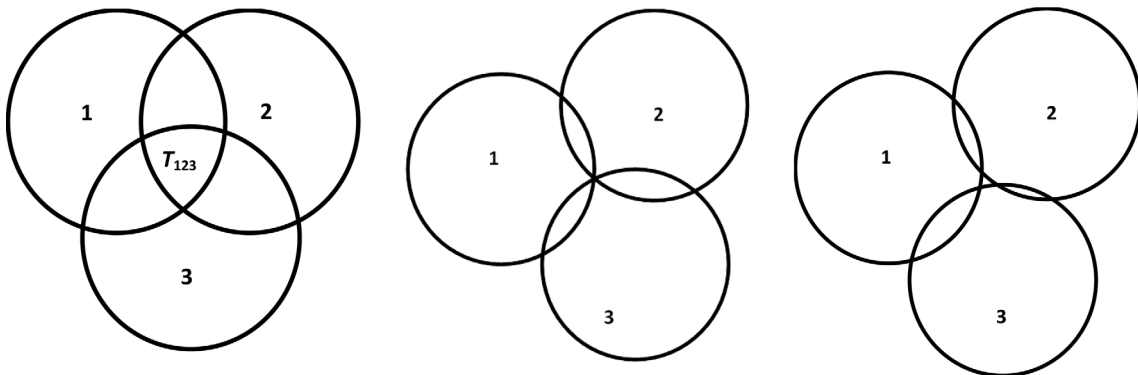


FIGURE 4 Overlapping uncertainties among three variables x_1 , x_2 , and x_3 : a: overlap; c: missing overlap; b: overlap = zero. (a) Overlap among three sets: $T_{123} > 0$. (b) No overlap among three sets: $T_{123} = 0$. A hole among three sets: $T_{123} < 0$

Since T_{123} is added, while T_{12} was *subtracted* in Equation (5), the sign of the last term representing mutual redundancy in three dimensions is opposite to that representing an even number of dimensions. In other words: $R_{12} = -T_{12}$ and $R_{123} = T_{123}$. Alexander Petersen has shown that the sign changes with the addition of each next dimension because of the sub-additivity of the entropy (Leydesdorff, Petersen, & Ivanova, 2017, p. 17).⁶ In summary, one can have both positive and negative loops in interactions among three dimensions.

In general, triads are the building blocks of systems (Bianconi et al., 2014; cf. Krackhardt, 1999). All higher-order configurations can be decomposed into triads (L. C. Freeman, 1996). In the case of more than three (sub)sets, one can compare triads among each three in terms of the redundancies generated. Triads may contain redundancy or uncertainty depending on the rotation (Figure 5; Ivanova & Leydesdorff, 2014).

The number of possible triads among n sets is $n * (n - 1) * (n - 2) / (2 * 3)$. (The denominator $[2 * 3]$ corrects for double counting.) Each *node* can partake in $n - 1$ links of which some are parts of triads which generate redundancy and others are not. Both links and nodes can be part of triads.⁷

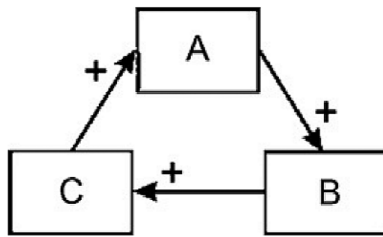


FIGURE 5 Schematic of a hypothetical three-component autocatalytic cycle (Source: Ulanowicz, 2009, at p. 1888, Figure 3)

3 | MUTUAL INFORMATION AND REDUNDANCY IN A SIMPLE TOY MODEL

Let us begin this discussion with a toy model. In this model (Table 1), four variables are attributed to five cases like column vectors of a matrix.

Using Shannon's formula ($H_i = -\sum p_i * \log_2 p_i$), the expected information content of the first vector (v_1), for example, can be elaborated as follows:

$$H_{v1} = -[3 * \{0 * \log_2(0)\}] - \left[\left(\frac{9}{13} \right) * \log_2 \left(\frac{9}{13} \right) \right] - \left[\left(\frac{4}{13} \right) * \log_2 \left(\frac{4}{13} \right) \right] = 0.890 \text{ bits}$$

(By convention, $0 * \log(0) = 0$). One can compute the joint entropy (H_{12}) and mutual information or transmission between the two dimensions of the matrix by following the steps in Table 2.

Column *e* in Table 2 contains the margin totals of the five rows of the toy model (columns *a* to *d*). Using the grand total of the matrix ($N = 45$) as denominator, relative frequencies are provided in columns *f* to *i*. In column *k* to *n*, the values in this two-dimensional probability distribution (p_{ij}) are transformed into the Shannon-type information ($-\sum p_{ij} * \log_2 p_{ij}$) in bits. It follows from the summation of the cell values that $H_{ij} = 3.23$ bits (at the bottom of column *o*). This is the two-dimensional information content of this matrix.

The margin totals in the vertical and horizontal direction provide us with the one-dimensional probabilities: the information values in column *e* add up to $H_1 = 2.19$ bits. Analogously on the basis of the values in the bottom row of columns *a* to *d*, $H_2 = 1.96$ bits. Using Equation (5) (above):

TABLE 2 Computation of the one- and two-dimensional information in the toy model

Toy model					Probabilities; relative frequencies (n/N)					Two-dimensional $H(12)$ in bits = $-\sum p_{ij} \log_2(p_{ij})$				
<i>v1</i>	<i>v2</i>	<i>v3</i>	<i>v4</i>		<i>p1</i>	<i>p2</i>	<i>p3</i>	<i>p4</i>		<i>i1</i>	<i>i2</i>	<i>i3</i>	<i>i4</i>	
<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>	<i>i</i>	<i>j</i>	<i>k</i>	<i>l</i>	<i>m</i>	<i>n</i>	<i>o</i>
0	0	3	0	3	0.00	0.00	0.07	0.00	0.07	0.00	0.00	0.26	0.00	0.26
0	6	0	4	10	0.00	0.13	0.00	0.09	0.22	0.00	0.39	0.00	0.31	0.70
9	0	0	3	12	0.20	0.00	0.00	0.07	0.27	0.46	0.00	0.00	0.26	0.72
4	4	0	5	13	0.09	0.09	0.00	0.11	0.29	0.31	0.31	0.00	0.35	0.97
0	3	4	0	7	0.00	0.07	0.09	0.00	0.16	0.00	0.26	0.31	0.00	0.57
13	13	7	12	45	0.29	0.29	0.16	0.27	1.00	0.77	0.96	0.57	0.92	3.23

$$T_{12} = H_1 + H_2 - H_{12} = 2.19 + 1.96 - 3.23 = 0.92 \text{ bits} \quad (8)$$

A matrix contains by definition a two-dimensional distribution; mutual information in two dimensions is necessarily positive (Theil, 1972). For the representation of a three-dimensional distribution, however, one would need three dimensions. We propose to use the triplet values in consecutive columns as vector representations in the x , y , and z dimensions of a three-dimensional vector space. The four vectors in Table 1 can be considered as consecutive triplets: $\{v1, v2, v3\}$, $\{v1, v2, v4\}$, $\{v1, v3, v4\}$, $\{v2, v3, v4\}$. One can compute for each triplet a three-dimensional H_{123} .⁸

Let us consider, for example, the first triple $\{v1, v2, v3\}$ in more detail. Table 3 provides this triplet itself in the top-panel. The relative frequencies are provided for the respective dimensionalities in the second row of matrices. The information values follow in the bottom row.

Using Equation (7) (above), it follows that in this triplet

$$\begin{aligned} T_{123} &= [H_1 + H_2 + H_3] - [H_{12} + H_{13} + H_{23}] + H_{123} \\ &= (0.89 + 1.53 + 0.99) - (2.21 + 1.86 + 2.27) + 2.69 \\ &= 3.40 - 6.34 + 2.69 = -0.24 \text{ bits} \end{aligned}$$

Analogously, the four other possible triplets as part of the toy model are: $T_{124} = -0.08$; $T_{134} = -0.23$, and $T_{234} = -0.08$. The values for the four triplets can be aggregated for the set (because of the sigma's in the Shannon formulas). We propose to attribute this redundancy as a synergy value to the nodes and links participating in the respective triads (Leydesdorff & Strand, 2013, p. 1895, n. 5). A routine is available at <https://www.leydesdorff.net/software/synergy.triads>, which permutes the column vectors of any matrix so that all possible combinations of variables are evaluated in terms of their values of T_{123} .

For example, $v2$ participates in the triads $\{v1, v2, v3\}$, $\{v1, v2, v4\}$, and $\{v2, v3, v4\}$, but not in $\{v1, v3, v4\}$. Among the triads in which a vector participates some will generate information ($T_{123} > 0$) and others redundancy ($T_{123} < 0$). We define the synergy value of $v2$ in this

TABLE 3 Exemplary elaboration of the computation of redundancy in the first triplet $\{v1, v2, v3\}$

Triplet values				V1			V2			V3			Margin totals	
				0			0			3			3	
				0			6			0			6	
				9			0			0			9	
				4			4			0			8	
				0			3			4			7	
				13			13			7			33	
Probabilities	One dimension			Two dimensions						Three dimensions				
	P1	P2	P3	P12		p13		P23		P123				
	0.00	0.00	0.43	0.00	0.00	0.00	0.15	0.00	0.15	0.00	0.00	0.09		
	0.00	0.46	0.00	0.00	0.23	0.00	0.00	0.30	0.00	0.00	0.18	0.00		
	0.69	0.00	0.00	0.35	0.00	0.45	0.00	0.00	0.00	0.27	0.00	0.00		
	0.31	0.31	0.00	0.15	0.15	0.20	0.00	0.20	0.00	0.12	0.12	0.00		
	0.00	0.23	0.57	0.00	0.12	0.00	0.20	0.15	0.20	0.00	0.09	0.12		
Sum	1.00	1.00	1.00	0.50	0.50	0.65	0.35	0.65	0.35	0.39	0.39	0.21		
Information in bits														
	H1	H2	H3	H12		H13		H23		H123				
	0.00	0.00	0.52	0.00	0.00	0.00	0.41	0.00	0.41	0.00	0.00	0.31		
	0.00	0.51	0.00	0.00	0.49	0.00	0.00	0.52	0.00	0.00	0.45	0.00		
	0.37	0.00	0.00	0.53	0.00	0.52	0.00	0.00	0.00	0.51	0.00	0.00		
	0.52	0.52	0.00	0.42	0.42	0.46	0.00	0.46	0.00	0.37	0.37	0.00		
	0.00	0.49	0.46	0.00	0.36	0.00	0.46	0.41	0.46	0.00	0.31	0.37		
Sum	0.89	1.53	0.99	2.21		1.86		2.27		2.69				

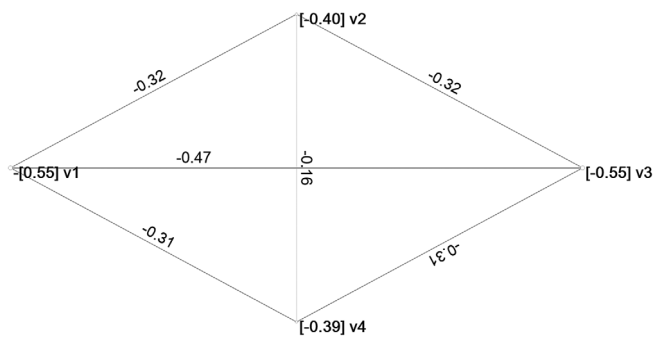


FIGURE 6 Synergy retention network of the toy model (in bits of information)

matrix as the sum of the negative values of the triplets in which v_2 participates. For v_2 , this would be $[-0.24 -0.08 -0.08] = -0.40$ bit of information. Both v_1 and v_2 participate in the triads $\{v_1, v_2, v_3\}$ and $\{v_1, v_2, v_4\}$ which generate -0.24 and -0.08 bits of redundancy, respectively. The link between v_1 and v_2 can be attributed with this redundancy shared between v_1 and v_2 . This is $[-0.24 -0.08] = -0.32$ bits. One can visualize the retention of synergy in this toy network as in Figure 6.

Redundancy values can be attributed both to nodes and links between them. One needs both components for the visualization of the resulting synergy network (Figure 6).

4 | EMPIRICAL APPLICATIONS

4.1 | Comparison of synergy with interdisciplinarity using citation relations among journals

As a first example of empirical data, we use the aggregated journal-journal citation matrix of 26 journals cited by publications in *Scientometrics* during 2017 more than a threshold value of 43 times.⁹ We chose this example because the disciplinary and interdisciplinary affiliations of journals are mostly intuitive (Table 4). We compare the 26 column vectors of the matrix (“citing”) containing the respective numbers of references to publications (in the Web-of-Science domain) during 2017.

Figure 7 provides a map of this set of journals on the basis of the cosine-normalized (column) vectors. The structure induced by Blondel et al.’s (2008) algorithm for decomposition is intuitively recognizable as three groups of journals: information-science journals in the direct environment of *Scientometrics*, multidisciplinary ones (e.g., *PNAS*, *PLOS One*, *Science*, and *Nature*) on the right side, and policy and management journals on the left side (e.g., *Research Policy* and *Technovation*).

Table 4 lists the 26 journals in terms of synergy values in the left-most column, and in terms of the two “true” interdisciplinarity indicators $^2D^3$ and DIV^* in the next two columns.

On the synergy indicator, *Science* ranks on the sixth position, and *Nature* follows on the eighth rank. Large journals with a pronouncedly disciplinary identity such as the *Am Econ Rev* and a number of journals in the management sciences generate more synergy than *Science* and *Nature*. Among the library and information science journals, the journal *Scientometrics* scores highest on synergy (with rank number 13). However, the journal *Social Networks* occupies the seventh position on the ranking of synergy values.

Pearson correlations and Spearman rank-order correlations among these and a number of the diversity and interdisciplinarity indicators (discussed above) are provided in the lower and upper triangles of Table 5, respectively. The Spearman rank-order correlation between the DIV^* and $^2D^3$ in this set of 26 journals is ~ 0.86 ($p < .01$; see Table 5). In other words, the two measures are statistically similar, but individual evaluations based on them can be considerably different (Table 4).

The synergy indicator correlates significantly ($p < .01$) with all these indicators at levels between $r = 0.4$ and $r = 0.7$. However, Table 6 provides a two-factor solution based on the Pearson correlation matrix. The varimax-rotated factor matrix shows that synergy is a specific (second) dimension different from the variety-indicators, which load on factor 1. As could be expected, the Gini-index correlates negatively since Gini is a measure of unbalance (Nijssen et al., 1998).

The difference in the second dimension between the synergy indicator and the interdisciplinarity indicators confirms that although embedded in “interdisciplinarity,” “synergy” provides an external factor structuring the correlations among the interdisciplinarity indicators in the background.

Let us now take a closer look on the synergy indicator itself. For $n = 26$ vectors, the number of possible triads is $(26 * 25 * 24)/(2 * 3) = 2,600$. Of these triads, 38 (1.4%) contribute to the redundancy. Consequently, the vast majority of triplets (98.6%) does not generate redundancy. However, 18 of the 26 (69.2%) journals participate in triplets, which generate redundancy.

Furthermore, each link can be part of $n * (n - 1)/2$ triads. For $n = 26$, this amounts to 325 possible values; 55 of them (16.9%) have a negative value. In Table 7 the links are listed in terms of most synergy. Combining the values for nodes and links, one can generate a network; Figure 7 visualizes this network; using VOSviewer, for both the clustering and the layout. (The computer routine provides among other things files “minus.net” and

TABLE 4 Rank order of 26 journals using Synergy in bits of information (column a), DIV^* (column b), and $^2D^3$, (column c), respectively

Journal	Synergy in bits	Journal	DIV^*	Journal	$2D^3$
<i>Am Econ Rev</i>	−4.27	<i>Scientometrics</i>	8.57	<i>J Assoc Inf Sci Tech</i>	2.40
<i>Expert Syst Appl</i>	−3.08	<i>J Assoc Inf Sci Tech</i>	8.55	<i>Scientometrics</i>	2.36
<i>Manage Sci</i>	−0.79	<i>J Informetr</i>	6.37	<i>Inform Process Manag</i>	2.33
<i>Strategic Manage J</i>	−0.75	<i>Technol Forecast Soc</i>	3.54	<i>Soc Stud Sci</i>	2.15
<i>Acad Manage J</i>	−0.65	<i>Inform Process Manag</i>	3.46	<i>J Inf Sci</i>	2.08
<i>Science</i>	−0.56	<i>Res Policy</i>	3.41	<i>J Informetr</i>	2.01
<i>Soc Networks</i>	−0.50	<i>Technovation</i>	2.68	<i>Res Policy</i>	1.94
<i>Nature</i>	−0.48	<i>J Technol Transfer</i>	2.58	<i>J Technol Transfer</i>	1.90
<i>Technol Forecast Soc</i>	−0.32	<i>J Inf Sci</i>	2.07	<i>Technol Forecast Soc</i>	1.87
<i>Phys Rev E</i>	−0.26	<i>Res Evaluat</i>	1.98	<i>Technovation</i>	1.83
<i>Res Policy</i>	−0.23	<i>Soc Stud Sci</i>	1.76	<i>Res Evaluat</i>	1.79
<i>P Natl Acad Sci USA</i>	−0.22	<i>J Doc</i>	1.58	<i>High Educ</i>	1.72
<i>Scientometrics</i>	−0.22	<i>Plos One</i>	1.36	<i>J Doc</i>	1.61
<i>Plos One</i>	−0.21	<i>Manage Sci</i>	1.32	<i>Manage Sci</i>	1.60
<i>Organ Sci</i>	−0.15	<i>Organ Sci</i>	1.25	<i>Phys Rev E</i>	1.52
<i>High Educ</i>	−0.08	<i>High Educ</i>	1.15	<i>Am Sociol Rev</i>	1.52
<i>J Technol Transfer</i>	−0.03	<i>Acad Manage J</i>	0.94	<i>Organ Sci</i>	1.43
<i>Am Sociol Rev</i>	0.00	<i>Expert Syst Appl</i>	0.80	<i>Soc Networks</i>	1.43
<i>J Inf Sci</i>	0.00	<i>P Natl Acad Sci USA</i>	0.77	<i>Expert Syst Appl</i>	1.38
<i>Inform Process Manag</i>	0.00	<i>Am Sociol Rev</i>	0.70	<i>Strategic Manage J</i>	1.30
<i>Technovation</i>	0.00	<i>Strategic Manage J</i>	0.66	<i>Acad Manage J</i>	1.27
<i>J Informetr</i>	0.00	<i>Nature</i>	0.63	<i>Plos One</i>	1.15
<i>J Assoc Inf Sci Tech</i>	0.00	<i>Phys Rev E</i>	0.62	<i>P Natl Acad Sci USA</i>	1.08
<i>Soc Stud Sci</i>	0.00	<i>Science</i>	0.48	<i>Am Econ Rev</i>	1.07
<i>J Doc</i>	0.00	<i>Soc Networks</i>	0.46	<i>Science</i>	1.04
<i>Res Evaluat</i>	0.00	<i>Am Econ Rev</i>	0.18	<i>Nature</i>	1.04

“minus.vec” in the Pajek format, which enable the user to proceed to the visualization and further analysis of the synergy network.)

Figure 8 is rather different from Figure 7 above. The interpretation of this figure raises all kinds of questions. For example, the relations between *Scientometrics* and the *American Economic Review* in the center of the synergy map are by more than an order of magnitude smaller than the relations between AER and management journals. Specialist journals are not highly positioned on this ranking, with the exception of *Social Networks* and to a lesser extent *Technological Forecasting and Social Change*. However, one should keep in mind that this was a single and potentially specific case. The purpose of this exercise was a proof of concept and a comparison of “synergy” with “interdisciplinarity.” More cases and refinement of parameter choices are needed before one can draw empirical conclusions.

Unlike most performance indicators, the synergy indicator was not generated in a research evaluation practice, but is theory-based (McGill, 1954; Ulanowicz, 1997; Yeung, 2008; cf. Krippendorff, 2009). Bridging the gap from theory to practice will require more examples. For example, in a next project, it may be interesting to study synergy in translation research (“from bench to bed”) because the generation of synergy is an explicit objective in this type of research.

4.2 | Synergy in international co-authorship relations among six western-mediterranean countries (2009)

Unlike interdisciplinarity, synergy can also be generated in extra-scientific contexts, such as university-industry relations or in geographical co-locations. Using data

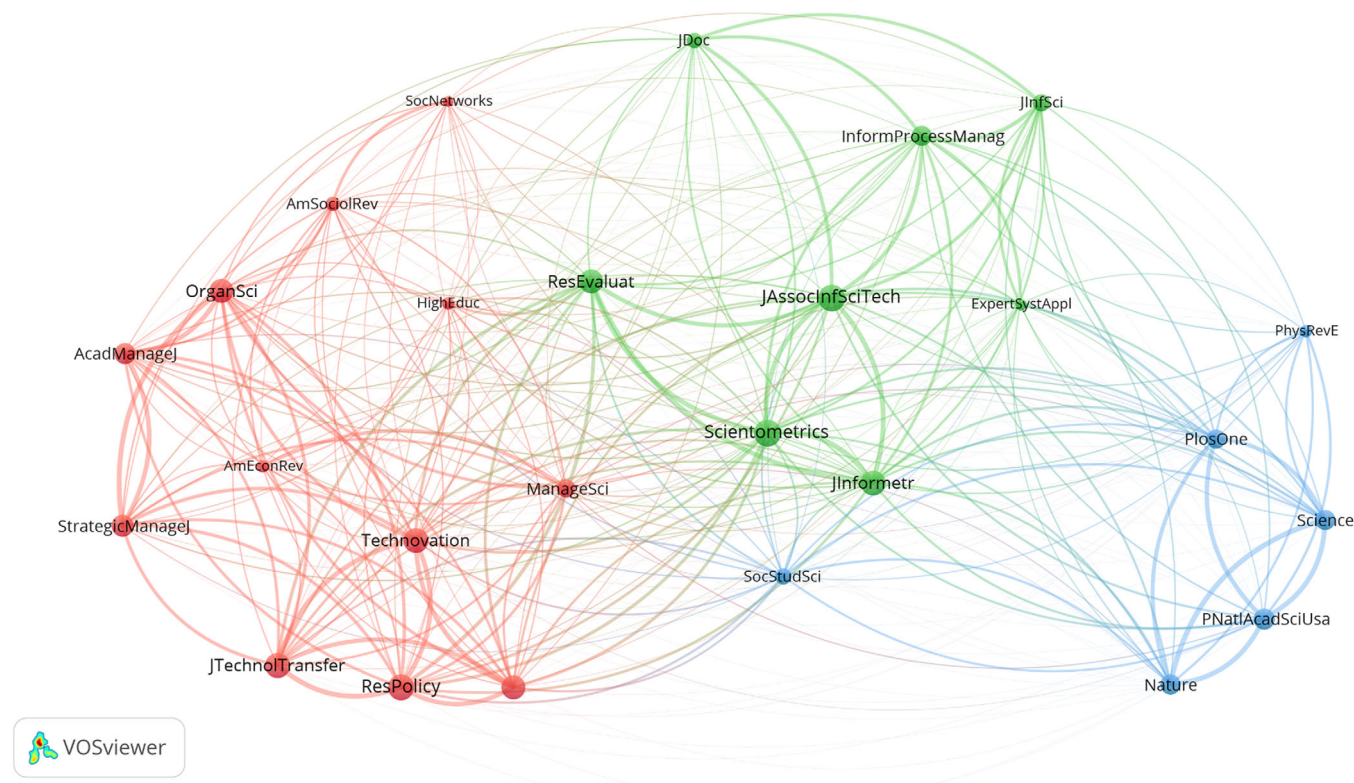


FIGURE 7 Map based on cosine-normalized citing patterns among 26 journals cited in *Scientometrics* during 2017. Clustering based on the Louvain algorithm (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008); VOSviewer was used for the layout and visualization [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 5 Pearson's correlations r (lower triangle) and Spearman's rank-order correlations ρ (upper triangle) among the various indicators

	DIV ^a	² D ³	Gini	Simpson	Shannon	Variety	Disparity	Synergy
DIV ^a		0.863 ^b	−0.960 ^b	0.858 ^b	0.943 ^b	0.955 ^b	0.851 ^b	0.632 ^b
² D ³	0.777 ^b		−0.828 ^b	0.635 ^b	0.805 ^b	0.833 ^b	0.791 ^b	0.425 ^b
Gini	−0.960 ^b	−0.839 ^b		−0.915 ^b	−0.992 ^b	−0.868 ^b	−0.738 ^b	−0.613 ^b
Simpson	0.593 ^b	0.544 ^b	−0.754 ^b		0.943 ^b	0.748 ^b	0.602 ^b	0.593 ^b
Shannon	0.820 ^b	0.795 ^b	−0.937 ^b	0.920 ^b		0.848 ^b	0.714 ^b	0.632 ^b
Variety	0.949 ^b	0.808 ^b	−0.942 ^b	0.611 ^b	0.834 ^b		0.885 ^b	0.565 ^b
Disparity	0.767 ^b	0.792 ^b	−0.773 ^b	0.583 ^b	0.745 ^b	0.859 ^b		0.497 ^b
Synergy	0.308 ^b	0.437 ^a	−0.445 ^a	0.770 ^b	0.648 ^b	0.363	0.438 ^a	

^aCorrelation is significant at the 0.05 level (2-tailed).

^bCorrelation is significant at the 0.01 level (2-tailed).

collected in another study (Leydesdorff, Wagner, Park, & Adams, 2013), Table 8 shows the internationally co-authored papers among six Western-Mediterranean countries in 2009: France, Italy, Spain, Morocco, Tunisia, and Algeria. Figure 9a shows the affiliations network of international co-authors among these six nations. As expected, France has relations mainly with Italy and Spain (within the EU), but one can expect a different

kind of relations with its former colonies in northern Africa.

Figure 9b shows the synergy network: the three European nations generate synergy from their collaborations as do the three northern-African nations among them. However, there is no synergy indicated in the network between France and the northern-African countries in 2009, although there was synergy in earlier years.

TABLE 6 The rotated component matrix of the Pearson correlations listed in Table 5

	Rotated Component Matrix^a	
	Component	
	1	2
Variety	0.945	0.231
Div*	0.944	.0191
Gini	−0.899	−0.382
² D ³	0.841	0.291
Disparity	0.829	0.296
Shannon	0.738	0.644
Synergy	0.135	0.941
Simpson	0.444	0.847

Note: Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.

^aRotation converged in 3 iterations. Two factors explained 89.7% of the variance. Values for the synergy indicator are boldfaced.

TABLE 7 Rank-ordering of journal-journal relations in terms of participation in triads that generate synergy: Twenty links with increasing values of T₁₂₃

Node A	Node B	T₁₂₃ in bits
Expert Syst Appl	Am Econ Rev	−3.08
Manage Sci	Am Econ Rev	−0.79
Strategic Manage J	Am Econ Rev	−0.75
Acad Manage J	Am Econ Rev	−0.65
Science	Am Econ Rev	−0.56
Soc Networks	Am Econ Rev	−0.50
Nature	Am Econ Rev	−0.48
Expert Syst Appl	Strategic Manage J	−0.33
Technol Forecast Soc	Am Econ Rev	−0.32
Expert Syst Appl	Science	−0.31
Nature	Expert Syst Appl	−0.29
Manage Sci	Expert Syst Appl	−0.28
Expert Syst Appl	Acad Manage J	−0.28
Phys Rev E	Am Econ Rev	−0.26
Expert Syst Appl	Technol Forecast Soc	−0.25
Expert Syst Appl	Phys Rev E	−0.25
Res Policy	Am Econ Rev	−0.23
P Natl Acad Sci USA	Expert Syst Appl	−0.22
P Natl Acad Sci USA	Am Econ Rev	−0.22
Scientometrics	Am Econ Rev	−0.22

Note that one can also combine, for example, authorship and disciplinary-specific variables. The example shows that “synergy” is different from “interdisciplinarity.”

Interdisciplinarity can also be considered a specific type of synergy. The synergy indicator can be used for the evaluation of any set of variables, including disciplinary affiliations, geographical address, or demographic characteristics.

5 | DISCUSSION AND CONCLUDING REMARKS

The objective of this study was to discuss some recent advances that have been made in the operationalization and measurement of “interdisciplinarity” and “synergy.” Using information theory, we operationalized synergy, employed it in two empirical examples, and showed how this indicator of “synergy” can be distinguished from “interdisciplinarity.” “Trans-disciplinary” is sometimes used as a residual category, which would also cover “synergy.” However, the measurement of “trans-disciplinarity” was hitherto not further developed. “Interdisciplinarity” has mainly been elaborated in bibliometrics on the basis of diversity indicators developed in ecology and economics.

Stirling (1998, 2007; cf. Rao, 1982) proposed to distinguish between variety, balance, and disparity as aspects of “interdisciplinarity” (A. L. Porter, Cohen, David Roessner, & Perreault 2007; Porter, Roessner, Cohen, & Perreault, 2006; Rafols & Meyer, 2007, 2010). Zhang et al. (2016) reformulated the Rao-Stirling measure of interdisciplinarity into the framework of “true” diversity (Jost, 2006). Leydesdorff et al. (2019) proposed to abandon “dual-concept” diversity (Stirling, 1998, p. 48) by using the Gini-index as a measure of imbalance (Nijssen et al., 1998). Rousseau (2019) finalized this series of studies by proposing *DIV** as a measure of “true” diversity.

Furthermore, one can distinguish “interdisciplinarity” or “synergy” in the “cited” and “citing” directions. Like measures of “novelty,” “disruption,” and “breakthrough,” the measurement of “interdisciplinarity” in bibliometrics has focused on integration of references from different domains into *citing* literature more than on knowledge diffusion. By *citing* documents from different knowledge bases, one integrates interdisciplinarily. When a paper is *cited* in a variety of domains, diffusion can be considered in terms of (inter)disciplinarity (Carley & Porter, 2012; Leydesdorff, Wagner, & Bornmann, 2018).

Recently, Wu et al. (2019) developed an indicator of disruptiveness using the differences between citing and cited patterns over generations of papers as an indicator of change. One of the referees suggested the comparison of disruptiveness with synergy as a subject for further research. Using Medical Subject Headings (MeSH) of MEDLINE/PubMed, Petersen, Rotolo, and Leydesdorff (2016) showed a

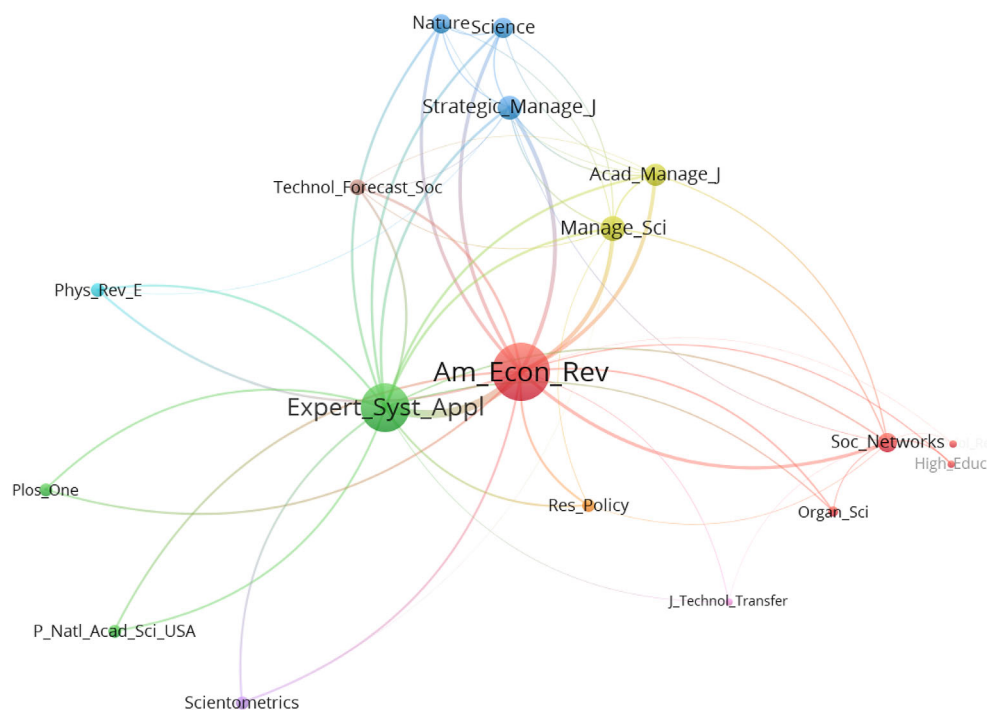


FIGURE 8 Synergy network among the citing patterns of 26 journals in the citation environment of *Scientometrics* in 2017 [Color figure can be viewed at wileyonlinelibrary.com]

	France	Italy	Spain	Morocco	Algeria	Tunisia
France	0	3,970	3,065	383	681	765
Italy	3,970	0	2,834	68	35	85
Spain	3,065	2,834	0	118	45	70
Morocco	383	68	118	0	33	53
Algeria	681	35	45	33	0	29
Tunisia	765	85	70	53	29	0

TABLE 8 International co-authorship relations among six western-Mediterranean countries in 2009

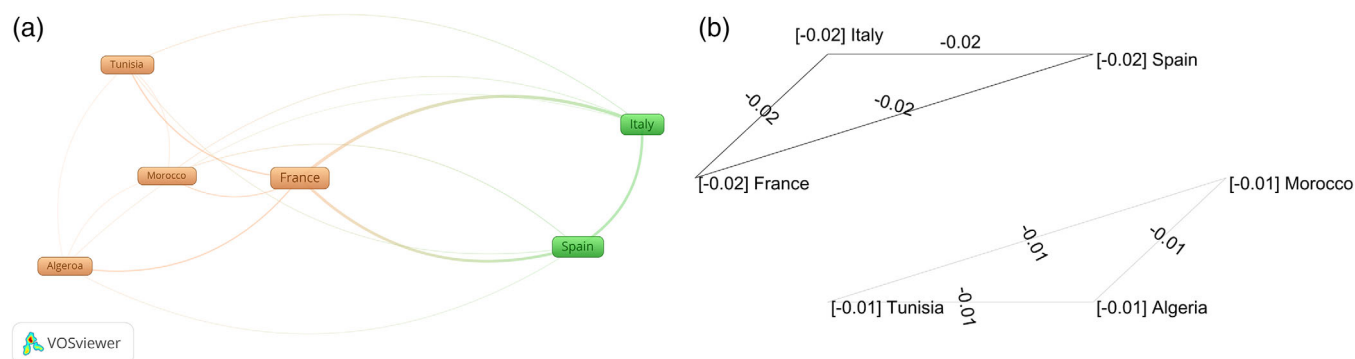


FIGURE 9 (a) Affiliations network among six western-Mediterranean countries. (b) Synergy network among six western-Mediterranean countries [Color figure can be viewed at wileyonlinelibrary.com]

relation between synergy-development and innovativeness during technology-specific periods of time.

The theoretical relevance of an indicator for reduction of uncertainty can, for example, be specified for innovation studies: the indicator can be appreciated

from two perspectives: reducing uncertainty or increasing redundancy. First, one can expect a configuration with less uncertainty to be more accommodating to risk-taking than a configuration with high uncertainty in the relevant selection environments. Reduction of

the prevailing uncertainty provides innovators with dynamic opportunities comparable to local niches (Schot & Geels, 2007). Note that reduction of uncertainty at the systems level provides an advantage for reflexive agency insofar as it is perceived. Second, the number of options available to an innovation system for realization can be as decisive for the system's survival as the historically already-realized innovations. Although uncertainty features in all innovation processes (C. Freeman & Soete, 1997), it poses crucial challenges to the governance of innovation. A system with no redundancy is out of options and thus deadlocked.

The current paper contains a proof of concept for the synergy indicator. Further research might address questions such as: what is the major difference between synergy and the other concepts in substantive terms? How are the dynamics different? Information-theoretical measures can be rewritten into a dynamic version (Kullback & Leibler, 1951; Leydesdorff, 1991; Theil, 1972). How does synergy evolve?

6 | NORMATIVE IMPLICATIONS

In our opinion, “synergy” is important for the measurement of the social functions of science. In translation research, for example, the objective is to accelerate the application of new knowledge from basic (e.g., molecular) biology in the clinic (“from bench to bed”) or vice versa to articulate demand at the bedside in terms which can be made relevant for research agendas. Mutatis mutandis, university-industry relations can be conceptualized as processes of transfer, application, and incubation. The mediation between supply and demand may also require managerial or governmental interventions. In university-industry-government (“Triple Helix”) relations, nonlinear feedbacks can become more important than linear transfer.

By appreciating redundancies, one can shift the focus from the measurement of past performance to the question of the number of available options. Whereas performance indicators are useful for improving the operational management of research, the measurement of synergy can also be relevant for the coupling to other areas of policy making (cf. Rotolo, Rafols, Hopkins, & Leydesdorff, 2017). Synergy refers to options which are possible, but not yet fulfilled, whereas most bibliometric indicators hitherto evaluate past performance; that is, options that have already been realized. More generally, the measurement of redundancy may provide methodologies opening a range of future-oriented indicators.

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ENDNOTES

- ¹ The Simpson index is equal to $\sum_i (p_i)^2$, and the Gini-Simpson to $[1 - \sum_i (p_i)^2]$.
- ² In the case of a correlation r or another measure which varies between -1 and $+1$, one can transform into a measure varying between 0 and 1 , using $(r + 1)/2$.
- ³ Pearson correlations and cosine values can be considered as proximity indicators in the vector space.
- ⁴ By cross-tabling α and β , Stirling (2007) derived four different “facets” of diversity, namely: variety, balance, disparity, and diversity (Mugabushaka, Kyriakou, & Papazoglou, 2016, p. 604).
- ⁵ Coherence $C = \sum_{i,j,i \neq j} p_i p_j d_{ij}$. Coherence can also be considered as a measure of the observed diversity potentially to be tested for significance against $\sum_{i,j,i \neq j} p_i p_j d_{ij}$ as the expected value.
- ⁶ Subadditivity means that $H_{12} \leq H_1 + H_2$ in the two-dimensional case.
- ⁷ For example, if the number of nodes $n = 4$, each of the four nodes can participate in $n - 1 = 3$ direct relations (e.g., (a) $n1 - n2$; (b) $n1 - n3$; (c) $n1 - n4$). The number of unique relations possible in this network is $4 * 4 / 2 = 6$; namely: (a) $n1 - n2$; (b) $n1 - n3$; (c) $n1 - n4$; (d) $n2 - n3$; (e) $n2 - n4$; (f) $n3 - n4$. The number of possible triads in this case is $(4 * 3 * 2) / (3 * 2) = 4$; in this case: (a) $n1 - n2 - n3$; (b) $n1 - n2 - n4$; (c) $n1 - n3 - n4$; and (d) $n2 - n3 - n4$.
- ⁸ The triplets are subsets of the matrix and the grand totals are different. Relative frequencies have to be recalculated for each triplet, since the probabilities have to add up to 1.
- ⁹ This threshold is based on using 1% of the total number of references summed over the papers in this journal (6,464) after subtraction of the 2,161 within-journal self-citations; 1% of $(6,464 - 2,161) = 4,303$ references.

REFERENCES

- Abramson, N. (1963). *Information theory and coding*. New York, NY: McGraw-Hill.
- Ahlgren, P., Jarneving, B., & Rousseau, R. (2003). Requirements for a cocitation similarity measure, with special reference to Pearson's correlation coefficient. *Journal of the American Society for Information Science and Technology*, 54(6), 550–560.
- Azoulay, P. (2019). Small research teams ‘disrupt’ science more radically than large ones. *Nature*, 566, 330–332.
- Bateson, G. (1972). *Steps to an ecology of mind*. New York, NY: Ballantine.
- Bianconi, G., Darst, R. K., Iacovacci, J., & Fortunato, S. (2014). Triadic closure as a basic generating mechanism of communities in complex networks. *Physical Review E*, 90(4), 042806.

- Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 8(10), 10008. <https://doi.org/10.1088/1742-5468/2008/10/P10008>
- Bower, J. L., & Christensen, C. M. (1995). *Disruptive technologies: Catching the wave*, 73 (1), 43–53.
- Bromham, L., Dinnage, R., & Hua, X. (2016). Interdisciplinary research has consistently lower funding success. *Nature*, 534 (7609), 684–687.
- Brooks, D. R., & Wiley, E. O. (1986). *Evolution as entropy*. Chicago, IL/London, England: University of Chicago Press.
- Bunders, J., & Leydesdorff, L. (1987). The causes and consequences of collaborations between scientists and non-scientific groups. In S. S. Blume, J. Bunders, L. Leydesdorff, & R. D. Whitley (Eds.), *The social direction of the public sciences: Causes and consequences of cooperation between scientists and nonscientific groups* *Sociology of the sciences yearbooks* (Vol. 11, pp. 331–347). Dordrecht, Netherlands/Boston, MA: Reidel.
- Bush, V. (1945). *The Endless Frontier: A Report to the President*. Reprinted, New York: Arno Press, 1980.
- Carley, S., & Porter, A. L. (2012). A forward diversity index. *Scientometrics*, 90(2), 407–427.
- Centre for Educational Research and Innovation. (1972). *Interdisciplinarity: Problems of teaching and research in universities*. Paris, France: OECD.
- Deacon, T. W. (2012). *Incomplete nature: How the mind emerged from matter*. New York, NY/London, England: Norton & Company.
- Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: From national systems and 'mode 2' to a triple helix of university-industry-government relations. *Research Policy*, 29 (2), 109–123.
- Freeman, C., & Soete, L. (1997). *The economics of industrial innovation* (3rd ed.). London, England: Pinter.
- Freeman, C., & Soete, L. (1997). *The Economics of Industrial Innovation*, 3rd ed. London: Pinter.
- Freeman, L. C. (1996). Cliques, Galois lattices, and the structure of human social groups. *Social Networks*, 18(3), 173–187.
- Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety, and regional economic growth. *Regional Studies*, 41(5), 685–697.
- Gibbons, M., Limoges, C., Nowotny, H., Schwartzman, S., Scott, P., & Trow, M. (1994). *The new production of knowledge: The dynamics of science and research in contemporary societies*. London, England: Sage.
- Hu, X., Leydesdorff, L., & Rousseau, R. (2017). Heterogeneity in an undirected network: Definition and measurement. *Journal of Informetrics*, 11(2), 669–682.
- Ivanova, I. A., & Leydesdorff, L. (2014). A simulation model of the Triple Helix of university-industry-government relations and the decomposition of the redundancy. *Scientometrics*, 99(3), 927–948. <https://doi.org/10.1007/s11192-014-1241-7>
- Jost, L. (2006). Entropy and diversity. *Oikos*, 113(2), 363–375.
- Junge, K. (1994). Diversity of ideas about diversity measurement. *Scandinavian Journal of Psychology*, 35(1), 16–26.
- Klavans, R., & Boyack, K. W. (2017). Which type of citation analysis generates the most accurate taxonomy of scientific and technical knowledge? *Journal of the Association for Information Science and Technology*, 68(4), 984–998.
- Klavans, R., & Boyack, K. W. (2017). Which type of citation analysis generates the most accurate taxonomy of scientific and technical knowledge? *Journal of the Association for Information Science and Technology*, 68(4), 984–998.
- Klein, J. T. (1990). *Interdisciplinarity: History, theory, & practice*. Detroit, MI: Wayne State University Press.
- Krackhardt, D. (1999). The ties that torture: Simmelian tie analysis in organizations. *Research in the Sociology of Organizations*, 16 (1), 183–210.
- Krippendorff, K. (2009). Information of Interactions in Complex Systems. *International Journal of General Systems*, 38(6), 669–680.
- Kullback, S., & Leibler, R. A. (1951). On Information and Sufficiency. *The Annals of Mathematical Statistics*, 22(1), 79–86.
- Kuhn, T. S. (1977). *The Essential Tension: Selected Studies in Scientific Tradition and Change*. Chicago: University of Chicago Press.
- Lakatos, I., & Musgrave, A. (Eds.). (1970). *Criticism and the growth of knowledge*. Cambridge, England: Cambridge University Press.
- Langford, C. H., Burch, R. D., & Langford, M. W. (1997). The 'well-stirred reactor': Evolution of industry-government-university relations in Canada. *Science and Public Policy*, 24(1), 21–27.
- Leinster, T., & Cobbold, C. A. (2012). Measuring diversity: The importance of species similarity. *Ecology*, 93(3), 477–489.
- Leydesdorff, L. (1991). The static and dynamic analysis of network data using information theory. *Social Networks*, 13(4), 301–345.
- Leydesdorff, L., Johnson, M., & Ivanova, I. (2018). Toward a calculus of redundancy: Signification, codification, and anticipation in cultural evolution. *Journal of the Association for Information Science and Technology*, 69(10), 1181–1192. <https://doi.org/10.1002/asi.24052>
- Leydesdorff, L., Petersen, A., & Ivanova, I. (2017). The self-organization of meaning and the reflexive communication of information. *Social Science Information*, 56(1), 4–27.
- Leydesdorff, L., & Strand, Ø. (2013). The Swedish system of innovation: Regional synergies in a knowledge-based economy. *Journal of the American Society for Information Science and Technology*, 64(9), 1890–1902 <http://dx.doi.org/10.1002/asi.22895>.
- Leydesdorff, L., Wagner, C. S., & Bornmann, L. (2018). Betweenness and diversity in journal citation networks as measures of interdisciplinarity – A tribute to eugene garfield. *Scientometrics*, 114(2), 567–592. <https://doi.org/10.1007/s11192-017-2528-2>
- Leydesdorff, L., Wagner, C. S., & Bornmann, L. (2019). Interdisciplinarity as diversity in citation patterns among journals: Rao-stirling diversity, relative variety, and the gini coefficient. *Journal of Informetrics*, 13(1), 255–264.
- Leydesdorff, L., Wagner, C. S., Park, H. W., & Adams, J. (2013). International collaboration in science: The global map and the network. *El Profesional de la Información*, 22(1), 87–94.
- McGill, W. J. (1954). Multivariate information transmission. *Psychometrika*, 19(2), 97–116.
- Mugabushaka, A.-M., Kyriakou, A., & Papazoglou, T. (2016). Bibliometric indicators of interdisciplinarity: The potential of the Leinster–Cobbold diversity indices to study disciplinary diversity. *Scientometrics*, 107(2), 593–607.

- Mulkay, M. J. (1976). The mediating role of the scientific elite. *Social Studies of Science*, 6, 445–470.
- Nijssen, D., Rousseau, R., & Van Hecke, P. (1998). The Lorenz curve: A graphical representation of evenness. *Coenoses*, 13(1), 33–38.
- Organisation for Economic Co-operation and Development. (1971). *Science, growth and society: A new perspective* ("Harvey Brooks report"). Paris, France: Author.
- Petersen, A., Rotolo, D., & Leydesdorff, L. (2016). A triple helix model of medical innovations: Supply, demand, and technological capabilities in terms of medical subject headings. *Research Policy*, 45(3), 666–681. <https://doi.org/10.1016/j.respol.2015.12.004>
- Ponomarev, I., Williams, D., Lawton, B., Cross, D., Seger, Y., Schnell, J., & Haak, L. (2012). Breakthrough paper indicator: Early detection and measurement of ground-breaking research. *11th International Conference on Current Research Information Systems, Prague*.
- Popper, K. R. [1935]. (1959). *The logic of scientific discovery*. London, England: Hutchinson.
- Porter, A., & Chubin, D. (1985). An indicator of cross-disciplinary research. *Scientometrics*, 8(3–4), 161–176.
- Porter, A. L., Cohen, A. S., David Roessner, J., & Perreault, M. (2007). Measuring researcher interdisciplinarity. *Scientometrics*, 72(1), 117–147.
- Porter, A. L., Roessner, J. D., Cohen, A. S., & Perreault, M. (2006). Interdisciplinary research: Meaning, metrics and nurture. *Research Evaluation*, 15(3), 187–195.
- Rafols, I. (2014). Knowledge integration and diffusion: Measures and mapping of diversity and coherence. In Y. Ding, R. Rousseau, & D. Wolfram (Eds.), *Measuring scholarly impact* (pp. 169–190). Cham, Switzerland/Heidelberg, Germany: Springer.
- Rafols, I., Leydesdorff, L., O'Hare, A., Nightingale, P., & Stirling, A. (2012). How journal rankings can suppress interdisciplinary research: A comparison between innovation studies and business & management. *Research Policy*, 41(7), 1262–1282.
- Rafols, I., & Meyer, M. (2010). Diversity and network coherence as indicators of interdisciplinarity: Case studies in bionanoscience. *Scientometrics*, 82(2), 263–287.
- Rafols, I., & Meyer, M. (2007). How cross-disciplinary is bionanotechnology? Explorations in the specialty of molecular motors. *Scientometrics*, 70(3), 633–650.
- Rakas, M., & Hain, D. S. (2019). The state of innovation system research: What happens beneath the surface? *Research Policy*, 48(9), 103787.
- Rao, C. R. (1982). Diversity: Its measurement, decomposition, apportionment and analysis. *Sankhy: The Indian Journal of Statistics, Series A*, 44(1), 1–22.
- Ricotta, C., & Szeidl, L. (2006). Towards a unifying approach to diversity measures: Bridging the gap between the Shannon entropy and Rao's quadratic index. *Theoretical Population Biology*, 70(3), 237–243.
- Rotolo, D., Rafols, I., Hopkins, M. M., & Leydesdorff, L. (2017). Strategic intelligence on emerging technologies: Scientometric overlay mapping. *Journal of the Association for Information Science and Technology*, 68(1), 214–233. <https://doi.org/10.1002/asi.23631>
- Rousseau, R. (2018). The repeat rate: From Hirschman to Stirling. *Scientometrics*, 116(1), 645–653.
- Rousseau, R. (2019). On the Leydesdorff-Wagner-Bornmann proposal for diversity measurement. *Journal of Informetrics*, 13(3), 906–907. <https://doi.org/10.1016/j.joi.2019.03.015>
- Schot, J., & Geels, F. W. (2007). Niches in evolutionary theories of technical change. *Journal of Evolutionary Economics*, 17(5), 605–622. <https://doi.org/10.1007/s00191-007-0057-5>
- Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal*, 27(July and October), 379–423 and 623–656.
- Stichweh, R. (1990). Self-organization and autopoiesis in the development of modern science. In W. Krohn, G. Küppers, & H. Nowotny (Eds.), *Selforganization: Portrait of a scientific revolution* (pp. 195–207). Dordrecht, Netherlands: Reidel.
- Stirling, A. (1998). *On the economics and analysis of diversity* (SPRU Electronic Working Paper Series No. 28). Retrieved from <https://www.sussex.ac.uk/webteam/gateway/file.php?name=sewp28&site=25>
- Stirling, A. (2007). A general framework for analysing diversity in science, technology and society. *Journal of the Royal Society Interface*, 4(15), 707–719.
- Studer, K. E., & Chubin, D. E. (1980). *The cancer mission: Social contexts of biomedical research*. Beverly Hills, CA/London, England: Sage.
- Theil, H. (1972). *Statistical decomposition analysis*. Amsterdam, Netherlands/London, England: North-Holland.
- Ulanowicz, R. E. (1997). *Ecology, the ascendent perspective*. New York, NY: Columbia University Press.
- Ulanowicz, R. E. (2009). The dual nature of ecosystem dynamics. *Ecological Modelling*, 220(16), 1886–1892.
- Uzzi, B., Mukherjee, S., Stringer, M., & Jones, B. (2013). Atypical combinations and scientific impact. *Science*, 342(6157), 468–472.
- van den Daele, W., & Weingart, P. (1975). Resistenz und Rezeptivität der Wissenschaft – zu den Entstehungsbedingungen neuer Disziplinen durch wissenschaftliche und politische Steuerung. *Zeitschrift fuer Soziologie*, 4(2), 146–164.
- Wang, J., Veugelers, R., & Stephan, P. (2017). Bias against novelty in science: A cautionary tale for users of bibliometric indicators. *Research Policy*, 46(8), 1416–1436.
- Wang, Q., & Schneider, J. W. (2020). Consistency and validity of interdisciplinarity measures. *Quantitative Science Studies*, 1, 239–263.
- Weaver, W. (1949). Some recent contributions to the mathematical theory of communication. In C. E. Shannon & W. Weaver (Eds.), *The mathematical theory of communication* (pp. 93–117). Urbana, IL: University of Illinois Press.
- Wu, L., Wang, D., & Evans, J. A. (2019). Large teams develop and small teams disrupt science and technology. *Nature*, 566(7744), 378–382.
- Yeung, R. W. (2008). *Information theory and network coding*. New York, NY: Springer.
- Zhang, L., Rousseau, R., & Glänzel, W. (2016). Diversity of references as an indicator for interdisciplinarity of journals: Taking similarity between subject fields into account. *Journal of the Association for Information Science and Technology*, 67(5), 1257–1265. <https://doi.org/10.1002/asi.23487>

- Zhang, L., Sun, B., Chinchilla-Rodríguez, Z., Chen, L., & Huang, Y. (2018). Interdisciplinarity and collaboration: On the relationship between disciplinary diversity in departmental affiliations and reference lists. *Scientometrics*, 117(1), 271–291.
- Zuckerman, H., & Merton, R. K. (1971). Patterns of evaluation in science: Institutionalisation, structure and functions of the referee system. *Minerva*, 9(1), 66–100.

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