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The relationship between the level of interdisciplinarity of journals and scientific impact – a Hungarian case study

Abstract

The evaluation of interdisciplinarity and its effect on research impact is prevalent in modern science. However, the evaluation of interdisciplinarity at the level of individual research papers is inconsistent with several different indicators used and is based predominantly on examinations of paper citations. Moreover, without considering the limitations of individual scientific disciplines, examinations of interdisciplinarity can present a distorted understanding of the research impact of a given paper or field. To overcome this issue, the paper established three different Levels of Interdisciplinarity based on the Web of Science Schema of research categories and assigned research areas at the level of individual journals where research papers were published. The relation of journals' Level of Interdisciplinarity to the research impact at the level of individual research papers (Impact Factor, Field Normalized Citation Impact) in a research area-dependent manner were analysed. Results demonstrate that the relationship between the Level of Interdisciplinarity and research impact varies by scientific field. Moreover, the study shows that the analysis of interdisciplinarity and research impact is less effective at an aggregated, institutional level and highlights the importance of disciplinary specialisations. The major advantage of this approach is that the measurement is independent of the changing number of citing papers and temporally changing citation categories.

Keywords: interdisciplinarity, journal level, research impact, disciplinary differences

JEL classification: I23

INTRODUCTION

The integration of different scientific fields into a complex problem-solving system is a well-known strategy at organizational (Sá, 2008), national (Lepori et al., 2007), and international levels (Bruce et al., 2004). These strategies both foster scientific collaboration among individual researchers and facilitate the creation of new knowledge by bringing together diverse research skills, techniques, and concepts originating from scholars representing different scientific areas (van Rijnsoever–Hessels, 2011). The concept of *interdisciplinarity* lies in the synthesis of theoretical and methodological activities from different scientific disciplines or research fields (Wang–Schneider, 2020). According to Porter et al. (2007), interdisciplinary research is a mode of scientific inquiry performed by teams or individuals that integrate two or more bodies of specialized knowledge or research practices. Therefore, interdisciplinary research is characterized by the combination of different perspectives/concepts/theories, tools/techniques, and information/data (Leydesdorff et al., 2019). Accordingly, the interdisciplinarity of a research project should be also captured on the level of the research output, crucial for the understanding and assessment of interdisciplinarity.

In analysing interdisciplinary research, various approaches are used; the most frequent among them being the analysis of scientometric data. However, empirical analyses of interdisciplinarity measures show remarkable differences, as the units of analysis and the mode of measurement are not identical. In their recent paper, Wang and Schneider (2020) outlined 16 interdisciplinary measures in four categories: (1) measures depending on a multi-classification system, (2) measures borrowed from other fields, (3) measures considering the similarity of research fields, and (4) measures that rely on networks. While these measures show remarkable differences, the aspect which all the above-mentioned features share is their tendency to capture the diversity or the differences in the body of knowledge. In addition, Zwanenburg et al. (2022) found 25 definitions and 21 different strands of interdisciplinarity and interdisciplinarity measures. To this end, the understanding of interdisciplinarity and its effect on scientific impact is still confusing and unsatisfying (Wang–Schneider, 2020). This study aims to fill this gap.

1. ASSESSING AND QUANTIFYING INTERDISCIPLINARITY: A REVIEW OF THE LITERATURE

The quantitative measurement of interdisciplinarity is a challenging issue, and several indicators and matrices have been developed to capture the interdisciplinary nature of research. At the level of individual journals, Morillo et al. (2003) measured interdisciplinarity through indicators based on the Institute for Scientific Information (ISI) multi-assignation of journals into subject categories. Through their cluster analysis, they differentiated between "big" and "small" interdisciplinarity, based on the interrelations between the categories identified. As a qualitative indicator, they introduced the percentage of multi-assigned papers, the pattern of multi-assignation, the diversity of relationship categories that journals share, and the strength of relationships between the two categories. The use of ISI categories as a proxy of interdisciplinarity was also used by Soós and Kampis (2011) revealing that this type of science overlay map can characterize the extent of interdisciplinarity. Although these studies are fundamental in terms of understanding interdisciplinarity at the level of individual journals through published papers, they did not analyse the relationship of the observed degree of interdisciplinarity to scientific impact.

To go a step further, Porter et al. (2007) used Web of Science Subject Categories (WoS SCs) instead of ISI as key units, and extended the analysis to include research article citations. To this end, they introduced "integration," which measures the extent to which a research paper cites diverse WoS SCs; and "specialization," which captures the spread of references that publications on a given WoS SC have cited compared to other WoS SCs. The citation-based indicators were also calculated at the level of individual research papers, journals, and their references, to capture the diversity of research fields. To this end, Zhang et al. (2016) used the Leuven-Budapest (ECOOM) subject-classification scheme and measure the disciplinary diversity considering variety (the evenness of the distribution of the subject field classification), balance (the distance between subject fields of references), disparity, and Hill-type diversity. While they found that the most interdisciplinary articles received the most citations, they also found scientific field-dependent differences.

Leydesdorff et al. (2018) used *betweenness centrality* and *diversity* to distinguish and rank journals in terms of interdisciplinarity, where betweenness centrality is considered as a measure of multi-disciplinarity and diversity as an indicator of co-citation in the citing documents. Contrary to Zhang et al. (2016), Leydesdorff et al. (2018) performed their analysis among journals instead of publications assessed by individual researchers. The authors concluded that, without the operational definition of disciplines, interdisciplinarity is difficult to define. Moreover, the citing dimension is independent from betweenness centrality, and diversity as interdisciplinarity remains a problem. In order to reveal the interrelations between different interdisciplinary measures, Wang and Schneider (2020) reviewed 23 different measures and found that they can be classified into two groups based on their dependence on a dissimilarity matrix. More importantly, the authors highlighted that the unit of analysis regarding interdisciplinarity is strongly dependent on the choice of measures and can result in conflicted findings. Their results are in line with the findings of Abramo et al. (2017), who highlighted that the literature analysing interdisciplinary research by bibliometric approaches shows distinct dimensions.

Similar to interdisciplinarity, the relationship between interdisciplinarity and research performance was also investigated using different data sources and methodologies, resulting in different, often controversial results. For example, while Okamura (2019)and interdisciplinary research (IDR showed that increasing the number of effective disciplines by one can increase the field-normalized citation-based research impact by 20%, Yegros-Yegros et al. (2015) concluded that scholars give less credit to those publications which are heterodox in terms of interdisciplinarity (measured as the relationship between interdisciplinarity and the Normalized Citation Score for each publication). Wang et al. (2015) analysed the relationship between the indicators of interdisciplinarity and research impact showing that the long-term increase in citations grows with variety and decreases with rate disparity; however, the long-term decrease of citations is associated with decreasing balance. During their analysis, Chen et al. (2015a) found that the top 1% most cited papers are characterized by higher levels of interdisciplinarity than papers in other citation rank classes. However, they also found that citation rates as a function of interdisciplinarity are higher for research areas with lower citation rates. In contrast, Rinia et al. (2001) identified a significantly negative relation between interdisciplinarity and the total number of citations, as well as the average number of citations by paper in the physical sciences. When these bibliometric indicators were corrected by the world-average citation rates of journals or fields, the correlations lost their significance. Van Noorden (2015) pointed out that interdisciplinary research takes time to have an impact (more than three years), and the results of Rinia et al. (2001) suggest that citation rates can show remarkable differences within the same research field and interdisciplinarity should be interpreted cautiously.

The common feature of studies analysing interdisciplinarity and its impact is the application of bibliometric data on a set of publications obtained from publication databases. While the use of co-authorship and/or citation coupling to calculate interdisciplinarity is widespread, this method is not ideal. For example, as highlighted by Porter et al. (2007) and Abramo et al. (2017), the examination of the research interest and specialization of a given researcher, as well as the identification of the research field is extremely time-consuming. The analysis of references as an indicator of the interdisciplinarity of journals could partially overcome this problem, however, further research is still needed to cover a large range of interdisciplinarity and discipline-dependent differences (Zhang et al., 2016).

The present study addresses the issue of measuring interdisciplinarity and its effect on research impact. While former studies scrutinized interdisciplinarity by introducing and analysing several quantitative indicators (Leydesdorff et al., 2018; Leydesdorff–Rafols, 2011; Rinia et al., 2001; Yegros-Yegros et al., 2015; Zhang et al., 2016), we have limited knowledge on the disciplinary differences of interdisciplinarity as well as on its effect on scientific impact. To overcome the problem of constantly changing citation patterns influencing the extent of interdisciplinarity indicators, similarly to Morillo et al. (2003) and Soós and Kampis (2011), we used as a proxy of interdisciplinarity the scientific coverage of journals. The assignment of research/subject categories and research areas of the Web of Science Core Collection (WoS) at the level of journals has several advantages: first, the number and type of WoS research categories and research areas at the level of individual journals, where research papers were published, can be calculated independently on the number of citations. Second, the WoS research category-based and research area-based designation of the level of interdisciplinarity is stable, thus the level of interdisciplinarity can be used as a permanent indicator without temporal change. Third, the level of interdisciplinarity can be calculated in a research category-dependent manner, making it possible to analyse discipline-dependent characteristics of the interplay between interdisciplinarity and research outputs.

Until recently, interdisciplinarity has been analysed predominantly on the level of given research fields at the global or national level, ignoring the contribution of individual research facilities (Chen et al., 2015b; Craven et al., 2019; Pan et al., 2012; Porter–Rafols, 2009). To fill this gap, our measures focus on the Eötvös Loránd University in Budapest, which has a diverse teaching and research portfolio, and is also the oldest continuously operating university in Hungary. With nearly 30,000 students, the institution is organized into eight departments (the Department of Law and Political Sciences, the Bárczi

Gusztáv Department of Special Education, the Department of Humanities, the Department of Informatics, the Department of Education and Psychology, the Department of Social Sciences, the Department of Elementary and Nursery School Teacher Training, and the Department of Sciences), in addition to the Institute of Business Economics. According to the Quacquarelly Symond Ranking 2020, Eötvös Loránd University is the best Hungarian university with its 28th place ranking, based on academic and employer reputation, faculty/student ratio, the number of papers published and their online appearances, the proportion of academic staff holding PhDs, the citation of publications, web impact, as well as the proportion of international members and international students. Based on the 2020 Times Higher Education World University Rankings by subject, Eötvös Loránd University has proved to be the best higher education institution in Hungary in the fields of the arts, humanities and psychology, as well as in life and natural sciences. Taking into account their proportion of international collaborations, education and research portfolio, the ranking of Eötvös Loránd University in national and international rankings, as well as its number of publications, we determined Eötvös Loránd University to be a model university.

The diverse examination approaches found in the literature led us to formulate a demand for a stable, implementable, and reproducible methodology able to describe the relationship between interdisciplinarity and research impact. The assignment of individual research articles into one or more WoS research categories and research areas can overcome this problem. The use of this measure of interdisciplinary allowed us to ask and answer how interdisciplinarity can influence scientific impact at the level of a whole institution, and how this relationship is dependent on scientific categories.

2. METHODOLOGY

Data collection: Research articles for the Eötvös Loránd University in Budapest (Hungary), including the journal name, the category normalized citation impact (CNCI) and impact factor (IF) were collected for five years between 2015 and 2019 from the WoS. To identify research categories and research areas we used the Web of Science Schema. Data collection was conducted in July 2020, resulting in 5,315 original research articles.

Based on the 2020 Times Higher Education World University Rankings by subject, Eötvös Loránd University has proved to be the best higher education institution in Hungary in the fields of the arts, humanities and psychology, as well as in life and natural sciences. Taking into account their proportion of international collaborations, education and research portfolio, the ranking of Eötvös Loránd University in national and international rankings, as well as its number of publications, we chose Eötvös Loránd University as a model university.

Level of IDR-calculation, temporal evolution: To establish the level of IDR, we first had to identify the main scientific disciplines for each research paper. To this end, we used the Web of Science Schema, which is comprised of five main research categories (1) Arts and Humanities, (2) Life Sciences and Biomedicine, (3) Physical Sciences,

(4) Social Sciences, and (5) Technology), subdivided into 228 research areas. Thus, for each research article, based on the journal where it was published, the research category/categories and subsequent research area/s were identified. This enabled us to assign research articles to one of the three Levels of IDR. The Single Area group corresponds to those journals where only one main research category, and within that main category, only one research area was present. The Same Category group contains those journals which are characterized by two or more research areas within the same main research category. The Different Categories group is made up of research journals which contain two or more research areas within two or more main research categories (Table 1).

Table 1 The Three Different Levels of IDR

Level of Interdisciplinarity	**Number of Research Categories**	**Number of Research Areas**
Single Area (N*=3,054)	1	1
Same Category (N=1,478)	1	2 or more
Different Categories (N=741)	2	2 or more

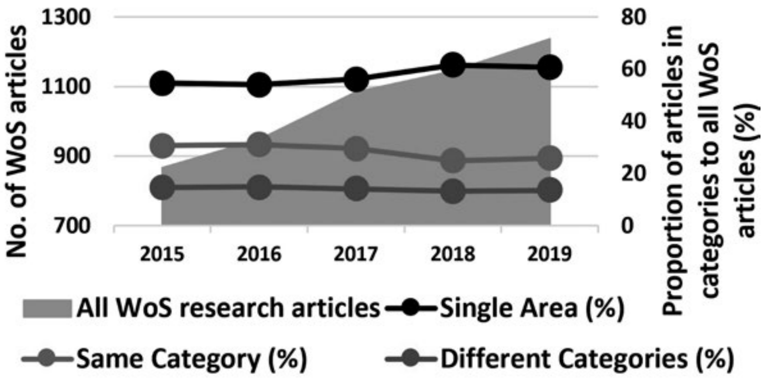
Source: Own table (from Web of Science Schema)
Note: N corresponds to the number of research articles in individual groups.

3. RESULTS

3.1 THE LEVEL OF IDR AND ITS EVOLUTION FROM 2015 TO 2016

To analyse how IDR changes over time, we established the Levels of IDR for each year between 2015 and 2019. We found that the total number of WoS research articles increased from 2015 to 2019, reaching 1,237 research articles in 2019, compared to 867 in 2015 (Figure 1 and Table 2). However, the proportion of papers based on the type of collaboration to all WoS research articles showed remarkable differences among the three Levels of IDR. While Single Area revealed an increasing tendency, the Same Category and Different Categories were characterized by a slight decrease. This contrast of temporal trends for all three Levels of IDR was strengthened by the results of linear correlation analysis between the year of publication and the number of research papers in individual groups (Table 2). Although the total number of all WoS articles increased over time, our results showed that this growth has predominantly been generated by papers from the Single Area group.

Figure 1 Temporal Evolution of WoS Research Articles between 2015 and 2019



Source: Own figure based on Web of Science data

Table 2 Number of WoS Research Articles and Research Articles with Different Levels of Interdisciplinarity

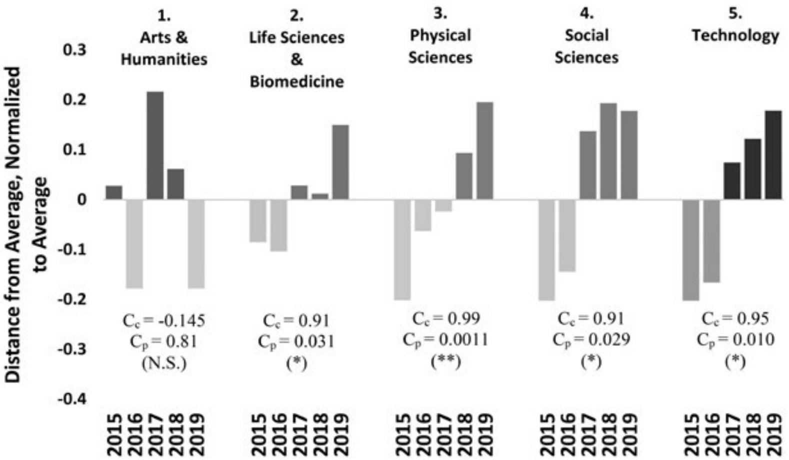
Year	2015	2016	2017	2018	2019	C_c	C_p
All WoS research articles	867	948	1,085	1,145	1,237	0.99	< 0.0001 ***
Single Area	474	513	610	706	751	0.98	0.0013 **
Same Category	266	294	322	286	319	0.66	N.S.
Different Categories	127	141	153	152	167	0.96	0.0089 **

Source: Own table based on Web of Science data

3.2 THE LEVEL OF IDR IN INDIVIDUAL RESEARCH CATEGORIES BETWEEN 2015 AND 2019

To explore individual research categories' contribution to the increase of all WoS research articles, we conducted a second analysis of research articles focusing on the five major WoS-based scientific categories. In terms of research article publication, the most productive scientific area between 2015-2019 was (3) Physical Sciences, followed by (2) Life Sciences & Biomedicine, (5) Technology, (4) Social Sciences, and (1) Arts & Humanities. We also found a significant positive correlation between the year of publication and the number of research articles published for (2) Life Sciences & Biomedicine, (3) Physical Sciences, (4) Social Sciences and (5) Technology. The major increase in research papers, as well as their strongest growth, was observed in the case of (3) Physical Sciences, followed by (2) Life Sciences & Biomedicine, (4) Social Sciences, and (5) Technology. Furthermore, (1) Arts & Humanities is characterized not only by the smallest number of research articles but also by a negative tendency in terms of their quantitative evolution (Figure 2).

Figure 2 Temporal Evolution of WoS Research Articles by Research Category, 2015–2019



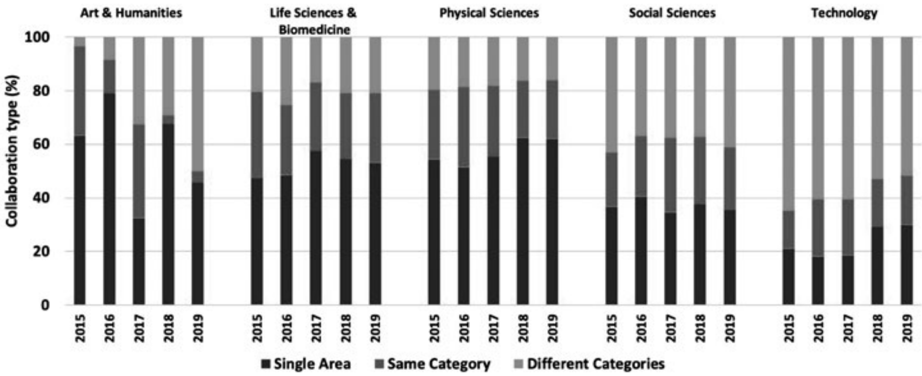
Source: Own figure based on Web of Science data

Note: The number of articles for each year was normalized by the five-year average of all the research articles in the same research category. Consequently, the distance from the average (after normalization, the average was equal to 1) was calculated by the extraction of the average (1) from the normalized value for each year. C_c = correlation coefficient, C_p = correlation probability; $^*p < 0.05$; $^{**}p< 0.01$; $^{***}P< 0.001$; N.S. = not significant

3.3 RESEARCH CATEGORIES AND PROPORTIONS OF THREE LEVELS OF IDR

When looking at the Level of IDR of research articles at the Research category level, we found that the (5) Technology group showed the highest average proportion of research papers operating with two or more research areas, accounting for 76.52% of all the published research articles in this group. This was followed by (4) Social Sciences (62.9%), (2) Life Sciences & Biomedicine (47.66%), (3) Physical Sciences (42.7%), and (1) Arts & Humanities (42.29%) (Figure 3). Thus, in the case of (2) Life Sciences & Biomedicine, (3) Physical Sciences, and (1) Arts & Humanities, the majority of research articles (more than 50% on average) are in the Single Area group. Moreover, the correlation between the year of publication and the number of research articles (Table 3) for the Single Area was positive, except for (1) Arts & Humanities, these correlations were significant. On the other hand, no significant correlation was found within the Single Category, and only the (3) Physical Sciences and (4) Social Sciences showed a significantly positive correlation in the Different Categories group. The prevalence of the Single Area cooperation type in (1) Arts & Humanities, (4) Social Sciences, and (5) Technology and consequent correlation analysis showed that on the Research category level, the increase in annual research performance is predominantly driven by research activities that operate within a single research area. However, the predominance of a Single Area is research category dependent.

Figure 3 Proportion of Levels of IDR for Each Research Category, 2015–2019



Source: Own figure based on Web of Science data
Note the prevalence of Single Area cooperation type at (2) Life Sciences & Biomedicine, and (3) Physical Sciences in Figure 3.

Table 3 Correlation Between Year of Publication and IDR for Each Research Category

	Single Area		**Same Category**		**Different Categories**	
	C_c	C_p	C_c	C_p	C_c	C_p
(1) Arts & Humanities	0.44	N.S.	-0.56	N.S.	0.85	N.S.
(2) Life Sciences & Biomedicine	0.91	0.03 (*)	0.1	N.S.	0.52	N.S.
(3) Physical Sciences	0.95	0.01 (*)	0.34	N.S.	0.93	0.02 (*)
(4) Social Sciences	0.89	0.04 (*)	0.79	N.S.	0.96	0.007 (**)
(5) Technology	0.89	0.04 (*)	0.81	N.S.	0.7	N.S.

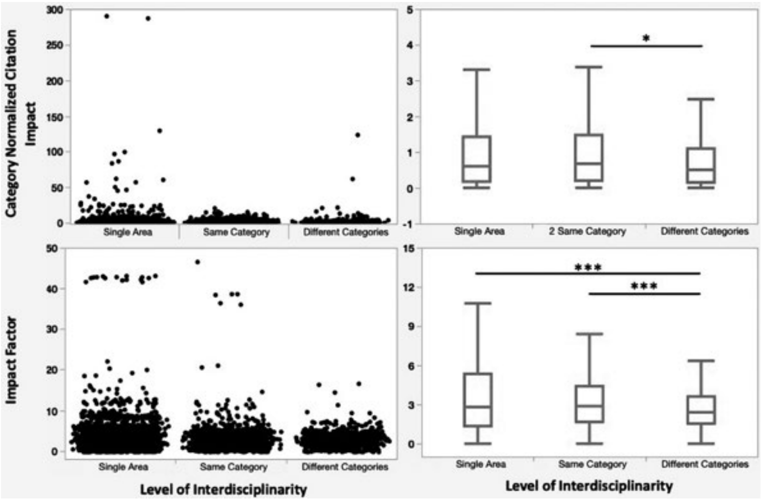
Source: Own table from analysis described above
Note: C_c = correlation coefficient, C_p = correlation probability; the level of significance is marked by asterisks: *p < 0.05; **p< 0.01; ***P< 0.001; N.S. = not significant

3.4 THE RELATIONSHIP BETWEEN THE LEVEL OF IDR AND SCIENTIFIC IMPACT

To reveal the relationship between IDR and research impact, we started by performing our analysis on all research papers without differentiating between scientific categories. This was done by comparing the CNCI and IF for each Level of IDR. We suggested that research impact correlates with an increase in IDR. To verify this, we used the following quantification of IDR: (1) Single Area = non-interdisciplinary, (2) Same Category = low level of IDR, and (3) Different Categories = high level of IDR (Abramo et al., 2017; Chen et al., 2015; Rinia, 2007). The aggregated results at the institutional level, without distinction between Scientific categories, did not support this hypothesis. As it is shown in Figure 4, the (3) Different Categories had the lowest CNCI, and this was significantly lower than the (2)

Same Category. Moreover, the IF of the (3) Different Categories was significantly lower compared to (2) Same Category and (1) Single Area. Furthermore, the correlation analysis between the Level of IDR and CNCI, as well as between the type Level of IDR and IF was significantly negative ($C_c = -0.03$, $C_p = 0.01$ for CNCI; $Cc = -0.09$, $Cp < 0.001$ for IF). Thus, on the institutional level, the Level of IDR is not increasing the scientific impact of papers.

Figure 4 Scientific Impact of All Research Papers by Type of Collaboration



Source: Own figure based on Web of Science data and own analysis
Note: Left panel: each black dot represents a research article. Right panel: the box plot visualization of data points on the left panel. * P < 0.05; ** P < 0.01; *** P < 0.001

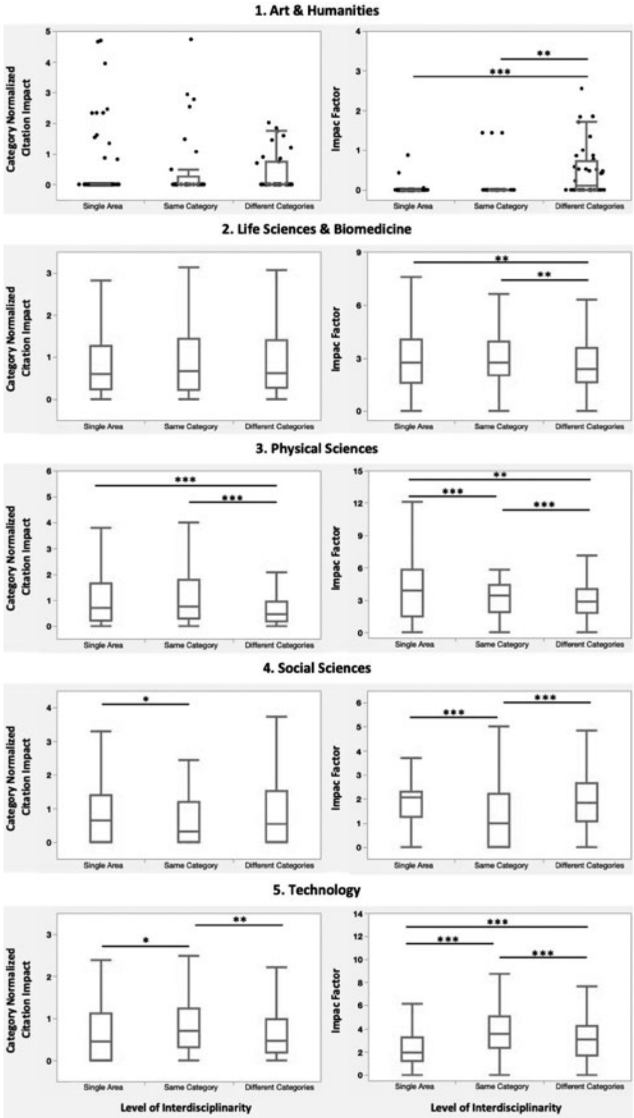
We are aware that the scientific impact is not comparable among scientific fields due to substantial differences between subject categories (Bordons et al., 2002; Bornmann–Marx, 2015; Dorta-González–Dorta-González, 2013). Therefore, the use of aggregated data without distinguishing between different research fields may distort the understanding of the scientific impact of Eötvös Loránd University. To overcome this problem, we reduplicated the statistical and correlation analysis between the Levels of IDR and the scientific impact for each of the five WoS scientific categories.

As expected, the plotting of the CNCI and IF against the Level of IDR (Figure 5), as well as the correlation analysis showed scientific category-dependent differences. The research papers in (1) Arts & Humanities were characterized by an increasing CNCI and IF with an increasing Level of IDR. However, this scientific category has the highest proportion of papers with 0 citations and journals without impact factors. This was also corroborated by the correlation analysis, where we found a positive correlation between the Level of IDR and the CNCI and a significantly positive correlation between the Level of IDR and the IF.

On the other hand, in the case of (2) Life Sciences & Biomedicine and (3) Physical Sciences we observed a tendency that was the reverse of the one seen in (1) Arts &

Humanities: in both scientific categories, the correlation between the Level of IDR and the analysed indicators of research impact were negative, moreover, this negative correlation was significant for both indicators within the (3) Physical Sciences group, and between the Level of IDR and the IF for (2) Life Sciences & Biomedicine.

Figure 5 The Scientific Impact of Research Papers as a Function of the Level of Interdisciplinarity, for All Five Research Categories



Source: Own figure based on Web of Science data and own analysis for Levels of IDR and WoS categories
Note: * P < 0.05; ** P < 0.01; *** P < 0.001

For (4) Social Sciences, the correlation coefficient between the Level of IDR and the CNCI was positive, and no correlation was found between the Level of IDR and the IF. On the other hand, for the (5) Technology scientific category, we identified a negative correlation between the Level of IDR and the CNCI and a weak positive correlation between the Level of IDR and the IF of the journals.

Thus, based on these results, the relationship between Level of IDR and research impact is highly dependent on the scientific category, as it is positive for (1) Arts & Humanities, negative for (2) Life Sciences and Biomedicine and (3) Physical Sciences, and showing a mixed character for (4) Social Sciences and (5) Technology.

4. CONCLUSIONS

The measurement of IDR is a challenging issue in qualitative and quantitative sciences (Greckhamer et al., 2008; Wang–Schneider, 2020). Studies focusing on citation research have found significant differences across and within scientific fields (Guerrero-Bote et al., 2007; Lillquist–Green, 2010). Thus, the analysis of IDR at the level of organizations with different structural and disciplinary representations is still needed. Our study fills this gap. The unique contribution of this paper lies in its use of the Web of Science Schema of research categories and research areas at the level of individual journals as a tool to characterize the Level of IDR.

In contrast to previous studies (Leahey et al., 2016; Porter–Rafols, 2009; Yegros-Yegros et al., 2015), the Level of IDR is not measured through the proportion of references from different scientific disciplines but as the interplay between different scientific research areas within the five main research categories at the level of individual journals. The advantage of this method is that IDR is measured independently from the properties of citations and co-authorship. Thus, the Level of IDR does not change over time (as it does not depend on the number of citations and the research area of the citing papers). Regardless of the IF of the publishing journal or the number of citations, the Level of IDR can be measured for all WoS research journals.

Based on the type of collaboration between the five major scientific categories and subsequent research areas, we derived three Levels of IDR: Single Area (one scientific category and one research area), Same Category (one scientific category with two or more research areas), and Different Categories (two or more scientific categories with two or more research areas). The proposed measure for the Level of IDR is scalable from the journal where the paper was published and can be applied in a scientific category-dependent manner. We have shown that the Level of IDR should be studied at the level of scientific categories, as neglecting scientific category-dependent contributions can distort the understanding of IDR at the level of a given organization. This approach establishes a suitable framework to investigate IDR at an institution's level, focusing on multifield teaching and research. Most importantly, we have shown that instead of a global evaluation of higher education institutions with multiple teaching and research focus, we should consider "dividing" research output (in this case, research articles) according to their assessment of research discipline (research category) and perform the analysis on that level. These results support the finding of Bornmann (2019), revealing that the possible influence of citations is less effective on an aggregated level of an institution.

However, our methodology limited the impact and reach of our results. First, the WoS provides several schemas of research areas. The use of different research schemas (for example, the use of WoS with five scientific categories and 228 research areas instead of the OECD Category Scheme of 6 major codes and 42 minor codes corresponding to the scientific categories and research areas of the WoS Schema) could result in different assignments of research articles to one of the three cooperation types correlating with the Level of IDR. Second, the Level of IDR reflects the interplay between research areas at the journal level, not at the level of individual research papers. The interplay between research areas at the level of a journal does not necessarily mean that the Level of IDR of a research paper reflects the IDR of the journal. Third, using IF and citation-based methods to reveal scientific impact also entails limitations. IF varies greatly between academic disciplines (Castellano-Radicchi, 2009). Moreover, compiling citations by journal can mask an asymmetric distribution of citations by published papers within the same journal (Kiesslich et al., 2020)the three highest-ranking journals from each JCR category were included in order to extend the analyses to non-medical journals. For the journals in these cohorts, the citation data (2018. There are also disciplinary differences in the number of citations attributed to individual research papers (Vaughan et al., 2017). Moreover, the citation time window also influences the citation impact (Clermont et al., 2020; Wang, 2013), and the research impact of IDR research also tends to gain more citations in the long term (van Noorden, 2015). We took two approaches to overcome these limitations: first, we did not compare the research impact of scientific disciplines; and second, we used CNCI instead of the citation count.

We have demonstrated that the analysis of the Level of IDR and consequent research impact of a multifield higher education institution at the research category level is relevant. However, we do not have a sufficiently long time window available to study the research impact of IDR on the most recent research articles.

We have convincing evidence that the Level of IDR can be captured at the level of individual journals, but the evolution of the relationship between the Level of IDR and research impact was not tested in this paper. Regarding further research, the analysis could be expanded to include a broader time window to analyse the temporal evaluation of research impact as a function of the Level of IDR. Moreover, it would be of interest to compare the similarity of IDR of a given journal and published research paper, as well as to compare the effect of IDR on research impact with other Hungarian higher education institutions and elaborate a method that could be used to compare Hungary with other countries.

It should be mentioned that we did not include any evaluation or consideration of the research fields of the papers citing the assessed interdisciplinary journals. For example, the most powerful relationship between the level of IDR and CNCI was observed for Art & Humanities. However, it is unknown, whether this is caused by the increased interdisciplinarity or by the higher score on the Science Citation Index.

We are aware that our study contains controversial results and could not solve the problem regarding the need for an indicator suitable to capture interdisciplinarity and its effect of scientific impact. There is still a need to measure interdisciplinarity on different bases, such as citation patterns and the origin of citations, or the relative share of references reflecting the knowledge integration. This should be analysed in more detail and with a more complex theoretical approach in the future.

REFERENCES

- Abramo, G.–D'Angelo, C. A.–Di Costa, F. (2017) Do interdisciplinary research teams deliver higher gains to science? *Scientometrics*, 111, pp. 317–336. https://doi.org/10.1007/s11192-017-2253-x
- Bordons, M.–Fernández, M. T.–Gómez, I. (2002) Advantages and limitations in the use of impact factor measures for the assessment of research performance. *Scientometrics*, 53, pp. 195–206. https://doi.org/10.1023/A:1014800407876
- Bornmann, L. (2019) Does the normalized citation impact of universities profit from certain properties of their published documents –such as the number of authors and the impact factor of the publishing journals? A multilevel modelling approach. *Journal of Informetrics,* 13, 170–184. https://doi.org/10.1016/j.joi.2018.12.007
- Bornmann, L.–Marx, W. (2015) Methods for the generation of normalized citation impact scores in bibliometrics: Which method best reflects the judgements of experts? *Journal of Informetrics*, 9, pp. 408–418. https://doi.org/10.1016/j.joi.2015.01.006
- Bruce, A.–Lyall, C.–Tait, J.–Williams, R. (2004) Interdisciplinary integration in Europe: The case of the Fifth Framework Programme. *Futures, Transdisciplinarity,* 36, pp. 457–470. https://doi.org/10.1016/j.futures.2003.10.003
- Castellano, C.–Radicchi, F. (2009) On the fairness of using relative indicators for comparing citation performance in different disciplines. *Arch. Immunol. Ther. Exp. (Warsz.)*, 57, pp. 85–90. https://doi.org/10.1007/s00005-009-0014-0
- Chen, S.–Arsenault, C.–Gingras, Y.–Larivière, V. (2015a) Exploring the interdisciplinary evolution of a discipline: the case of Biochemistry and Molecular Biology. *Scientometrics*, 102, pp. 1307–1323. https://doi.org/10.1007/s11192-014-1457-6
- Chen, S.–Arsenault, C.–Larivière, V. (2015b) Are top-cited papers more interdisciplinary? *J. Informetr.*, 9, pp. 1034–1046. https://doi.org/10.1016/j.joi.2015.09.003
- Clermont, M.–Krolak, J.–Tunger, D. (2020) Does the citation period have any effect on the informative value of selected citation indicators in research evaluations? *Scientometrics*, 126, pp. 1019–1047. https://doi.org/10.1007/s11192-020-03782-1
- Craven, D.–Winter, M.–Hotzel, K.–Gaikwad, J.–Eisenhauer, N.–Hohmuth, M.–König-Ries, B.–Wirth, C. (2019) Evolution of interdisciplinarity in biodiversity science. *Ecol. Evol.*, 9, pp. 6744–6755. https://doi.org/10.1002/ece3.5244
- Dorta-González, P.–Dorta-González, M. I. (2013) Comparing journals from different fields of science and social science through a JCR subject categories normalized impact factor. *Scientometrics*, 95, pp. 645–672. https://doi.org/10.1007/s11192-012-0929-9
- Greckhamer, T.–Koro-Ljungberg, M.–Cilesiz, S.–Hayes, S. (2008) Demystifying Interdisciplinary Qualitative Research. *Qual. Inq.*, 14, pp. 307–331. https://doi.org/10.1177/1077800407312049

- Guerrero-Bote, V. P.–Zapico-Alonso, F.–Espinosa-Calvo, M. E.–Gómez-Crisóstomo, R.–de Moya-Anegón, F. (2007) Import-export of knowledge between scientific subject categories: The iceberg hypothesis. *Scientometrics*, 71, pp. 423–441. https://doi.org/10.1007/s11192-007-1682-3
- Kiesslich, T.–Beyreis, M.–Zimmermann, G.–Traweger, A. (2020) Citation inequality and the Journal Impact Factor: median, mean, (does it) matter? *Scientometrics*, 126, pp. 1249–1269. https://doi.org/10.1007/s11192-020-03812-y
- Leahey, E.–Beckman, C. M.–Stanko, T. L. (2016) Prominent but Less Productive: The Impact of interdisciplinarity on scientists' research. *Adm. Sci. Q.*, 62, 1, pp. 105–139. https://doi.org/10.1177/0001839216665364
- Lepori, B.–van den Besselaar, P.–Dinges, M.–Potì, B.–Reale, E.–Slipersæter, S.–Thèves, J.–van der Meulen, B. (2007) Comparing the evolution of national research policies: What patterns of change? *Sci. Public Policy*, 34, pp. 372–388. https://doi.org/10.3152/030234207X234578
- Leydesdorff, L.–Rafols, I. (2011) Indicators of the interdisciplinarity of journals: Diversity, centrality, and citations. *J. Informetr.*, 5, pp. 87–100. https://doi.org/10.1016/j.joi.2010.09.002
- 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. *J. Informetr.*, 13, pp. 255–269. https://doi.org/10.1016/j.joi.2018.12.006
- 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, pp. 567–592. https://doi.org/10.1007/s11192-017-2528-2
- Lillquist, E.–Green, S. (2010) The discipline dependence of citation statistics. *Scientometrics*, 84, pp. 749–762. https://doi.org/10.1007/s11192-010-0162-3
- Morillo, F.–Bordons, M.–Gómez, I. (2003) Interdisciplinarity in science: A tentative typology of disciplines and research areas. *J. Am. Soc. Inf. Sci. Technol.*, 54, pp. 1237–1249. https://doi.org/10.1002/asi.10326
- Okamura, K. (2019) Interdisciplinarity revisited: evidence for research impact and dynamism. *Palgrave Commun.*, 5, pp. 1–9. https://doi.org/10.1057/s41599-019-0352-4
- Pan, R. K.–Sinha, S.–Kaski, K.–Saramäki, J. (2012) The evolution of interdisciplinarity in physics research. *Sci. Rep.*, 2, 551. https://doi.org/10.1038/srep00551
- Porter, A. L.–Cohen, A. S.–David Roessner, J.–Perreault, M. (2007) Measuring researcher interdisciplinarity. *Scientometrics*, 72, pp. 117–147. https://doi.org/10.1007/s11192-007-1700-5
- Porter, A. L.–Rafols, I. (2009) Is science becoming more interdisciplinary? Measuring and mapping six research fields over time. *Scientometrics*, 81, 719. https://doi.org/10.1007/s11192-008-2197-2
- Rinia, E. J. (2007) *Measurement and evaluation of interdisciplinary research and knowledge transfer.* PhD Thesis. Leiden Univ.
- Rinia, E. J.–van Leeuwen, Th. N.–van Vuren, H. G.–van Raan, A. F. J. (2001) Influence of interdisciplinarity on peer-review and bibliometric evaluations in physics research. *Res. Policy*, 30, pp. 357–361. https://doi.org/10.1016/S0048-7333(00)00082-2
- Sá, C. M. (2008) 'Interdisciplinary strategies' in U.S. research universities. *High. Educ.*, 55, pp. 537–552. https://doi.org/10.1007/s10734-007-9073-5
- Soós, S.–Kampis, G. (2011) Towards a typology of research performance diversity: the case of top Hungarian players. *Scientometrics*, 87, pp. 357–371. https://doi.org/10.1007/s11192-011-0351-8
- Van Noorden, R. (2015) Interdisciplinary research by the numbers. *Nature*, 525, pp. 306–307. https://doi.org/10.1038/525306a

- van Rijnsoever, F. J.–Hessels, L. K. (2011) Factors associated with disciplinary and interdisciplinary research collaboration. *Res. Policy*, 40, pp. 463–472. https://doi.org/10.1016/j.respol.2010.11.001
- Vaughan, L.–Tang, J.–Yang, R. (2017) Investigating disciplinary differences in the relationships between citations and downloads. *Scientometrics*, 111, pp. 1533–1545. https://doi.org/10.1007/s11192-017-2308-z
- Wang, J. (2013) Citation time window choice for research impact evaluation. *Scientometrics*, 94, pp. 851–872. https://doi.org/10.1007/s11192-012-0775-9
- Wang, J.–Thijs, B.–Glänzel, W. (2015) Interdisciplinarity and Impact: Distinct Effects of Variety, Balance, and Disparity. *PLOS ONE*, 10, e0127298. https://doi.org/10.1371/journal.pone.0127298
- Wang, Q.–Schneider, J. W. (2020) Consistency and validity of interdisciplinarity measures. *Quant. Sci. Stud.*, 1, pp. 239–263. https://doi.org/10.1162/qss_a_00011
- Yegros-Yegros, A.–Rafols, I.–D'Este, P. (2015) Does interdisciplinary research lead to higher citation impact? The different effect of proximal and distal interdisciplinarity. *PLOS ONE*, 10, e0135095. https://doi.org/10.1371/journal.pone.0135095
- Zhang, L.–Rousseau, R.–Glänzel, W. (2016) Diversity of references as an indicator of the interdisciplinarity of journals: Taking similarity between subject fields into account. *J. Assoc. Inf. Sci. Technol.*, 67, pp. 1257–1265. https://doi.org/10.1002/asi.23487
- Zwanenburg, S.–Nakhoda, M.–Whigham, P. (2022) Toward greater consistency and validity in measuring interdisciplinarity: a systematic and conceptual evaluation. *Scientometrics*, 127, pp. 7769–7788. https://doi.org/10.1007/s11192-022-04310-z