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Detecting Communities in Digital Disruptive Innovation and Dynamic Capabilities Using Social Network Analysis

Detectando Comunidades em Inovação Disruptiva Digital e Capacidades Dinâmicas Usando Análise de Redes Sociais

Detección de Comunidades en Innovación Disruptiva Digital y Capacidades Dinámicas Mediante Análisis de Redes Sociales

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RESUMO

Objetivo: Identificar e analisar a estrutura social e redes relacionais no campo conceitual que liga inovação disruptiva digital a capacidades dinâmicas.
Metodologia: Utilizou-se a Análise de Redes Sociais (SNA) com dados bibliográficos extraídos do Web of Science (WoS) e do Scopus. Redes foram construídas usando o software Gephi para analisar artigos científicos publicados de 2010 a 2021.
Originalidade: Este estudo aborda um campo emergente de pesquisa, focando nas conexões sociais entre inovação disruptiva digital e capacidades dinâmicas, destacando a centralidade dos Estados Unidos e suas parcerias institucionais.
Principais resultados: Os Estados Unidos mantêm uma posição central e influente nas redes de pesquisa, com parcerias significativas em áreas como saúde e tecnologia. O estudo revela uma rede bem estruturada e forte, indicando oportunidades para estudos futuros.
Contribuições teóricas: A pesquisa reforça a importância da proximidade geográfica e institucional na formação de redes de inovação, oferecendo insights sobre como as redes sociais científicas podem influenciar a pesquisa em inovação disruptiva digital.

Palavras-chave: Inovação Disruptiva, Disrupção Digital, Capacidades Dinâmicas, Análise de Redes Sociais, Bibliometrix, Gephi

ABSTRACT
Objective: Identify and analyze the social structure and relational networks in the conceptual field linking digital disruptive innovation to dynamic capabilities.
Methodology: Social Network Analysis (SNA) was used with bibliographic data extracted from Web of Science (WoS) and Scopus. Networks were built using Gephi software to analyze scientific articles published from 2010 to 2021.
Originality: This study addresses an emerging research field, focusing on social connections between digital disruptive innovation and dynamic capabilities, highlighting the centrality of the United States and its institutional partnerships.
Main results: The United States maintains a central and influential position in research networks, with significant partnerships in areas such as health and technology. The study reveals a well-structured and strong network, indicating opportunities for future studies.
Theoretical contributions: The research reinforces the importance of geographical and institutional proximity in forming innovation networks, offering insights into how scientific social networks can influence research in digital disruptive innovation.

Keywords: Disruptive Innovation, Digital Disruption, Dynamic Capabilities, Social Network Analysis, Bibliometrix, Gephi

RESUMEN

Objetivo: Identificar y analizar la estructura social y las redes relacionales en el campo conceptual que vincula la innovación disruptiva digital con las capacidades dinâmicas.
Metodología: Se utilizó el Análisis de Redes Sociales (SNA) con datos bibliográficos extraídos de Web of Science (WoS) y Scopus. Se construyeron redes utilizando el software Gephi para analizar artículos científicos publicados de 2010 a 2021.
Originalidad: Este estudio aborda un campo de investigación emergente, centrándose en las conexiones sociales entre la innovación disruptiva digital y las capacidades dinámicas, destacando la centralidad de los Estados Unidos y sus asociaciones institucionales.
Principales resultados: Los Estados Unidos mantienen una posición central e influyente en las redes de investigación, con asociaciones significativas en áreas como salud y tecnología. El estudio revela una red bien estructurada y sólida, lo que indica oportunidades para estudios futuros.
Contribuciones teóricas: La investigación refuerza la importancia de la proximidad geográfica e institucional en la formación de redes de innovación, ofreciendo perspectivas sobre cómo las redes sociales científicas pueden influir en la investigación en innovación disruptiva digital.

Palabras clave: Innovación Disruptiva, Disrupción Digital, Capacidades Dinámicas, Análisis de Redes Sociales, Bibliometrix, Gephi.

1 INTRODUCTION

Digital disruption (DD) is “the rapidly unfolding process through which digital innovation fundamentally alters historically sustainable logic for creating and capturing value, separating and recombining links among resources or generating new ones” (Skog et al., 2018, p. 432). Through new digital technologies, DD changes customer experience, processes, and business models, thus altering how value is co-created by actors in an ecosystem (Bolton et al., 2019). Consequently, it replaces traditional products with digital devices, creating new market opportunities (Naimi-Sadigh et al., 2021).

DD is a type of environmental turmoil that originates at the firm level and potentially produces disruptions in established industrial structures (Skog et al., 2018) that almost always stumble on innovations (Christensen, 1997). A frequent theme in the literature indicates reasons incumbents fail to detect or address disruptive innovations to explain these challenges (Riemer & Johnston, 2019). Christensen (1997) assesses that they should invest in existing capabilities to delay interruptions. Studies often examine the resources and capabilities of incumbents (Karimi & Walter, 2015) in response to digital disruption.

In recent years, the complexity of this topic strongly pushed for scientific research concerning these theoretical fields, and researchers have conducted a wide variety of studies (Skog et al., 2018). These research efforts increased the amount of information that poses challenges regarding direction, emphasis, and how researchers have formed partnerships to conduct studies linking Dynamic Capabilities (DC) in response to Disruptive Digital Innovation (DDI).

This study raises the following question: what is the established social structure that links DDI to DCs? Therefore, the main objective is to identify and analyze the social structure and relational networks in this conceptual field that links DDI to DCs, highlighting the main partners' relationship of this scientific community (co-authorship analysis of countries and institutions). To achieve this objective, this article presents an exploratory analysis aimed at uniting two theoretical fields. We adopted Social Network Analysis (SNA), evaluating both the graphical properties of the network and spatial interaction among network nodes. We adopted this methodological research approach because it is an appropriate solution capable of answering research questions since it enables academics to identify the most influential social structures in a field (Forliano et al., 2021). The operationalization of this study is based on the analysis of scientific articles published in journals indexed in the Web of Science (WoS) and Scopus database from 2011 to 2021.

From this perspective, we intend to help the scientific community identify relevant academic literature, considering countries and institutions, and their relationships, as well as the most discussed research topics, and thus, update knowledge that can reveal different perspectives for research.

2 THEORETICAL FOUNDATIONS

Christensen (1997) widely popularized the literature on disruptive innovation and details how new entrants to an industry gradually overtake established companies. By introducing technology that underperforms those existing in key markets, disruptive technologies eventually disrupt and redefine the trajectory of established companies. The ability to introduce features and performance attributes different from conventional technologies and offer simpler, more convenient, and cheaper products attract new or less demanding customers (Adner, 2002; Christensen, 1997; Christensen & Raynor, 2003). Since this new product is unattractive to conventional customers when it is introduced, a new segment of customers sees value in new attributes of innovation and a lower price (Christensen & Raynor, 2003).

Disruptive technologies are characterized by the following aspects: (1) a new disruptive technology becomes dominant in the main market by presenting inferior performance in performance dimensions that are most important to conventional consumers; (2) conventional consumers shift their purchases to products based on new pervasive technology, despite products being inferior on key performance dimensions; and (3) established companies that do not respond to disruptive technologies timely (Adner, 2002).

Disruptive innovations are possible because they start in a low-end market where innovations provide similar characteristics to existing technologies, but cost substantially less (Christensen & Raynor, 2003; Nagy et al., 2016), for example, Airbnb (Guttentag, 2015). They create a new value network, such as new-market disruptions that offer simpler-to-use products, for example, personal computers and Netflix (Christensen et al., 2015; Christensen & Raynor, 2003) that is, it creates new demand for new technology (Nagy et al., 2016).

In the last decades, with the integration of technologies and digital resources that radically changed the nature of products and services, a type of disruption emerges, labeled digital (Tekic & Koroteev, 2019; Yoo et al., 2012). Digital disruption is “the rapidly unfolding process through which digital innovation fundamentally alters historically sustainable logic for creating and capturing value, separating and recombining links among resources or generating new ones” (Skog et al., 2018, p. 432).

Skog et al. (2018) base their proposed conceptualization of digital disruption on the following propositions: (1) digital disruption processes originate from digital innovations that quickly erode competitive positions; (2) they impact ecosystems of value-creating actors by breaking and recombining links among resources, breaking down barriers, and facilitating more direct interactions and transactions; and (3) original digital innovation processes are orchestrated by one or several companies. However, the effects of value creation and value capture are systemic.

Disruption paralyzing effect, in particular digital disruption (Christensen & Raynor, 2003), has been a recurring debate to understand why large companies fail or how they respond to market discontinuities (Kammerlander et al., 2018; Karimi & Walter, 2015). The literature has often relied on dynamic capabilities theory to explain how incumbent companies can face these innovations (Gholampour Rad, 2017; Hopp et al., 2018; Karimi & Walter, 2015). Identifying dimensions that create Dynamic capabilities has the potential to help delineate core elements needed to create dynamic resources in response to digital disruption (Karimi & Walter, 2015).

Dynamic capability is a company's ability to integrate, create, and reconfigure internal and external competencies to address rapidly changing environments and is an integrative approach to understanding new and innovative sources of competitive advantage (Teece et al., 1997). Definitions of dynamic capabilities involve organizational routines that alter and reconfigure resource bases (acquire, eliminate, integrate, and recombine) to generate new value-creation strategies (Teece et al., 1997; Zahra & George, 2002).

The dynamic capabilities approach adequately explains how organizations can address rapidly changing environments by integrating, building, and reconfiguring internal and external competencies (Teece et al., 1997). They can help companies effectively deal with turbulent environments (Ning et al., 2020), which is beneficial to respond to digital innovations (Karimi & Water, 2015).

3 METHODOLOGICAL PROCEDURES

We retrieved data for this study from two main repositories commonly used by researchers, Web of Science (WoS) and Scopus (Rodríguez-Soler et al., 2020). We chose the WoS database because it is estimated to be one of the primary interdisciplinary databases of the highest quality standard (Akbari et al., 2021; Merigó et al., 2015) and one of the most reliable (Clarivate, 2021). Scopus indexes more than 20,000 active titles, including peer-reviewed journals, books, and conference proceedings, and contains about 69 million records (Forliano et al., 2021).

To define the search strategy, we first analyzed the terms within previous literature that dealt with the topics. Then we consulted with experts to ensure we employed the best strategy. After completing all rounds of suggestions and several tests using different search expressions, we determined the pertinent string to be TS= ("disruptive innov*") OR TS = ("disruptive technology") OR TS= ("disruptive business model") AND TS = ("*digital*") AND TS = ("dynamic capab*") AND 2011 to 2021 AND Articles (Document Types). The purpose of adopting these words is to investigate works that cover two important themes for this study, DDI and DC. The search returned 1,352 articles in the WoS and 3 in Scopus, which were duplicates. The data were loaded and exported with all information in appropriate formats (BibTex and plain text) for tools applied in the analysis (Aria & Cuccurrulo, 2017).

We adopted Social Network Analysis (SNA) to measure the degree of connectivity and examine the relational ties among authors' countries and institutions (Forliano et al., 2021). We had to prepare files retrieved from the WoS to build a networks graphics in Gephi. Initially, they were exported to bibexcel and then to Excel to prepare nodes and edges worksheets. After this process, spreadsheets were imported into Gephi software following guidelines recommended by Bastian et al. (2009). Table 1 summarizes the data that compose the database.

Table 1
Summary of main information

Description	Outcomes
Source	WoS and Scopus
Period	2011–2021
Documents	1,352 (1.276 articles, 3 book chapters, 56 anticipated articles, and 17 conference articles)
Authors	3,832 (258 articles with unique authorship and 3,574 articles with co-authorships)
Average of documents per author	0.354
Average number of authors per document	2.83
Average of coauthors per document	3.09
Collaboration index	3.32

Source: Prepared by the authors based on data from Bibliometrix (2021)

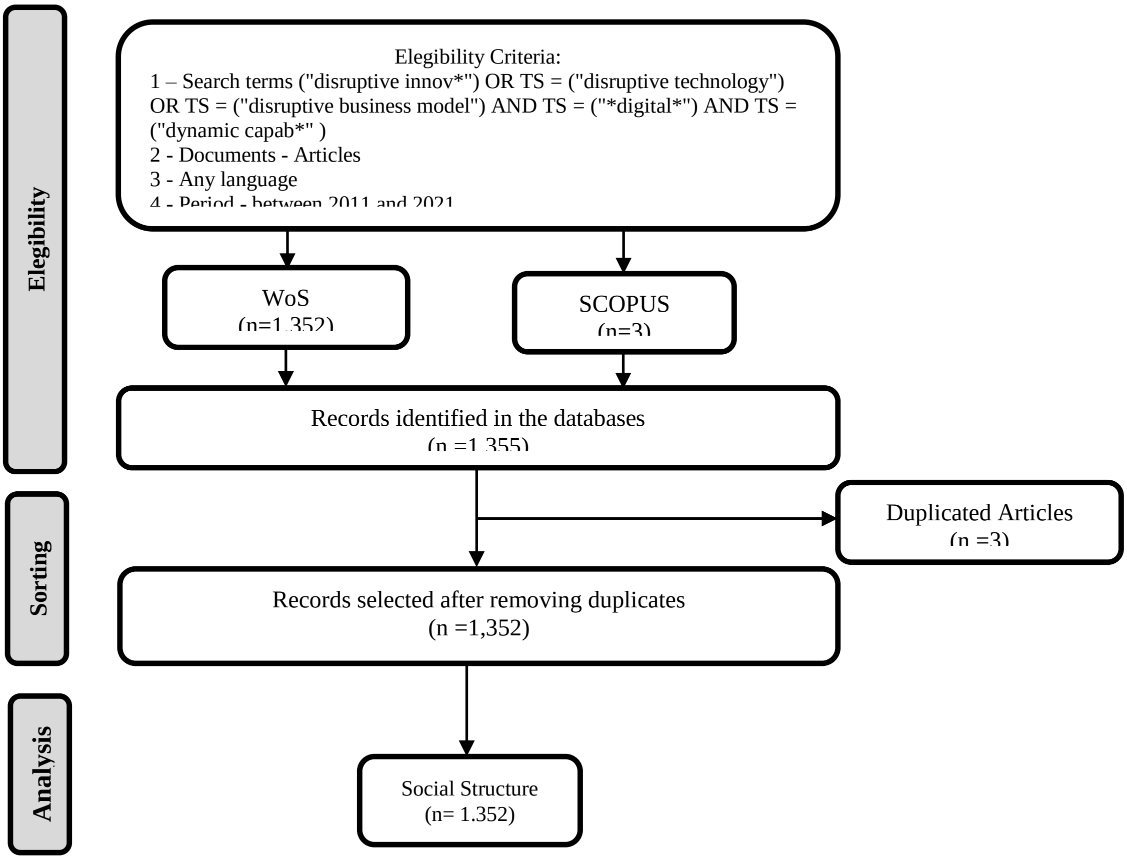
3.1 Analytical methods for elaboration of scientific production indicators

The initial Gephi network is randomly formed and as the total number of connections increases, a giant component form. A giant component is the largest group of individuals connected so that any node in the set can be reached from any other, traversing a suitable path of intermediate collaborators (Newman, 2001; 2004). The existence of a giant component allows scientific information to reach most members of the network, and information can circulate much faster (Newman, 2004).

Each network presents a series of metrics. The average degree of the network indicates the weight of nodes according to the number of their connections, that is, it reflects the number of ties or collaborations an actor has (Wong et al., 2021). Density of a graph explains the level of connectivity of nodes and varies from 0 to 1. Zero means that there are no relationships among actors in a network, and 1 is when the network is complete and there is a high level of relationship among them (Dias et al., 2020). Modularity is a measure of the relative density of a network in which a community has a high density relative to other nodes in its module, but a low density relative to external ones (Muñoz & Riaño-Casallas, 2021). That is, it reflects the strength of a graph divided into communities or clusters. Networks with modularity greater than 0.3 are considered to contain strongly intertwined communities with dense connections that represent strongly coordinated groups indicating a good partition of a network (Arora et al., 2019).

To analyze significant performance, a range of measures of centrality can identify the most important actors in a collaboration network, such as centrality degree and betweenness centrality (Arora et al., 2019; Kumar, et al., 2021). Centrality degree reflects the number of relational ties that a node has in a given network (Kumar et al., 2021). Weighted centrality degree is calculated by multiplying the total number of relational ties by the strength of each tie (Kumar et al., 2021). Betweenness centrality refers to the number of nodes that pass through all the shortest paths in a network related to the ability of a node to bring together groups of otherwise unconnected nodes (Kumar et al., 2021; Wang et al., 2021).

Figure 1
Fluxogram of articles selection



Source: adapted from PRISMA ScR (Tricco et al., 2018)

The summarized steps of this research are described in Figure 1 and section 4 main findings.

4 FINDINGS

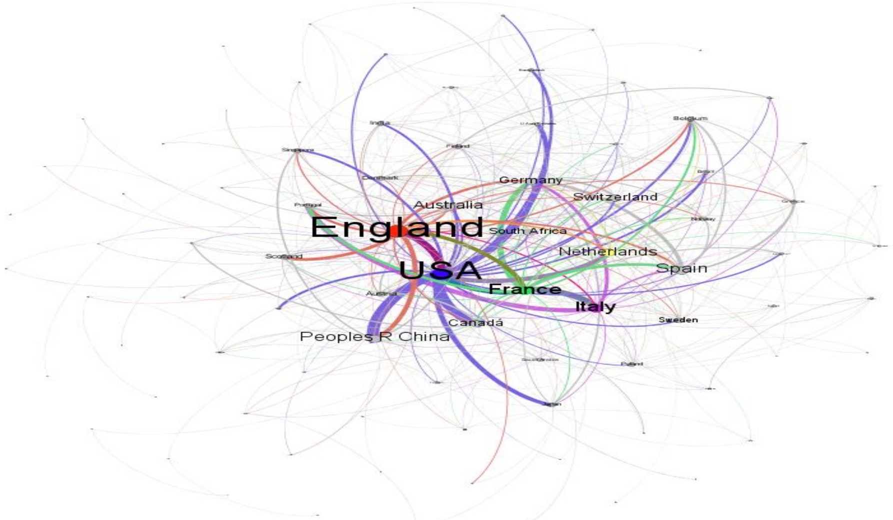
4.1 Social Structure

4.1.1 Collaboration profile of co-authorship among countries

To demonstrate the exchange among countries, an initial network generated connectivity statistics indicating 94 nodes (countries) and 502 connections (edges). A Giant component network (Figure 2) is formed by 86 nodes that represent 91.49% of the initial network (justifying isolated analysis) that establish 499 cooperation relationships (edges). Nodes represent actors and simple edges represent, at least once, with whom an actor has related to another in the network (Aggrawal & Arora, 2016). The average degree of a giant component network is 10.163, which enables us to say that this is the average each country is connected to a giant component network. The density measure of the graph of a giant component network is 0.12, which can be considered low, indicating that few connections were made and there is low cohesion among actors. Modularity is 0.233 which can be considered low, as a giant component network formed only 4 communities.

Figure 2 provides a spatial view of how production and partnerships are distributed among the most prominent countries. Each color represents an actor and its adjacent pairs that comprise its cooperation network. Sizes of nodes and labels (names) are proportional to the centrality degree of an actor, which is determined by the total number of relational ties that each node shares with others in the network (Fahimnia et al., 2015; Kumar, et al., 2021). The larger nodes show greater author centrality, more contributors, and greater influence (Wang et al., 2021). A co-authoring network measures the collaboration extension (Burton et al., 2020).

Figure 2
Giant Component Network of Countries



Source: Prepared by the authors based on data extracted from Gephi (2021)
Note. Layout of giant component network formed by Fruchterman Reingold algorithm (1.413 nodes)

For this graph (Figure 2) the degree of connectivity among countries was considered with at least one connection generated through Fruchterman Reingold (Fruchterman & Reinhold, 1991), avoiding overlaps. This algorithm assumes that vertices connected by an edge must be drawn close to each other and a competitive repulsive force pushes vertices away from each other, whether they are connected or not (Fruchterman & Reinhold, 1991; Hansen et al., 2010).

Scholars from ninety-four countries have published collaborative studies involving DDI and DC. Table 2 demonstrates that researchers from England, The United States, France, Italy, and China are most prominent in terms of the number of partnerships signed, due to the strength of ties established and because they are more willing to bring together groups. The highest centrality degree, weighted degree, and betweenness centrality are presented in Table 2.

Table 2

Relations of countries with greater centrality degree

Country	Centrality Degree	Weigted Degree	Betweenness Centrality
England	50	693	949.0099
The United States	46	1152	568.5729
France	34	571	186.0794
Italy	32	395	118.3808
China	30	348	269.2847
Spain	30	320	211.2991
Nerthelands	29	247	148.5440
Austria	28	167	128.7584
Switzerland	27	174	70.74533
German	26	422	148.0826

Source: Prepared by authors based on data extracted from Gephi (2021)

England is the country that establishes more connections with different countries (50) and has the greatest capacity to form communities (949.009938). However, The United States produces the strongest partnerships among countries it has a relationship with (1,152).

Table 3 highlights 20 countries with the greatest weight in a giant component network, which translates into the strongest collaborations formed. Table 3 shows that in addition to being the country that nurtured the largest number of these partnerships (8 among the top 20), the United States has the strongest ties, especially with Chinese and Canadian researchers. North American authors also built an intellectual exchange with British, Dutch, Japanese, United Arab Emirates, and Turkish researchers. We also observed that England has 6 strong partnerships in this group, among them are the United States, France, China, Scotland, Germany, and Portugal

Table 3
Cooperative relations with greater weight among countries

Source	Target	Weight
China	The United States	138
Canada	The United States	128
France	Italy	100
England	The United States	97
Netherlands	The United States	83
Italy	Portugal	81
France	The United States	74
France	German	70
Japan	The United States	63
England	France	62
England	China	59
United Arab Emirates	The United States	58
England	Scotland	55
France	Spain	50
German	Spain	48
France	Portugal	46
England	German	44
German	Italy	43
England	Portugal	40
Turkey	The United States	36

Source: Prepared by authors based on data extracted from Gephi (2021)

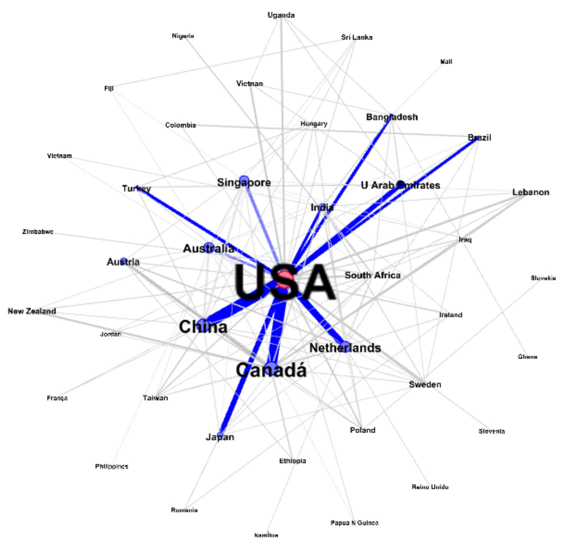
Evidence indicates that authors from advanced economies are highly engaged, such as The United States and especially those from European countries. Fragility regarding international cooperation represents real obstacles to a country's progress (Fortuna et al., 2020). The results exhibit there is a low exchange among academics from emerging countries and developing economies [1], represented in this ranking only by China, United Arab Emirates, and Turkey.

a) Analysis of partnership relationships among clusters

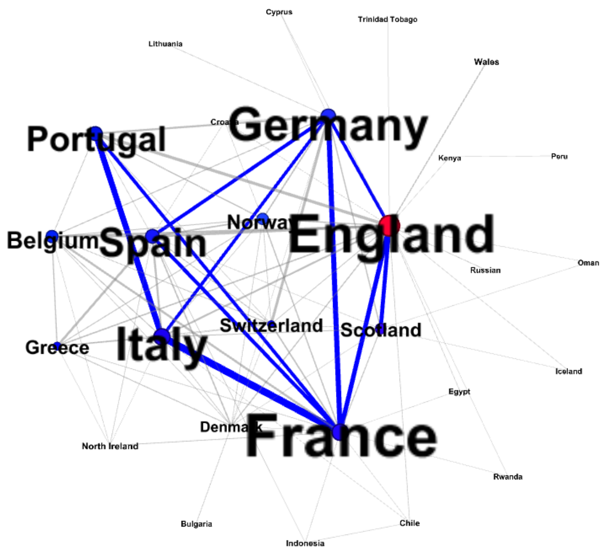
It is common to address a group of countries, institutions, or people, as communities if members of that group often interact. If these types of actors engage in frequent interactions of a large network, it is known as community detection (Aggrawal & Arora, 2016). In the dataset, the running community detection algorithm revealed six communities with a modularity value of 0.233, which indicates that these groups are not strongly connected. Networks with modularity greater than 0.3 are strongly intertwined communities with dense interconnectivity that represent strongly coordinated groups (Aggrawal & Arora, 2016).

A cluster analysis generated from a giant component network focuses on central actors, which are countries with the highest centrality degree, The United States and England (Figure 3), and are also the two largest clusters formed.

Figure 3
Cluster 1: The United States Network
Cluster 2: England Network



Cluster 1



Cluster 2

Source: Prepared by the authors based on data extracted from Gephi (2021)
Note. Node highlighted in red indicates centrality of country. Nodes highlighted in blue point out 9 countries with the highest weighted degree. Node size is proportional to weighted degree. Edges highlighted in blue indicate the 10 strongest dyadic relationships among countries in the cluster and their thickness is proportional to relationships strength.

The largest cluster in terms of the number of nodes, identified as cluster 1 (Figure 3), is composed of 42 countries that established 133 partnership relationships. The central node is The United States, which has the highest number of partnerships (weighted grade 29), the highest number of partnerships among countries (weighted grade 836), and the greatest capacity to bring groups together (grade of intermediation 316.512973). The United States maintains the top 10 strongest relationships in this cluster with China (138), Canada (128), Netherlands (83), Japan (63), United Arab Emirates (58), Bangladesh (36), Singapore (36), Turkey (36), Brazil (32), and India (32). The United States extends its collaboration network to a wide variety of countries.

Cluster 2 (Figure 3) is composed of 28 countries that have established 91 partnership relationships. The central node is England, which has the highest number of partnerships (weighted degree 22) and the greatest capacity to bring together groups (betweenness degree of 182.36746).

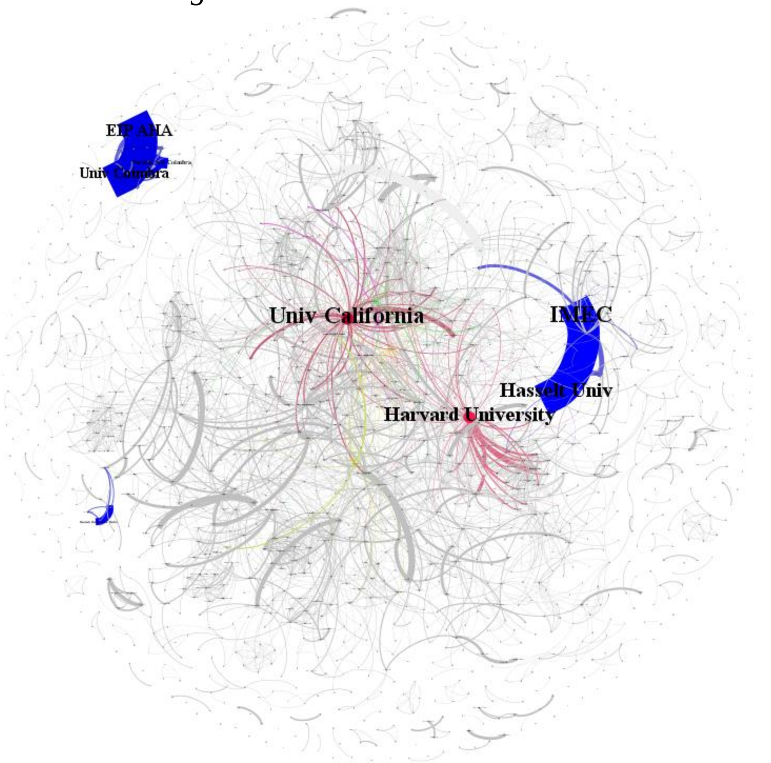
England has the highest degree and the greatest capacity for intermediation, France has the highest number of partnerships among countries (weighted degree 410) and maintains the strongest relationship in the cluster with Italy (100). The most important partnerships are established between Italy and Portugal (81), France and Germany (70), England and France (62), England and Scotland (55), France and Spain (50), Germany and Spain (48), France and Portugal (46), England and Germany (44), and Germany and Italy (43). In this cluster, the strongest relationships are established among countries spatially closer located in Europe.

4.1.2 Collaboration profile of co-authorship among institutions

The initial collaboration network among institutions is composed of 1,592 nodes (unique institutions) connected through 3,628 edges (Figure 4). It consists of 288 connected components representing small communities within the general network. The largest connected component (Figure 5) is formed by 982 nodes, which consist of 61.68% of the initial network and are interconnected through 3,056 edges. The network has a diameter of 12 and a density of 0.006, which is considered a low-density sparse network. The giant component has a modularity value of 0.829.

Figure 4

Initial collaboration network among institutions

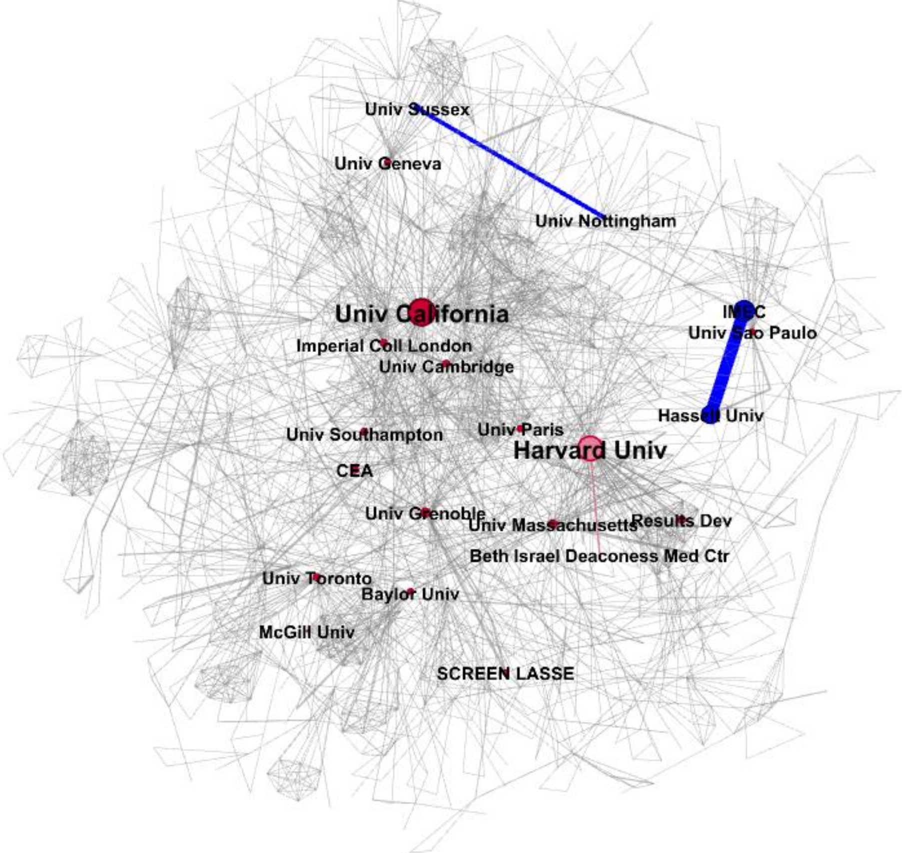


Initial network metrics
Nodes: 1,592
Edges: 3,628
Graph density: 0.003
Modularity: 0.865
Communities:307
Connected components: 288

Source: Prepared by the authors based on data extracted from Gephi (2021)
Note. Layout of networks formed by Fruchterman Reingold algorithm

Twenty institutions highlighted in red (Figure 5) are classified by weighted degree. The University of California occupies the central position because it has a higher centrality degree (95), higher weighted degree (267), and higher betweenness degree (120827.442). Harvard University occupies the second position with a centrality degree (54), centrality weighted degree (228), and betweenness (71468.62709). These results suggest that these two institutions are most prominent because they maintain the largest number of relational ties in the network. Relationships maintained with other institutions are the strongest and exhibit the greatest ability to connect a group of institutions and act as gateways of knowledge (Kumar et al., 2021)

Figure 5
Giant Component Network among institutions



Giant Component Network Metrics:
Nodes: 982
Edges: 3,056
Graph density: 0.006
Modularity: 0.829
Communities: 24
Connected Components: 1
Source: Prepared by the authors based on data extracted from Gephi (2021)
Note. Layout of networks formed by Fruchterman Reingold algorithm

The Table 4 highlights the 20 most important institutions in the giant component network, which translates into the strongest collaborations established. The relationship between Hasselt University and IMEC and between the University of Nottingham and the University of Sussex are the strongest in the network. IMEC, (Interuniversity Center for Microelectronics) a world-renowned research and development center in the fields of nanoelectronics and digital technologies, located in Leuven, Belgium established 14 partnerships in the network. Hasselt University is a public university in Belgium that has worked in cooperation with five other institutions. The University of Nottingham and the University of Sussex, located in England, presented 10 and 7 works developed in cooperation, respectively.

Table 4
Cooperation relationships with the highest weight

Institutions 1	Institutions 1	Weight
IMEC	Hassel University	169
University Sussex	University of Notiingham	53
University Massachusetts	Edith Nourse Rogers Memorial Veterans Hospital	38
DZHK - German Centre for Cardiovascular Research	Deutsch Herzzentrum Berlin	38
University Grenoble	Lasse (Laser Systems & Solutions of Europe)	35
University of Tennessee	Oak Ridge Natl Lab	33
Johannes Kepler Univ Linz	McMaster University	30
Epworth	Deakin University	30
Stmicroelect	CEA-LE TI	27
Hasselt University	Flanders Make VZW	26
IMEC	Flanders Make VZW	26
Results for Development	Harvard University	24
Zeynep Kamil Maitern & Childrens	Baylor University	24
University of California	Kaiser Permanente Baldwin Medical Center	24
University PSL (Paris Sciences & Letters)	Institute Langevin	22
Lasse (Laser Systems & Solutions of Europe)	CNR - ISTI	21
Witten Herdecke University	Bayer Akiengesell	20
Stmicroelect	Insa- Lyon	20
Harvard University	Beth Israel Deaconess Med Cir	18
Fabrx Ltd	UCL School of Pharmacy	16

Source: Prepared by the authors based on data extracted from Gephi (2021)

Although The United States participates with five institutions ranked among the top 20 that maintain the strongest relationships and two have greater centrality (Figure 5), the strongest relationships are by IMEC and Hasselt University, located in Belgium (Table 4).

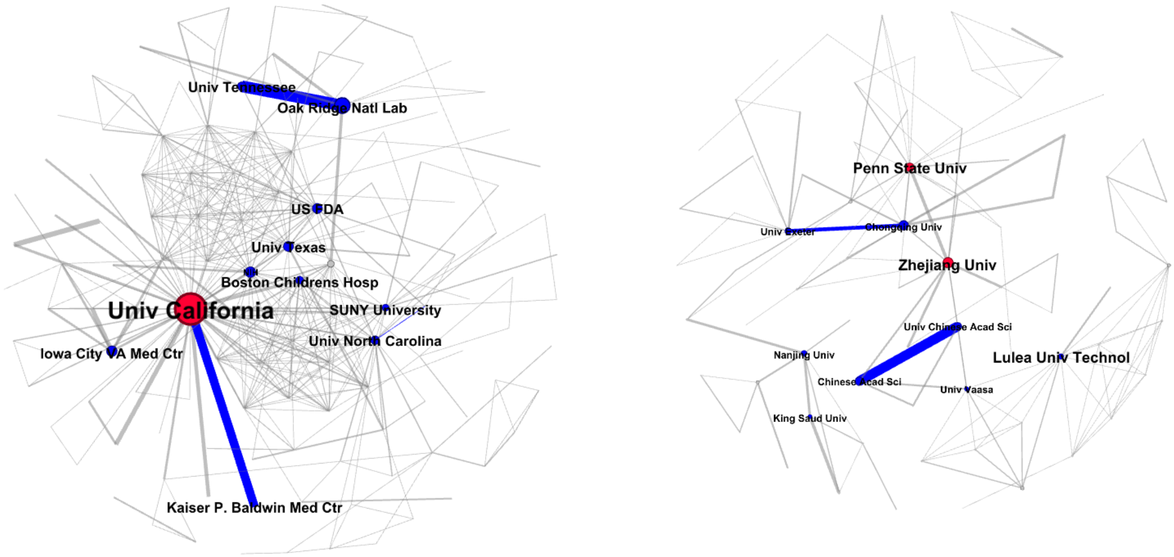
The findings show that in the set of the 20 largest partnerships with greater weight, relationships occur among institutions in the same country. Only partnerships between

Johannes Kepler University Linz (Austria) and McMaster University (Canada), Zeynep Kamil Matern & Childrens (Turkey) and Baylor University (USA), and Lasse - Laser Systems & Solutions of Europe (France) and CNR (Italy) occurred in different countries. This result highlights that the strongest relationships are established among institutions geographically closer.

A) Partnership relations among clusters

The giant component generated 26 communities (clusters). This study focuses on the four largest communities described in Table 5 and indicates the top 10 institutions that form clusters. The largest cluster (Figure 6), in terms of the number of nodes, is composed of 129 institutions (nodes) among universities, research institutes, and companies that have established 420 (edges) partnership relationships (Table 5). The central actor is the University of California in The United States, which also occupies the same position in the giant component network. Among 55 partnerships established (13.09% in the cluster), the main ones are with Kaiser Permanente Baldwin Medical Center (24) in The United States, the University of Warsaw (12) in Poland, and HRL Laboratories (10), a research facility located in Malibu, California. Other more important partnership relationships are between Oak Ridge National Laboratory and the University of Tennessee (33) in The United States, between CalTech (California Institute of Technology) and SRI International, a research and development institute (14), both in California, and VA Iowa City Health Care and VA Portland Health Care System (12), two medical centers located in The United States.

Figure 6
Cluster 1: University of California Network
Cluster 2: Zhejiang University Network



Source: Prepared by the authors based on data extracted from Gephi (2021)
Note. Nodes highlighted in red indicate centrality of institution. Nodes highlighted in blue indicate another 9 institutions with the highest weighted degree. Size of nodes is proportional to weighted degree. Edges marked in blue indicate the strongest dyadic relationships among institutions in the cluster and their thickness is proportional to relationships strength.

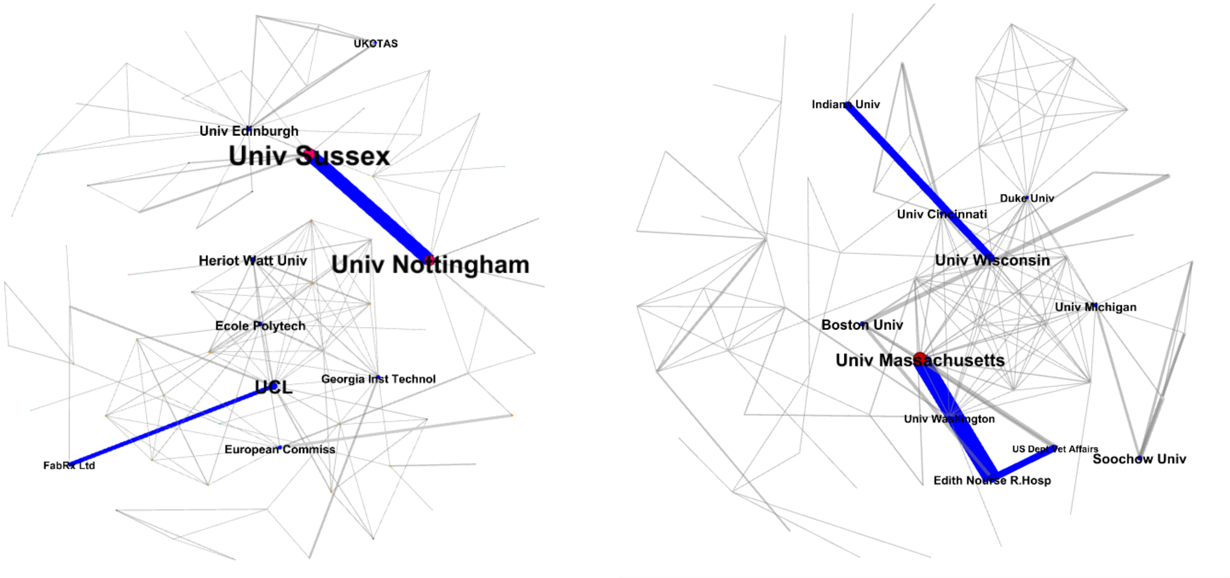
Institutions (281) in The United States have partnerships in their own country, consisting of 18 of the 20 strongest ones. The United States also carried out partnerships with institutions in Japan (39), Canada (16), France (15), and the Netherlands (15), among others. Japan is the second-ranked country, with 53 partnerships established.

The second cluster (Figure 6) includes 74 actors and 135 edges, whose central actor is Penn State University, a North American university, with the highest number of partnerships (16) and the highest betweenness degree (1463.5). Zhejiang University is an important player in this network because of its weighted degree (29). Partnerships established with Zhejiang University (13), located in China, are very diverse and are stronger than Penn State University (5), which is one of the 10 most important. Regarding to the importance of cooperative relations, studies between the Chinese Academy of Science and the University Chinese Academy of

Science (weight 15) and the University of Exeter in England and Chongqing University (6) in China, are more prominent.

Two countries stand out, The United States which presented in 51 partnerships, and China in 43 partnerships. In terms of internal cooperation, The United States showed 29 relations and China 15. Chinese institutions are the most in cooperation with those of The United States (13). In this community, there are also links among institutions in England that signed 19 partnerships, but only one internally. Finland is also a strong player in this context, as it has signed 18 partnerships, three of which are internal. China leads with 17 partnerships. In addition, partnerships among emerging and developing economies countries predominated.

Figure 7
Cluster 3 - University Sussex Network
Cluster 4 - University Massachusetts Network



Source: Prepared by the authors based on data extracted from Gephi (2021)
Note. Nodes highlighted in red indicate centrality of institution. Nodes highlighted in blue indicate another 9 institutions with the highest weighted degree. Size of nodes is proportional to weighted degree. Edges marked in blue indicate the strongest dyadic relationships among institutions in the cluster and their thickness is proportional to relationships strength.

The third largest cluster (Figure 7) is formed by 73 institutions that have established 167 partnerships (Table 5). Three central actors can be considered, Ecole Polytech, located in

France, which presents the greatest number of partnerships (17), the University of Sussex, which stands out for having the greatest weight among established relationships (73), and the University of Nottingham for having the greatest ability to form communities. The last two are located in England and the partnership established among them is the strongest in the cluster (50). In addition, three important positions, in terms of weight in this community, are presented between FabRx Ltd, a pharmaceutical company specializing in biotechnology, and UCL School of Pharmacy (weight 16), both in England; between Technion - Israel Institute of Technology in Israel and the European Commission (10), and between the University of Sussex and Finnish Environm Institute (08) in Finland.

Institutions in England dominate as they have established 74 relationships, of which 16 are internal. Scotland (12) and Germany (8) are the most frequent. We also highlight links established among institutions in France (33) and Germany (31). Regarding the 20 most important partnerships, England leads, as it is present in 14 of them. Furthermore, partnerships among countries with developed economies predominate.

The fourth largest cluster (Figure 7) consists of 62 institutions that form 164 edges. The central actor is the University of Massachusetts in The United States which built stronger relationships (77) and greater competence in developing communities (280), despite Duke University having a greater number of joint work (17). In this set of 164 co-participations established, 88% have a weight below 2 and 1, indicating the presence of weak ties. The strongest ties are between the University of Massachusetts and Edith Nourse Rogers Hospital (38) and the University of Wisconsin and Indiana University (16). Edith Nourse Rogers Hospital, the University of Massachusetts, and Boston University have the stronger relationships in the top ten.

Concerning institutions to countries of origin, collaborations have been the most nourished with The United States, with 134 strong relationships, 110 of which are with institutions within the own country. The country with which it maintains the greatest proximity is China within 11 relations. Then comes China with 31 cooperations, 15 of which are internal. Table 5 presents the metrics of all clusters.

Table 5
Metrics of clusters

Cluster 1			
Nodes			129
Edges			420
Middle grade			6.512
Weighted average grade			11.938
Network diameter			7
Graph Density			0.051
Institutions	**Degree**	**Weight Degree**	**Betweenness Centrality**
Univ California	55	188	3941.51111
Oak Ridge Nat Lab	7	58	438.5
NIH	31	42	927.044444
Iowa City VA Med Ctr	6	42	0
Univ Texas	27	41	1266.872222
US FDA	19	41	306.994444
Univ Tennessee	4	39	61.5
Univ North Carolina	24	38	1642.45
Boston Childrens Hosp	15	36	0
Michigan State Univ	18	30	847

Cluster 2			
Nodes			74
Edges			135
Middle grade			3.649
Weighted average grade			6,514
Network diameter			11
Graph Density			0,05
Institutions	**Degree**	**Weight Degree**	**Betweenness Centrality**
Zhejiang Univ	12	29	1320.5
Chongqing Univ	10	27	732.5
Penn State Univ	16	24	1463.5
Chinese Acad Sci	4	24	35.5
Univ Chinese Acad Sci	4	22	35.5
Univ Exeter	8	18	478
Nanjing Univ	6	16	600
Lulea Univ Technol	12	15	743
Univ Vaasa	8	12	952
King Saud Univ	3	11	0

Cluster 3			
Nodes			73
Edges			167
Middle grade			4.575
Weighted average grade			9.589
Network diameter			11
Graph Density			0.064
Institutions	**Degree**	**Weight Degree**	**Betweenness Centrality**
Univ Sussex	7	73	407
Univ Nottingham	10	65	1460
UCL	16	45	338.833333
Heriot Watt Univ	10	29	71
Univ Edinburgh	14	27	773
Ecole Polytech	17	25	1314.166667
European Commiss	8	22	1292
Georgia Inst Technol	13	21	807
UKCTAS	4	18	0
FabRx Ltd	2	18	0

Cluster 4			
Nodes			62
Edges			164
Middle grade			5.29
Weighted average grade			10.613
Network diameter			9
Graph Density			0.087
Institutions	**Degree**	**Weight Degree**	**Betweenness Centrality**
Univ Massachusetts	14	77	280
Edth Nourse Rogers	3	59	0
Univ Wisconsin	15	32	625
Boston Univ	5	27	118
US Dept Vet Affairs	3	27	0
Soochow Univ	4	26	0
Univ Cincinnati	14	22	174
Univ Michigan	15	21	228
Indiana Univ	3	19	119
Duke Univ	17	18	238

Source: Prepared by the authors based on data extracted from Gephi (2021)
Note: Institutions are ordered by weighted grade.

5 DISCUSSIONS

The objective of this work focused on identifying social networks that link DDI to DC through Social Network Analysis. We extracted bibliographic data from the Web of Science (WoS) in the last 11 years. The main findings suggest that five countries, England, The United States, France, Italy, and China excel in terms of quantity and strength of relational ties and their ability to form communities. Despite England producing greater quantities, The United States established stronger ties with partners, especially China and Canada (see Tables 2 and 3). There is evidence that authors in countries with advanced economies, such as The United States and European countries, are highly involved in joint research. Emerging countries with developing economies are underrepresented among these strongest ties. Only China, United Arab Emirates, and Turkey are in this relationship.

The United States occupies a central position when observing partnership relationships with the University of California and Harvard University occupying central positions in giant component networks. They are the most relevant due to the number and relational ties strength, in addition to having a greater capacity to connect a group of institutions and operate as a gateway to generate knowledge (Kumar et al., 2021).

In cluster analysis, agglomerations are formed around a university or research institute considering that seven universities (the University of California in The United States in cluster 1, Penn State University in The United States and Zhejiang University in China in cluster 2, Ecole Polytech, located in France, the University of Sussex and the University of Nottingham in England in cluster 3, the University of Massachusetts and the University of Wisconsin in The United States in cluster 4) play a central role, due to the number of partnerships formed for maintaining the strongest relationships or by centrality degree. This result corroborates Clarysse et al. (2014) who emphasized that the proximity of companies to local universities and public research organizations plays a central role in advancing technological innovation within ecosystems by sharing information. Universities are seen as crucial pillars for the development of a region (Spigel, 2017), reinforcing that co-authorship works, in general, flourish among geographically neighboring institutions.

In all clusters, exchanges took place globally with countries around the world. However, it is North American institutions that most develop research in cooperation, either internally or with institutions outside the country. This is observed in clusters 1, 2, and 4. Cluster 1 brings together 129 institutions from 17 different countries. Among them, 91 are in The United States and work in cooperation with others from 14 countries. Cluster 2 groups 74 institutions from 23 countries, among which 26 from The United States have co-authored work with others from seven countries. Cluster 4 assembles 62 institutions from 20 countries. In this set, 27 are from The United States who cooperated with nine from other countries. This result suggests The United States is the country that most influences research in this field.

There is an indication that cooperation is concentrated between authors located geographically closer. This fact can be reinforced by observing the strength of ties which confirms that among institutions that collaborated, most relationships are built internally to the countries. This evidence is strong with The United States, which despite spreading relations with countries around the world, most of them are drawn locally. In cluster 1, among 382 partnerships, 281 are among those in their own country. In cluster 2, among 51 cooperations, 29 are internal, and in Cluster 4, among 134 partnerships, 110 are among local companies. In clusters 2 and 4, relationships of Chinese institutions also followed this behavior. In the first case, among 43 partnerships, 15 were within the country, and in the second, among 31 partnerships, 14 were internal.

Findings of social structure can reinforce the importance of proximity among actors in facilitating information sharing, cooperation, interaction, and establishment of formal ties of scientists and companies (Audretsch & Feldman, 1996; Gertler, 2003; Malmberg & Maskell, 2002). Spatial proximity and organizational proximity can be considered key to effective production, transmission, and knowledge sharing (Gertler, 2003). However, there is an issue of spatial scale that includes the notion of local and regional, which are often central to analyses of spatial proximity (Malmberg & Maskell, 2002). All clusters that partnerships are directed towards technologies involve areas of medicine and health, non-profit organizations to fight against inequality in emerging countries and tech companies indicating multidisciplinary fields.

6 CONCLUSIONS

This study involved a decade of research into DDI and DC. It differs from previous bibliometric research because it investigates connections aligned with relationships between these two research fields through SNA among countries and institutions.

Examining 1,352 documents published over years, the growth of publications indicates that this subject has the potential to be explored and the research field to mature. When analyzing scientific collaboration networks, relationships with authors around the world and countries such as England, The United States, France, Italy, and China are most prominent. However, The United States has stronger ties and maintains a centralized position regarding networks among institutions suggesting it is the greatest influencer on this research field.

In addition, designing these cooperations is more intense among authors located geographically closer showing that proximity facilitates circulation and exchange of knowledge. Given this scenario, we suggest that overcoming geographical distance can enrich exchanges, especially in joint work among countries from advanced economies with emerging countries and developing economies are polished given that these connections are still not very representative among these stronger ties.

This study included an analysis of social networks among countries and institutions without getting involved with cooperative relationships among authors. Future studies may be concerned with this, even establishing different weights for authorship order. Our findings can help researchers deeply explore this relationship and understand how productive these partnerships are. It would be beneficial to investigate partnership relationships that are useful to address issues or how partnerships can compete to produce disruptive products.

As an agenda for future studies, one suggestion is to expand temporality to understand the evolution of themes since the emergence of disruptive innovation theory. Bibliometric or systematic review studies would observe aspects that impact an incumbents' adaptation to technological changes, which can increase the list of what was raised in this study. Furthermore, a study would be interesting to understand how these aspects can contribute to the introduction of disruptive products.

As a contribution, this research favors the discussion of public policies aimed at encouraging partnerships among universities and institutes with companies in their surroundings and encouraging joint research between advanced economies and emerging countries. Simultaneously, it can help researchers and professionals to have a comprehensive view of relationships that form around two theories. In addition, researchers can use findings to guide future studies considering paths that have been proposed.

Notas finais:

[1] For further clarification, visit the United Nations, World Bank, or International Monetary Fund list

REFERENCES

Adner, R. (2002). When are technologies disruptive? a demand-based view of the emergence of competition. *Strategic Management Journal*, 23(8), 667–688. https://doi.org/10.1002/smj.246

Aggrawal, N., & Arora, A. (2016). Visualization, analysis and structural pattern infusion of DBLP co-authorship network using Gephi. *2016 2nd International Conference on Next Generation Computing Technologies* (NGCT), 494–500. https://doi.org/10.1109/NGCT.2016.7877466

Akbari, M., Khodayari, M., Khaleghi, A., Danesh, M., & Padash, H. (2021). Technological innovation research in the last six decades: A bibliometric analysis. *European Journal of Innovation Management*, 24(5), 1806-1831. https://doi.org/10.1108/EJIM-05-2020-0166

Aria, M., & Cuccurullo, C. (2017). Bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, 11(4), 959-975. https://doi.org/10.1016/j.joi.2017.08.007

Arora, N., Jain, R., Gupta, V., Aggarwal, U., Gupta, C., Kumari, M., Chaudhary, N., Jain, P., & Pal, R. (2019). Investigating factors influencing scholastic execution at undergrad level using network analytics. *Proceedings of the Third International Conference on Advanced Informatics for Computing Research*, 1–6. https://doi.org/10.1145/3339311.3339319

Audretsch, D.B., & Feldman, M.P. (1996). R&D spillovers and the geography of innovation and production. *The American Economic Review*, 86(3), 630-640. https://www.jstor.org/stable/2118216

Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: An Open Source Software for Exploring and Manipulating Networks. *Proceedings of the International AAAI Conference on Web and Social Media*, *3*(1), 361-362. https://doi.org/10.1609/icwsm.v3i1.13937.

Burton, B., Kumar, S., & Pandey, N. (2020). Twenty-five years of The European Journal of Finance (EJF): A retrospective analysis. *The European Journal of Finance*, *26*(18), 1817–1841. https://doi.org/10.1080/1351847X.2020.1754873

Christensen, C.M. (1997). *The Innovator's Dilemma* —When New Technologies Cause Great Firms to Fail. Harvard Business School Press.

Christensen, C.M., & Raynor, M. (2003). *The innovator's solution*. Harvard Business School Press.

Christensen, C. M., Raynor, M. E., & McDonald, R. (2015). What is disruptive innovation.

Harvard Business Review, 93(12), 44–53. https://hbr.org/2015/12/what-is-disruptive-innovation

Clarysse, B., Wright, M., Bruneel, J., & Mahajan, A. (2014). Creating value in ecosystems: Crossing the chasm between knowledge and Business Ecosystems. *Research Policy*, 43(7), 1164-1176. https://doi.org/10.1016/j.respol.2014.04.014

Clarivate. *Web of Science Core Collection* (2020). https://clarivate.com/webofsciencegroup/solutions/web-of-science-core-collection/. Acessed: 23 de agosto de 2021.

Dias, A., Ruthes, S., Lima, L., Campra, E., Silva, M., Gragança de Sousa, M., & Porto, G. (2020). Network centrality analysis in management and accounting sciences. *RAUSP Management* Journal, 55(2), 207-226. https://doi.org/10.1108/RAUSP-02-2019-0021

Fahimnia, B., Sarkis, J., & Davarzani, H. (2015). Green supply chain management: A review and bibliometric analysis. *International Journal of Production Economics*, 162, 101- 114. https://doi.org/10.1016/j.ijpe.2015.01.003

Forliano, C., De Bernardi, P., & Yahiaoui, D. (2021). Entrepreneurial universities: A bibliometric analysis within the business and management domains. *Technological Forecasting and Social Change, 165,* 120522. https://doi.org/10.1016/j.techfore.2020.120522

Fortuna, G. Aria, M., Piscitelli, A., Mignogna, M., & Klasser, G. (2020). Global research trends in complex oral sensitivity disorder: A systematic bibliometric analysis of the structures of knowledge. *Journal of Oral Pathology & Medicine, 49*(6), 565-579 https://doi.org/10.1111/jop.13077

Fruchterman, T. M. J., & Reingold, E. M. (1991*)*. Graph drawing by force-directed placement. *Software: Practice and Experience,* 21(11), 1129–1164. https://doi.org/10.1002/spe.4380211102

Gertler, M. (2003). Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there). *Journal of Economic Geography*, 3(1), 75-99. https://doi.org/10.1093/jeg/3.1.75

Gholampour Rad, M. (2017). Disruptive innovation in media industry ecosystem and need for improving managerial cognitive capabilities in polymediation era. *Cogent Business & Management*, 4. https://doi.org/10.1080/23311975.2017.1352183

Guttentag, D. (2015). Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism*, 18(12), 1192–1217. https://doi.org/10.1080/13683500.2013.827159

Hansen, D., Shneiderman, B., & Smith, M.A. (2010). *Analyzing social media networks with NodeXL: Insights from a connected world*. Morgan Kaufmann Publishers.

Hopp, C., Antons, D., Kaminski, J., & Salge, O. (2018). Perspective: The topic landscape of disruption research a call for consolidation, reconciliation, and generalization. *Journal of Product Innovation Management*, 35(3), 458-487. https://doi.org/10.1111/jpim.12440

Kammerlander, N., König, A., & Richards, M. (2018). Why do incumbents respond heterogeneously to disruptive innovations? he interplay of domain identity and role identity. *Journal of Management Studies,* 55(7), 1122-1165. https://doi.org/10.1111/joms.12345

Karimi, J., & Walter, Z. (2015). The role of dynamic capabilities in responding to digital disruption: A factor-based study of the newspaper industry. *Journal of Management Information Systems,* 32(1), 39–81. https://doi.org/10.1080/07421222.2015.1029380

Kumar, S., Pandey, N., Burton, B., & Sureka, R. (2021). Research patterns and intellectual structure of managerial auditing journal: A retrospective using bibliometric analysis during 1986-2019. *Managerial Auditing Journal*, 36(2), 280-313. https://doi.org/10.1108/MAJ-12-2019-2517

Malmberg, A., & Maskell, P. (2002). The elusive concept of localization economies: Towards a knowledge-based theory of spatial clustering. *Environment and Planning A,* 34(3), *429*–449. https://doi.org/10.1068/a3457

Merigó, J. M., Mas-Tur, A., Roig-Tierno, N., & Ribeiro-Soriano, D. (2015). A bibliometric overview of the journal of business research between 1973 and 2014. *Journal of Business Research.* 68(12), 2645–2653. https://doi.org/10.1016/j.jbusres.2015.04.006

Muñoz, P. A. E., & Riaño-Casallas, M. (2021). Relación entre felicidad en el trabajo y desempeño laboral: análisis bibliométrico, evolución y tendencias. *Revista Virtual Universidad Católica del Norte*, 64, 241-280. https://doi.org/10.35575/rvucn.n64a10

Naimi-Sadigh, A., Asgari, T., & Rabiei, M. (2022). Digital Transformation in the Value Chain Disruption of Banking Services. *Journal of the Knowledge Economy*, *13*(2), 1212–1242. https://doi.org/10.1007/s13132-021-00759-0

Nagy, D., Schuessler, J., & Dubinsky, A. (2016). Defining and identifying disruptive innovations. *Industrial Marketing Management,* 57, 119–126. https://doi.org/10.1016/j.indmarman.2015.11.017

Newman, M. (2001). The structure of scientific collaboration networks. *Proceedings of the National Academy of Sciences of the United States of America*, 98(2). 404-409. https://doi.org/10.1073/pnas.98.2.404

Newman, M. E. J. (2004). Coauthorship networks and patterns of scientific collaboration. *Proceedings of the National Academy of Sciences,* 101(Supplement 1), 5200–5205. https://doi.org/10.1073/pnas.0307545100

Ning, C., Xiaoming, M., & Tiantian, S. (2020). Entrepreneurial bricolage, dynamic capabilities and disruptive innovation: Theoretical model. *Journal of Economics, Business and Management,* 8(2), 86-90. https://doi.org/10.18178/joebm.2020.8.2.618

Riemer, K. & Johnston, R. B. (2019). Disruption as worldview change: A kuhnian analysis of the digital music revolution. *Journal of Information Technology,* 34(4), 350–370. https://doi.org/10.1177/0268396219835101

Rodríguez-Soler, R., Uribe-Toril, J., & De Pablo, J. (2020). Worldwide trends in the scientific production on rural depopulation, a bibliometric analysis using bibliometrix R-tool. *Land Use Policy*, 97, 104787. https://doi.org/10.1016/j.landusepol.2020.104787

Scopus. (2020). *Sources*. Elsevier B. V. https://www.scopus.com/sources.uri

Skog, D. A., Wimelius, H., & Sandberg, J. (2018). Digital disruption. *Business and Information Systems Engineering*, 60(5), 431–437. https://doi.org/10.1007/s12599-018-0550-4

Spigel, B. (2017). The Relational Organization of Entrepreneurial Ecosystems. *Entrepreneurship Theory and Practice*, *41*(1), 49–72. https://doi.org/10.1111/etap.12167

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal,* 18(7), 509–533.

https://doi.org/10.1142/9789812796929_0004
Tekic, Z., & Koroteev, D. (2019). From disruptively digital to proudly analog: A holistic typology of digital transformation strategies. *Business Horizons*, 62(6), 683-693. https://doi.org/10.1016/j.bushor.2019.07.002
Tricco, A.C., Lillie, E., Zarin, W., O'Brien, K.K., Colquhoun, H., Levac, D., Moher, D., Peters, M.D.J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M.G., Garritty, C., ... Straus, S.E. (2018). PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. *Annals of internal medicine*, 169(7), 467-473. http://dx.doi.org/10.7326/M18-2205
Wang, L., Gong, Z., Shi, L., Hu, Z., & Shah, A. (2021). Knowledge mapping analysis of research progress and frontiers in integrated disaster risk management in a changing climate. *Natural Hazards*, 107, 2033-2052. https://doi.org/10.1007/s11069-020-04465-z
Wong, A.K.F., Koseoglu, M.A., & Kim, S. (2021). Creation and dissemination of hospitality and tourism research outputs in the new millennium. *International Journal of Contemporary Hospitality Management*, 33(2), 377-401. https://doi.org/10.1108/IJCHM-05-2020-0493
Yoo, Y., Boland, R.J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science*, 23(5), 1398-1408. https://doi.org/10.1287/orsc.1120.0771
Zahra, S. & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *The Academy of Management Review*, 27(2), 185-203. https://doi.org/10.2307/4134351

Contribuições dos autores

Autor a – Contribuição principal com definição do problema, desenvolvimento de hipóteses, revisão da literatura, resultados, análises e conclusões.
Autor b – Contribuição principal com definição do problema, desenvolvimento de hipóteses, método, resultados e conclusões.
Autor c – Contribuição principal com análise de dados.
Autor d – Contribuição principal com revisão.

Conflito de Interesse

Os autores afirmam que não existem conflitos de interesse.