BIBLIOMETRIC ANALYSIS OF FUNCTIONAL NEAR-INFRARED SPECTROSCOPY (FNIRS) IN NEUROIMAGING LITERATURE

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ABSTRACT

BIBLIOMETRIC ANALYSIS OF FUNCTIONAL NEAR-INFRARED SPECTROSCOPY (FNIRS) IN NEUROIMAGING LITERATURE

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This thesis study aims to explore the Functional Near Infrared Spectroscopy (fNIRS) literature by utilizing bibliometric analysis techniques. In particular, we aimed to investigate the interdisciplinary nature of the fNIRS literature by analyzing co-authorship patterns across departments and countries, and utilizing various bibliometric mapping techniques to identify the oprominent authors, trending research themes and collaboration networks. The raw dataset of fNIRS related articles that were published betweem 1980-2020 were retrieved from the ISI Web of Science database and subjected to bibliometric analysis using the Bibliometrix & biblioshiny-R packages, CiteSpace, and VOSviewer programs. The findings indicated that fNIRS articles that were products of interdisciplinary and international collaboration have a significantly higher share in top JIF quartile categories, which had become more evident especially in the last few years. The most commonly co-cited journals included J Appl Physiol, Biochim Biophys Acta, J Neurosurg, Am J Physiol, Biophys J, Nature, Adv Exp Med Biol, Lancet, Arch Dis Child-Fetal and Pediatr Res. fNIRS literature suggests that at the beginning this field had been led primarily by studies conducted at specific departments such as Biophysics, Physiology, Bioengineering, Medical Physics. Such groundwork studies were then transformed into studies incorporating authors from multiple departments, firstly within medical sciences such as Pediatrics, Surgery, Geriatrics, and then in more applied fields such as Human Factors, Social Psychology, and Economics as evidenced in the diversity of the affiliations of the co-authors in fNIRS publications. The Bibliometric maps highlight the sustained impact of institutions based in the USA, England, Japan and Germany over this field, as well as the recent emergence of China. Departments such as Radiology, Bioengineering, Biomedical Engineering, Medicine, Health, Neuroscience and Neurobiology constitute the core set of disciplines for fNIRS research. Overall, the findings of this thesis study suggest that fNIRS is an increasingly interdisciplinary field of study within Neuroimaging, whose impact is growing as fNIRS is increasingly utilized in previously unexplored settings thanks to its portability and advances in instrumentation and signal processing. Our findings also demonstrate that bibliometric techniques can be used to effectively explore the trends and seminal studies in a field.

Keywords: fNIRS, neuroimaging, bibliometric, disciplinary, collaboration

ÖZ

NÖROGÖRÜNTÜLEME LİTERATÜRÜNDE FONKSİYONEL YAKIN-KIZILÖTESİ SPEKTROSKOPİNİN (FNIRS) BİBLİYOMETRİK ANALİZİ

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Bu tez çalışması, bibliyometrik analiz tekniklerini kullanarak Fonksiyonel Yakın Kızılötesi Spektroskopi (fNIRS) literatürünü keşfetmeyi amaçlamaktadır. Özellikle, fNIRS literatürünün disiplinlerarası doğasını çeşitli bibliyometrik analiz yöntemleri ve göstergeleri yardımıyla araştırmayı amaçladık. Ham veriler 1980-2020 yılları arasında ISI Web of Science veri tabanından alınmış ve Bibliometrix & biblioshiny-R paketleri, CiteSpace ve VOSviewer programları kullanılarak analiz edilmiştir. Disiplinler arası ve uluslararası işbirliğinin ürünü olan fNIRS makaleleri, özellikle son birkaç yılda daha belirgin hale gelen Q1 ve Q2 kategorilerinde önemli ölçüde daha yüksek bir paya sahiptir. En sık ortak atıf yapılan dergiler arasında J Appl Physiol, Biochim Biophys Acta, J Neurosurg, Am J Physiol, Biophys J, Nature, Adv Exp Med Biol, Lancet, Arch Dis Child-Fetal ve Pediatr Res yer almaktadır. fNIRS literatürü, başlangıçta bu alanın öncelikle Biyofizik, Fizyoloji, Biyomühendislik, Medikal Fizik gibi belirli bölümlerde yürütülen çalışmalarla yönlendirildiğini göstermektedir. Bu tür temel çalışmalar daha sonra, öncelikle Pediatri, Cerrahi, Geriatri gibi tıp bilimlerinde ve daha sonra fNIRS yayınlarındaki ortak yazarların bağlantılarının çeşitliliğinde kanıtlandığı gibi İnsan Faktörleri, Sosyal Psikoloji ve Ekonomi gibi daha uygulamalı alanlarda birden fazla bölümden yazarları içeren çalışmalara dönüşmüştür. Bibliyometri haritaları, ABD, İngiltere, Japonya ve Almanya merkezli kurumların bu alan üzerindeki sürekli etkisinin yanı sıra son zamanlarda Çin'in ortaya çıkışını vurgulamaktadır. Radyoloji, Biyomühendislik, Biyomedikal Mühendisliği, Tıp, Sağlık, Sinirbilim ve Nörobiyoloji gibi bölümler fNIRS araştırmaları için çekirdek disiplinler kümesini oluşturmaktadır. Genel olarak, bu tez çalışmasının bulguları, fNIRS'in Nörogörüntüleme içinde giderek daha disiplinlerarası bir çalışma alanı olduğunu ve taşınabilirliği ile enstrümantasyon ve sinyal işlemedeki ilerlemeler sayesinde daha önce keşfedilmemiş ortamlarda fNIRS'in giderek daha fazla kullanılmasıyla etkisinin arttığını göstermektedir. Bulgularımız ayrıca bibliyometrik tekniklerin bir alandaki eğilimleri ve ufuk açıcı çalışmaları etkin bir şekilde keşfetmek için kullanılabileceğini göstermektedir.

Anahtar Kelimeler: fNIRS, nörogörüntüleme, bibliyometrik, disipliner, işbirliği

To My Family,

To URAP Center

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LIST OF ABBREVIATIONS

BA	Bibliometric Analysis
CI	Citation Impact
CNCI	Normalized Citation Impact
CPP	Citation per Publication
PPF	Puplication Per Faculty
CPF	Citation Per Faculty
DOI	Digital Object Identifier
ECoG	Electrocorticography
EEG	Electroencephalo graphy
fNIRS	Functional Near-Infrared Spectroscopy
HEI	Higher Education Institution
HiCi	Highly Cited
ISI	Institute for Scientific Information
IREW	Impact Relative to World
ICoR	Intracortical recordings
JIF	Journal Impact Factor
MEG	Magnetoencephalo graphy
PUBMED	Publication of Medicine
NLM	National Library of Medicine
PET	Positron emission tomography
SCI	Science Citation Index
SSCI	Social Sciences Citation Index
URAP	University Ranking by Academic Performance
VBA	Visual Basic for Applications
WOS	Web of Science

CHAPTER I

INTRODUCTION

The past decade has brought an exponential explosion in the growth of scientific literature, particularly in the field of life and health sciences. The growth of active researchers in these fields, the proliferation of electronic publishing and the emergence of open acess journals have altogether contributed to this outcome. The growing literature makes it increasingly challenging for even experienced researchers to keep up with the current state of the art in active research domains such as neuroscience and bioinformatics. Especially for the newcomers to such fields, the growing volume of publications makes it very difficult to identify the seminal studies in the field and trace the progression of ideas among the publications. Citation databases such as Web of Science, PubMed and Scopus provide powerful text-based search tools, reference tracing possibilities, subject taxonomies and impact statistics to aid the researchers. However, given the pace of the growth, its still difficult to locate and access key publications and make sense of the broader connections implicit in those publications through search results. In particular, newcomers to a field may lack the knowledge of the relevant keywords to narrow down and navigate the search space. Therefore, there is an increasing need for tools and techniques that can help researchers navigate and make sense of the ever-growing scientific literature.

This thesis focuses on the use of bibliometric methods and tools to explore their potential in mitigating some of the complexities involved with exploring a research domain within life and health sciences. Functional Near Infrared Spectroscopy (fNIRS) optical brain imaging literature is selected as a case study due to its recent proliferation as an emerging and promising brain-imaging modality in neuroscience research in the past 25 years. The current study utilizes the state-of-the-art bibliometric analysis methods over the citation records of publications on fNIRS optical brain imaging to explore what kind of insights can be gained regarding the inception and growth of this burgeoning field.

The thesis also investigates the level of interdisciplinarity in this domain and to what extent interdisciplinarity relates to the impact of publications in the optical brain imaging research. In the rest of this introduction section, short descriptions of some of the key concepts underlying the current study will be presented to situate this work within the broader domains of medical informatics and bibliometrics, which is followed by the research goals pursued in the thesis.

1.1. Bibliometrics

Bibliometrics is the quantitative analysis of articles in the scientific literature through their bibliographic content (Bellis, 2009). Alan Pritchard first explained the term in an article published in 1969 as "…the application of mathematical and statistical methods to books and other communication media" (Pritchard, 1969, p. 349). Ethmologically the term bibliometrics combines the words biblios and metrics, where biblios means book and metric means measurement in ancient Greek (Sengupta, 1992). Bibliometrics also refers to an innovative method in the context of literature research, whose most significant benefits are realized through the methods devised for analyzing many scientific publications in a specific field and visualizing their general characteristics and interrelationships (Zhang et al., 2015).

Applying quantitative analysis and statistics to publications like journal articles and their citations is known as bibliometric analysis. In almost all areas of science, quantitative analysis of publication and citation data is now used to evaluate scientific community development, maturity, leading authors, conceptual and intellectual maps, and trends. Research performance evaluation also extensively utilizes bibliometric techniques (Aria & Cuccurullo, 2017). Moreover, these quantitative methods also allow researchers to conduct descriptive analyses of a targeted literature by computing bibliometrics for different time periods to investigate temporal and conceptual trajectories in that field (Mcburney & Novak, 2002).

The bibliometric approach facilitates the analysis of an extensive body of research, potentially encompassing thousands of studies. Since bibliometric techniques are centered on a substantial volume of academic works, they may not necessarily yield detailed insights into the outcomes of individual publications. However, the network maps built on these data sets offer important insights by unveiling critical information, such as patterns in terminology usage and citation interplay, which may serve to enhance the understanding of a specific field of study (Zupic & Carter, 2015).

Bibliometric studies can be broadly grouped under two categories, namely text mining approaches and visualization/mapping efforts. Bibliometric text mining is a rapidly growing field that combines bibliometric analysis with natural language processing and machine learning techniques to extract valuable insights from large-scale scholarly literature datasets. The main goal is to devise metrics that capture the degree of relationship among scientific documents based on their full-text or indexing data (e.g. title, abstract, keyword, authors, affiliations, references). The metrics serve as a basis for clustering related entities to summarize the dataset so as to aid interpretation.

Computing the co-occurrence of words in titles, abstracts or full-texts is one of the most basic means to derive relationships among keywords. Likewise, co-citation measures relate two authors based on the frequency both authors appear on the reference list of documents. More complex measures can be devised by relating different text elements available in a citation database. For instance, lexical information obtained from titles and abstracts can be combined with citation information to derive semantic relationships among a set of journals hosting those articles (Liu et al., 2019).

Text mining approaches can be further improved by invoking linguistic structures to relate different types of keywords of interest. For instance, in a study related to this thesis study, French et al. (2012) annotated the abstracts of a corpus of comparative neurology literature containing a wide diversity of terms, species, and brain region names, in an effort to relate specific brain regions with terms describing their function. The authors designed the WhiteText web interface for neuroscientists extracting neuroanatomical references from text and also focus on summary statements in the abstracts to extract the brain regions mentioned and the relationships between them.

Text mining analysis typically leads to a similarity or a distance matrix that captures the strength of the relationship among any two entities (e.g. authors, affiliations, source articles) of interest. Since citation databases contain a huge amount of information, clustering algorithms and visualization techniques play an important role on the interpretation of bibliometric analysis outcomes. Such methods form the backbone of the maps of scientific fields popularly employed in bibliometric studies.

Bibliometric maps of scientific fields also open up the possibility of utilizing network-based metrics in the study of scientific fields. By converting bibliometric text data into a graph, network metrics such as centrality, diffusion, brokerage can be studied in the context of science studies. According to graph theory, a network is a series of nodes and links. In the context of bibliometrics, nodes typically represent authors, keywords, or affiliation information. The links between the nodes may represent various types of relationships including citations, co-citation similarity, co-word occurrences, and bibliometric coupling (Grauwin & Jensen., 2011).

Science mapping has emerged as an important research area not only within academic research, but also for practical purposes. In addition to numerical measurements, the emerging visual maps are increasingly recognized as a helpful tool for decision-makers in solving real problems of research planning and development. (Boyack and Klavans., 2010). The maps are also conceived as search interfaces for exploring scientific fields, especially for the newcomers (Ding et al., 2000).

With the increased computing power, many software tools have become available for science mapping analysis (Cobo, Lopez-Herrera, HerreraViedma, & Herrera, 2011). Several software tools/packages have been developed to enable the visualization and analysis of bibliometric networks such as the Bibliometrix R Package (Aria & Cuccurillo, 2017), Gephi (Bastian, Heymann & Jacomy, 2009), CiteSpace (Chen, 2006), and VosViewer (Van Eck & Waltman, 2010).

1.2. Neuroimaging

Neuroimaging is a branch of medical imaging that focuses on studying the structure, function, pharmacology, and the pathology of the nervous system. In clinical medicine, neuroimaging is used when the physician needs a more detailed examination of a patient who is suspected of having a neurological disease following a neurological examination. With the development of noninvasive neuroimaging techniques, these methods have been increasingly utilized in studies that aim to explore the neurological underpinnings of human cognition and behavior. Pharmocology is another major area where neurimaging techniques are employed to investigate the effects of drugs and various chemicals on the nervous system.

Given its increasing influence in medicine and life sciences, the field of Neuroimaging has gone through an exponential growth as evidenced in the volumes of data produced in the form of scientific publications, image databases, nucleotide sequences, and protein structures. For example, the number of scientific articles published and indexed by PubMed related to Neuroimaging is approximately 270.000 today, with an average of 15.000 new articles added annually. Therefore, tracking the published materials in Neuroimaging is nearly impossible for researchers without automated tools and efficient search engines.

1.2.1. Neuroimaging Modalities

Many new imaging methods have been developed thanks to the discoveries made in nuclear physics and biomedicine fields, which enabled researchers and medical professionals to investigate the structural and functional features of the brain. Brain imaging techniques such as Electroencephalography/ Magnetoencephalography (EEG/MEG), structural/functional Magnetic Resonance Imaging (MRI/fMRI), Computed Tomography (CT), Positron Emission Tomography (PET), Diffusion Tensor Imaging (DTI), and functional Near Infrared Spectroscopy (fNIRS) have been used to explore the structural and functional properties of the brain (Bandettini, 2009). Moreover, neurostimulation techniques such as Transcranial Magnetic Stimulation (TMS) and Transcrainal Direct/Alternating Current Stimulation (tDCS/tACS) have been employed to systematically manipulate neural activity to further explore the causal links between brain activity and behavior (Edwards et al., 2017).

EEG is the oldest brain imaging technique, developed in the 1920s. This technique is performed by recording the electrical potential changes in the brain with the help of electrodes placed on the scalp (Luck, 2014). EEG provides excellent temporal resolution for detecting neural activity since the electrodes can pick up the aggregated electrical potential changes of vertically aligned pyramidal neuron populations in the cortical columns. However, due to the factors affecting the conduction of electrical potentials inside the nervous tissue, locating the origin of those electrical discharges are difficult. For that reason, EEG offers limited spatial resolution as compared to other neuroimaging modalities.

MEG is a closely related technique to EEG that detects magnetic field disturbances due to brain activity (Hari & Puce, 2017). Similar to EEG, MEG is used to measure the effects that occur in the brain from outside the head. Since magnetic field changes are coupled to electrical potential changes, MEG has equivalent temporal resolution as compared to EEG. MEG offers superior spatial resolution as compared to EEG since magnetic field changes are not disturbed by the tissue. However, certain geometric alignments of neurons may not produce disturbances detectable by MEG sensors, and the method requires expensive equipment and shielding from the earth's magnetic field, which limit their availability (Hari & Puce, 2017).

CT is a diagnostic method that allows taking image sections from the body with the help of X-rays and processing them into image computers. CT is one of the most widely used imaging modalities today. It is routinely used in body scans to detect the presence of cancerous tissue or other abnormalities in brain structure. Since high energy radiation is used, caution is needed when CT is used with children, pregnant, and other risky groups (Bunge & Kahn, 2009).

PET displays the distribution of positron-emitting radioactive substances (usually glucose labeled with radioactive phosphorus) after they are injected into the body (Raichle, 1983). In this way, the physiological properties of tissues and organs, such as metabolism and blood flow can be evaluated. In the context of functional neuroimaging, PET allows researchers to observe the changes in brain oxygenation by following the distribution and density of positron emissions during a cognitive task (Bunge & Kahn, 2009). Similarly, SPECT is a technique that shows regional brain perfusion (how the brain blood flow is distributed regionally). 3D images are created by capturing and recording the photons emitted by the injected radioactive compound by SPECT cameras that rotate around the patient. SPECT images provide the researcher with both functional and anatomical information (Bunge & Kahn, 2009). Overall, tomography-based techniques are mainly used in clinical settings to investigate brain structure, drug effects and brain functions. The high energy and invasive nature of the measurements limit their use beyond clinical settings.

The MRI method stimulates protons in the tissues by creating high magnetic fields (Liang & Lauterbur, 2000). Signals reaching the receivers are converted into images by computer analysis. MRI is frequently used in creating fine images of brain tissue, imaging soft tissues, diagnosing central nervous system diseases, sports injuries, and musculoskeletal system diseases and evaluating neurological diseases (Bunge & Kahn, 2009). Functional MRI (fMRI) is an extension of the magnetic resonance imaging technique that allows visualization of the brain's function with instant and millimetric differences (Ogawa et al., 1993). This technique is based on the difference in the magnetic properties of oxygen-bound hemoglobin and deoxygenated hemoglobin (deoxyhemoglobin) in the blood. Because fMRI measures the change in blood oxygenation over time, it gives researchers information about brain functions and allows the location of the activity to be determined in millimeters. Therefore, fMRI is considered as an imaging technique with high spatial resolution. It is frequently used by neuroscientists in studying visual imagery, memory, attention, memory and learning (Keles & Kol, 2015).

fNIRS is an optical imaging technique that utilizes infrared light to monitor changes in light atteneuation due to the presence of oxygenated and deoxygenated blood in the brain. fNIRS utilizes light within the optical window (i.e. 700–900nm) in the near-infrared part of the spectrum, which can penetrate through skull and tissue to reach the capillary beds within the cortical tissue. Jobsis (1977) demonstrated that it is possible to monitor cortical oxygenation changes by shining infrared light over the scalp with a light source and a detector located nearby. Although the discovery of this technique dates back to 1930-1940s, the emergence of fNIRS as a neuroimaging modality occurred in early 1990s (Ferrari & Quaresima, 2012). Despite its limitation in terms of the depth of measurable brain tissue, due to its safe, portable and noninvasive nature, fNIRS has gained increasing popularity as a neuroimaging modality in the neuroimaging literature, especially in field applications.

1.3. Studies on Neuroimaging related to Bibliometrics

Neuroimaging has become an increasingly popular research domain, particularly between 1998 and 2002, given the growth of the number of published materials in neuroimaging starting in those years (Sharifi et al., 2008). Figure 1 below summarizes the growth in the number of publications utilizing the main types of neuroimaging modalities in the past 30 years. The publication counts reflect only the contents of the journals, books and conference proceedings in the WoS database that are explicitly classified under the Neurosciences and Neuroimaging field according to the WoS subject taxonomy. Although EEG is the oldest modality, neuroimaging literature seems to be driven by the introduction of the MRI and then fMRI in late 1990s. The PET modality also plays an important role in this timeframe, which is followed by a declining trend with the prominence of non-invasive and more portable modalities like EEG and fNIRS.

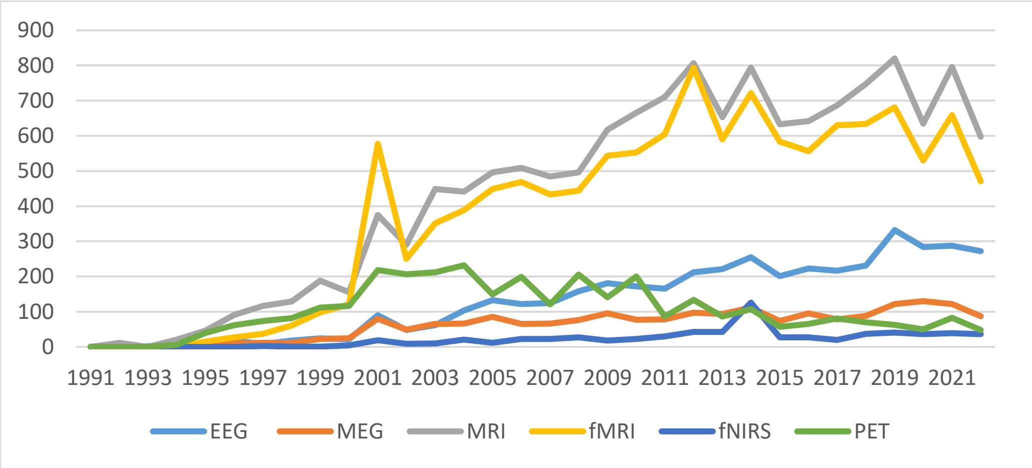

Figure 1: The number of publications utilizing neuroimaging modalities from 1990-2022 in journals indexed under Neurosciences and Neuroimaging subject categories in the WoS database.

Figure 2 provides a broader view of the publications in the WoS database without the subject category restriction. When the search is expanded beyond neuroimaging and neurosciences, it can be observed that the MRI and PET modalities are utilized in more publications given their significance in clinical research and practice.

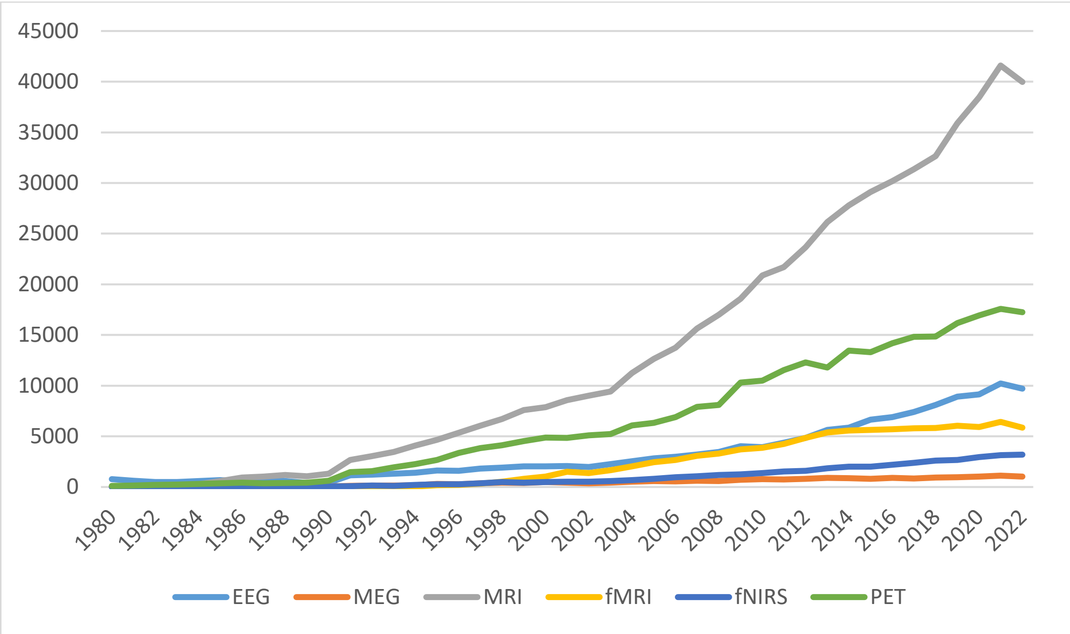

Figure 2: The number of publications utilizing neuroimaging modalities from 1980-2022 in the entire WoS database.

The growing size of the literature utilizing various neuroimaging modalities have brought the need to develop methods for processing and synthesizing the information communicated in these publications. Bibliometric methods have been employed to address this need at varying levels in the scientometrics/bibliometrics literature. One of the most prominent uses of bibliometric data in the neurosciences/neuroimaging domain is to evaluate the research output at the level of institutions and countries. For instance, such evaluations were conducted in the case of China (Xu et al., 2003), Cuba (Dorta-Contreras, 2008), India (Bala and Gupta 2010), Italy (Berardelli et al., 2005), Spain (Gomez et al., 1990), and Sweden (Glanzel, 2003; Mela & Mancardi, 2002), where the studies focused on the scientific productivity of the respective countries in this domain. These studies typically compare the output of several countries as in the case of Bala and Gupta (2010), who observed that India urgently needed to expand research in Neuroimaging given the trends in more developed nations. Similar studies focusing on the scientific output in the fNIRS field is relatively recent, given its emerging status in the neuroimaging literature (Yan et al., 2020; Devezas, 2021; Xiangyin et al., 2023).

Another use of bibliometrics in this domain has been to identify collaboration links among countries and institutions based on the co-authorship and affiliation information in Neuroimaging related publications, as exemplified by Braun et al. (1995). Such studies revealed the central roles fulfilled by developed nations such as USA, Germany, Canada, and Japan, as well as the emergence of China, in the development of neuroimaging tools and their use in clinical and applied research.

Studies focusing on the publication output and co-authorship tend to provide a global view of the neuroimaging literature. However, such methods do not reveal much about the information content and the semantic connections in the published literature. There are also attempts that aim go beyond the basic publication data by utilizing additional measures derived from text-mining approaches together with citation information. For instance, French et al. (2012) aimed to construct a corpus of manually annotated mentions of brain regions in neuroimaging publications. An important goal in neuroimaging is to explore the functional organization of the brain, and functional roles attributed to specific brain regions form an important part of this effort. In French et al.'s corpus, there are 1,377 abstracts and 18,242 annotations of brain regions. Over 6,000 unique midbrain region terms and 17,000 words were found in their vocabulary. The authors then utilized straightforward dictionary approaches as well as intricate natural language processing methods to automatically extract mentions of brain regions. French et al.'s study presents one of the first corpus of manually annotated biomedical abstracts with mentions of brain regions. However, the approach is limited to availability of the hand-made annotations which is a tedious process limiting the scalability of the approach. Moreover, shifts in the literature such as increasing emphasis on brain networks rather than individualized brain regions may also bring challenges to annotation-based approaches since the annotation schemes and the annotations need to be updated to accommodate such shifts.

In another related text-based bibliometric study, Crasto et al. (2003) developed the NeuroText program to supplement the Neuroimaging databases by reviewing the natural language texts of Neuroimaging articles. As it becomes increasingly difficult to keep up with the expanding literature, the authors proposed an automated text mining tool to map the content of a given article to the existing structure of these knowledge databases. A keyword-frequency-based approach is used to search for relevant publications by their abstracts, and then bibliometric analysis is performed by subjecting them to lexical and semantic analysis to match the abstract content with the knowledge base structure in the target database. When the structure of the identified publications matches the knowledge organization of the database, the reported results can be added to the database to support further query processing. However, this approach also lacks the abovementioned flexibility due to the assumptions made regarding the knowledge structure, which is primarily targeting the behavior of specific cell types sampled from particular brain regions from predominantly animal models. Therefore, the kind of information accumulated in the database requires restructuring when new methodologies emerge, for instance focusing on network characteristics that require a different knowledge ontology.

Overall, several related studies in the literature have utilized bibliometric methods to explore various aspects of neroimaging research. Bibliometric methods have been used to summarize overall publication volume, citation links, collaboration, and topic patterns, as well as more in-depth analysis of text to provide further insights into the knowledge claims made by the authors regarding functional roles of various components of the nervous system. Studies that utilize text-mining approaches tend to be limited to a smaller data set due to the challenges involved with data annotation and semantic interpretation. There have also been recent advances in the bibliometrics literature including new indicators for network properties, impact measures and tools for visualizing relationships among publications, authors and institutions, which have not been explicitly employed in studying neuroimaging literature to the best of our knowledge.

The primary objective of this dissertation study is to present a scientific map of the global fNIRS literature, a rapidly expanding field of study in neuroimaging. The aim will be to investigate to what extent incorporating text mining and data visualization methods improves the accuracy of scientific field clustering and classification in a neuroimaging domain as a case study. The choice of the fNIRS literature is due to its expanding but manageable size, and the availability of historical in-depth reviews of the progress in recent fNIRS research, which can guide the interpretation of the maps generated over bibliometric data. The ISI Web of Science citation database was used to obtain the bibliometric data for the fNIRS literature from 1980 to 2020. Based on bibliometric measures such as bibliographic matching, co-occurrence statistics, and co-citation similarity, density maps and cluster maps of organizations, authors, and journals are created using modern bibliometric analysis tools such as VOSviewer, CiteSpace, and R-Biblioshiny. By considering different levels of analysis such as authors, institutes, countries, or keywords to reflect knowledge structures in this field at the micro and macro levels, the thesis will aim to explore the fNIRS literature in terms of its course of development, prominent authors and main concepts. Another goal would be to evaluate these tools and techniques in terms of uncovering patterns and structures from bibliometric data resources.

The rest of this thesis is organized as follows. The next chapter will provide further conceptual background for this study via a review of the related literature and bibliometric concepts. This is followed by a description of the bibliometric resources utilized to explore the fNIRS literature. The fourth chapter presents the results obtained through the use of bibliometric data analysis techniques. The thesis concludes with a discussion of the findings and recommendations for further research.

CHAPTER II

LITERATURE SURVEY

This chapter provides further conceptual background for this dissertation study. The next section covers the basics of the functional near infrared spectroscopy (fNIRS) as an emerging neuroimaging modality, which is the primary domain of interest of this bibliometric study. Basic concepts and some of the application areas of fNIRS are reviewed to assist the interpretation of the bibliometric analysis results and maps that will be presented in this dissertation. This is followed by an introduction to the basic concepts and tools used in bibliometric analysis, and an overview of bibliometrics studies of the fNIRS literature.

2.1. fNIRS

fNIRS is an optical imaging technique that utilizes infrared light to monitor changes in light atteneuation due to the presence of oxygenated and deoxygenated blood in the brain (Ferrari and Quaresima, 2012; Quaresima and Ferrari, 2019; Jones and Ekkekakis, 2019). Optical methods originate from muscle oximetry, which Glenn Millikan first developed in the 1940s (Ferrari and Quaresima, 2012). Similar to its current use, real-time non-invasive tissue oxygenation was recorded for the first time in 1977, and it was determined that the brain tissue was permeable in the near-infrared range (Jöbsis et al., 1977). Although the discovery of oximetry dates back to 1940s, the emergence of fNIRS as a neuroimaging modality occurred in early 1990s (Ferrari & Quaresima, 2012). Despite its limitation in terms of the depth of measurable brain tissue, due to its safe, portable and noninvasive nature, fNIRS has gained increasing popularity as a neuroimaging modality in the neuroimaging literature, especially in field applications.

fNIRS is a neuroimaging modality based on monitoring the hemodynamic response of the vascular system to supply oxygen to activated brain regions. Several neuroimaging modalities such as fMRI, PET and fNIRS are based on methods for monitoring the hemodynamic changes in the brain due to neuronal activity. Neuronal activity can be deduced from changes in oxygenation since variation in cerebral hemodynamics is related to functional brain activity through a mechanism called neurovascular coupling (Obrig et al., 2000). Neurons require energy to get activated, which is supplied by the metabolization of glucose via astrocytes (Heeger & Ress, 2002). The metabolization process requires oxygen supplied by the hemoglobin molecules being present in the capillary beds within the vascular system. When a group of neurons fire, they initially consume the oxygen present in their vicinity, which will produce an initial increase in the concentration of deoxyhemoglobin (HbR) and a dip in the concentration of oxyhemoglobin (HbO). In the order of 4-6 seconds, the vascular system responds to this local energy need by supplying more oxygenated blood towards that location, which causes an increase in the concentration of HbO and washes away the HbR. As the neural population returns to its baseline activity level, HbR and HbO concentrations also come back to their baseline levels. The change in relative concentrations of HbR and HbO due to neuronal activity is called the hemodynamic response (Figure 3).

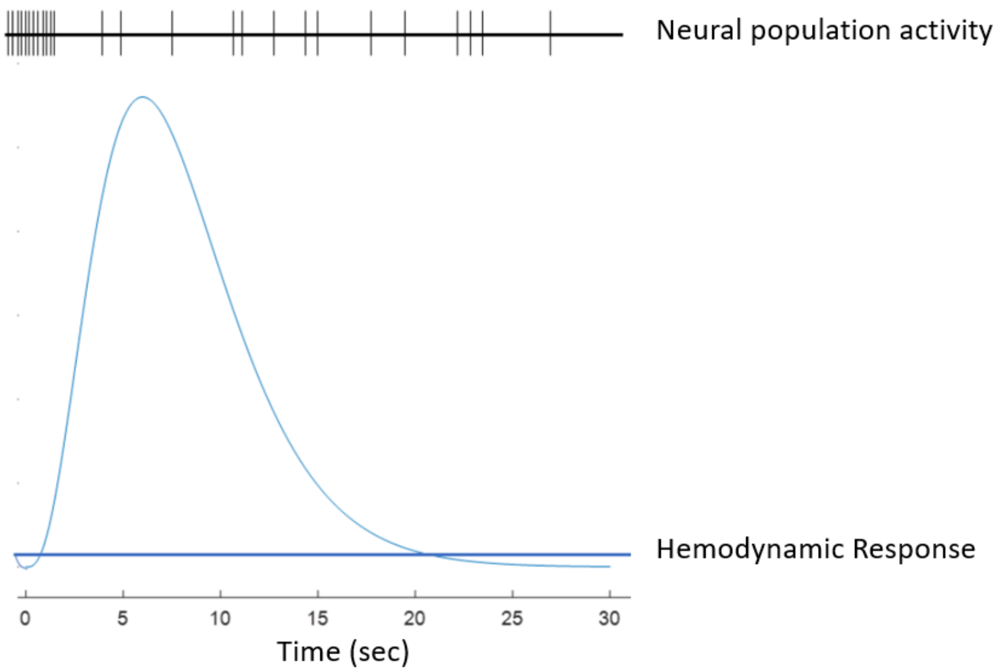

Figure 3: A schematic respresentation of the hemodynamic response induced by the electrical activity of a neuron population.

fNIRS technology uses specific wavelengths of light, introduced at the scalp, to enable the non-invasive measurement of changes in the relative ratios of HbR and HbO in the capillary beds during brain activity. Typically, an optical apparatus for fNIRS consists of at least one near infrared light source and a detector that receives light after it has interacted with the tissue. Near-infrared light is known to diffuse through the intact scalp and skull, which makes it suitable for tracing relative changes in the concentration of specific chromophores in the neural tissue with non-invasive spectroscopic methods (Wray et al., 1988). Although most biological tissues (including water) are relatively transparent to light in the near infrared range between 700 to 900 nm, hemoglobin is a strong absorber of light waves in this range of the spectrum. Figure 4 below shows the absorption characteristics of elements present in biological tissue. Within 700 to 900 nm, HbO and HbR are among the highest absorbers of infrared light. Moreover, within this range, the absorption characteristics of these molecules criss-cross each other, which makes it possible to separate the two chromophores from each other. This provides an optical window into neural tissue where one can approximate relative changes in the concentration of HbO and HbR based on how infra-red light is attenuated in neural tissue.

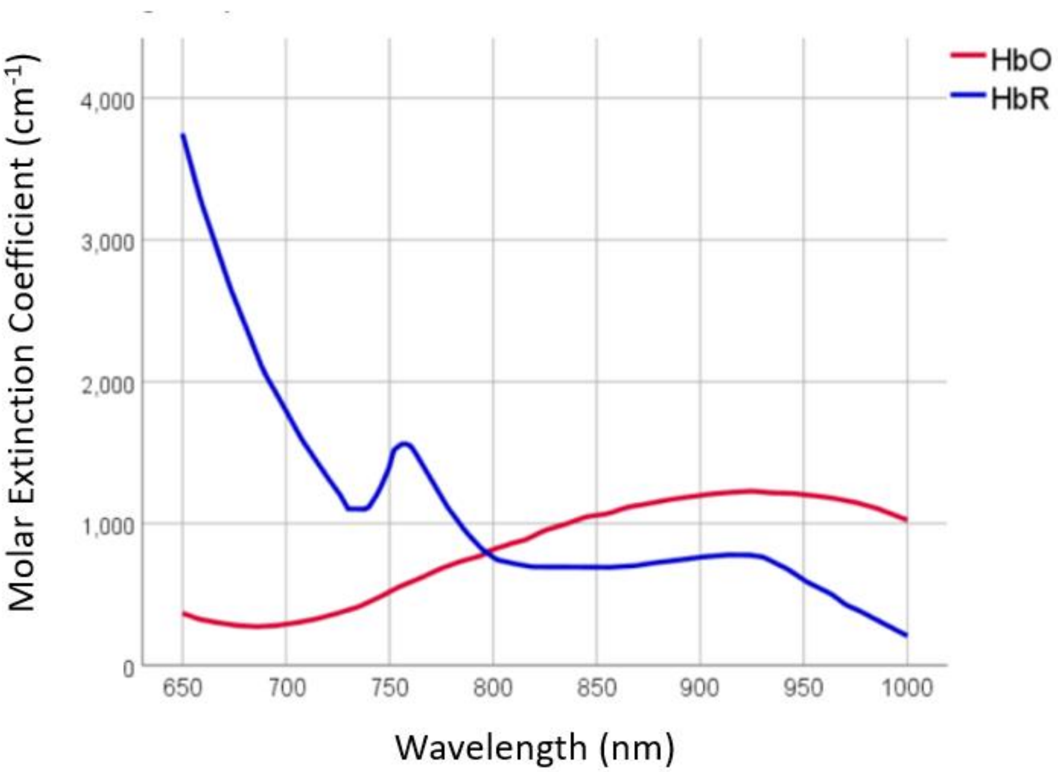

Figure 4: The absorption characteristics of HbO and HbR molecules in the optical window defined by the wavelength range 700-900nm.

Photons that enter tissue undergo two different types of interaction: absorption and scattering (Obrig et al., 2000). Two chromophores, HbO and HbR, are strongly linked to tissue oxygenation and metabolism. The absorption spectra of HbO and HbR remain significantly different from each other allowing spectroscopic separation of these compounds to be possible by using only a few sample wavelengths. Once photons are introduced into the human head, they are either scattered by extra- and intracellular boundaries of different layers of the head (skin, skull, cerebrospinal fluid, brain, etc.) or absorbed mainly by HbO and HbR. If a photodetector is placed on the skin surface at a certain distance from the light source, it can collect the photons that are scattered and thus have travelled along a "banana shaped path" (Figure 5) from the source to the detector, which carry important information about the optical properties of the diffused neural tissue. By using the Modified Beer Lambert Law, this information is converted into estimations of changes in relative concentrations of HbO and HbR (Izzetoglu et al., 2005).

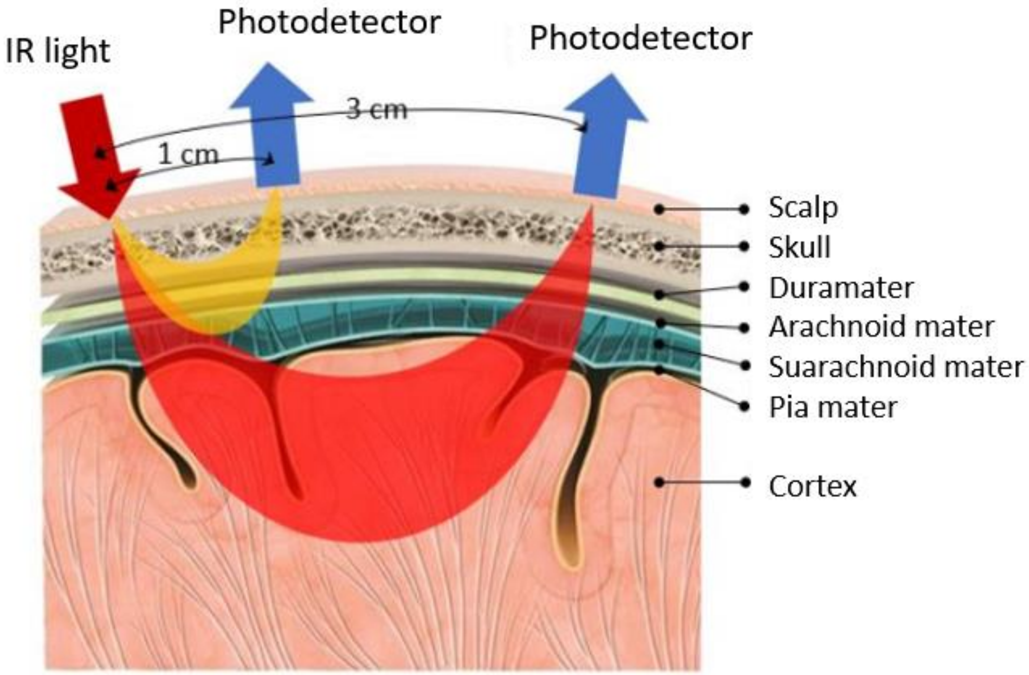

Figure 5: A schematic representation of the banana shaped photon path from the IR light source to the photodetectors of an fNIRS probe.

2.2. Current Uses of fNIRS

This section provides a quick overview of some of the research areas where fNIRS is currently utilized in recent publications. The aim is not to provide a comprehensive review of all fNIRS studies, but a summary of recent applications to aid the interpretation of bibliometric analysis results.

2.2.1. Cognitive Neuroscience Research

fNIRS is used to study a wide range of cognitive processes, including attention, working memory, language processing, decision-making, and social cognition. Studies have shown that fNIRS can provide similar spatial and temporal resolution as functional magnetic resonance imaging (fMRI) but with greater portability and ease of use. For example, a recent study published in Scientific Reports used fNIRS to investigate the neural correlates of decision-making in a gambling task and found that prefrontal cortex activity was associated with risky decision-making (Quaresima & Ferrari, 2019). Another study published in Frontiers in Psychology used fNIRS to investigate the neural mechanisms underlying social cognitive deficits in children with autism spectrum disorder (ASD), and found reduced activation in regions of the brain associated with social cognition. (Pinti et al., 2020)

2.2.2. *Clinical Applications*

fNIRS is being explored as a diagnostic tool for neurological and psychiatric disorders, including traumatic brain injury, stroke, depression, and schizophrenia. Studies have shown that fNIRS can provide sensitive and specific measures of cortical activity in patients with these disorders and may have the potential for monitoring brain function during neurosurgery. For example, a recent study published in Brain Injury used fNIRS to assess cognitive function in patients with traumatic brain injury, and found that reduced prefrontal cortex activity was associated with poorer cognitive outcomes (Hibino et al.,2013) Another study published in Psychiatry Research: Neuroimaging used fNIRS to investigate the neural correlates of auditory hallucinations in patients with schizophrenia and found increased activation in regions of the brain associated with speech processing (Rahman et al., 2020).

2.2.3. *Sports Science*

fNIRS is being used to study athletes' brain activity during exercise and training, to improve performance and reduce the risk of injury. Studies have shown that fNIRS can provide real-time measures of oxygenation and blood flow in the brain, allowing researchers to investigate the neural mechanisms underlying fatigue, recovery, and performance. For example, a recent study published in the Journal of Sports Sciences used fNIRS to investigate the effects of exercise intensity on prefrontal cortex activity during cycling and found that high-intensity exercise led to greater activation in regions of the brain associated with executive function and decision-making. (Carius et al., 2022).

2.2.4. *Human-robot Interaction*

fNIRS is used to study the neural mechanisms underlying trust, cooperation, and communication in human-robot interaction. Studies have shown that fNIRS can provide measures of cortical activity in response to social cues and feedback, allowing researchers to investigate the neural correlates of social cognition and affective processing. For example, a recent study published in Frontiers in Neurorobotics used fNIRS to investigate the neural correlates of trust and cooperation in a human-robot interaction task and found that participants showed increased activation in brain regions associated with social cognition and reward processing when the robot responded contingently to their actions. (Canning & Scheutz, 2013).

2.2.5. *Brain-computer interfaces:*

fNIRS is being investigated as a potential input modality for brain-computer interfaces (BCIs), which allow individuals to control external devices using their brain activity. Studies have shown that fNIRS can provide reliable measures of cortical activity in real-time, allowing users to control BCIs with high accuracy and precision. For example, a recent study published in PLOS ONE used fNIRS to develop a BCI for controlling a wheelchair, where participants were able to control the wheelchair using their brain activity accurately (Naseer et al., 2015). There are also several applications of fNIRS in gaming where some of the controls are initiated by systematic changes in brain oxygenation (Ayaz et al., 2011).

Overall, fNIRS has a wide range of potential applications in various fields, and ongoing research is likely to find even more uses for this promising technology. fNIRS has an increasing use in both treatment follow-up and diagnosis and research. These usage areas can be listed as follows (Izzetoglu et al.,2005):

- **Neurology**
  Epilepsy
  Parkinson's Disease
  Dementia
  Alzheimer's
  Rehabilitation

- **Psychiatry**
  Anxiety Disorder
  Eating disorders
  Personality Disorders
  Substance Abuse Disorders
  Psyochotic Disorders

- **Psychology/Education**
  Attention
  Developmental Disorders
  Feelings
  Functional Connections in the Brain
  Memory
  Perception
  Logic (Reasoning)

2.3. Comparison of the fNIRS Method with Other Neuroimaging Methods

In 1924, German physician Hans Berger (1873-1941) recorded the first electroencephalogram from a living brain, which can be considered as the beginning of functional neuroimaging of the human brain (Berger, 1929). Since then, the range of functional neuroimaging methods available has grown steadily. Generally, two types of functional neuroimaging methods can be classified based on the nature of the brain signal being measured: Neuronal activity is directly measured using electrophysiologic (or neuroelectric) techniques. This group involves electroencephalography (EEG), electrocorticography (ECoG) (Penfield and Rasmussen, 1950), and magnetoencephalography (MEG) (Cohen, 1968). The second group includes a group of techniques based on hemodynamics, such as positron emission tomography (PET) (TerPogossian et al., 1975), invasive optical imaging, functional near-infrared spectroscopy (fNIRS) (Jobsis, 1977), and fMRI (Ogawa et al., 1990), which provide indirect measurements of neural activity (Figure 6).

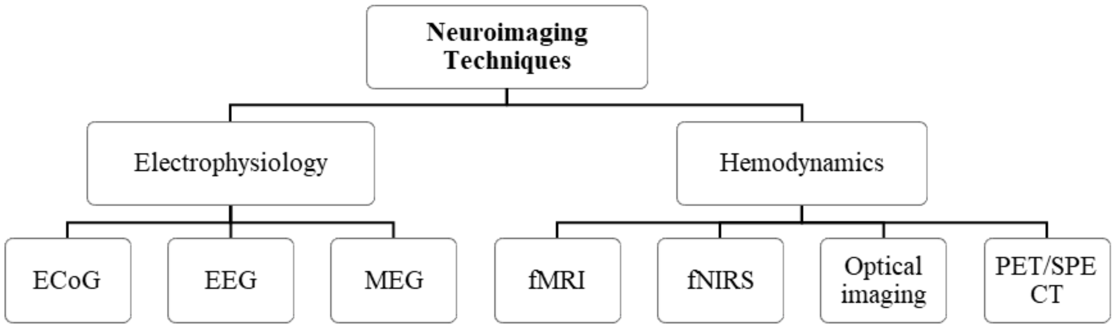

Figure 6: Classification of current Neuroimaging techniques.

Each functional neuroimaging technique has its own set of advantages and disadvantages. Table 1 below summarizes relative advantages and disadvantages of the most frequently used neuroimaging modalities in terms of their temporal/spatial resolution, coverage, invasiveness, and portability/mobility.

Table 1: Characteristic of presently available functional neuroimaging methods.

Neuroimaging Method	**Type of signal**	**Resolution**		**Brain Coverage**	**Invasive-ness**	**Mobility**	**Cost**
		Temporal	**Spatial**				
Electroencephalography (EEG)	Neuroelectric	+++	+	+	+	+++	+
Magnetoencephalography (MEG)	Electromagnetic	+++	++	+	+	++	+++
Electrocorticography {ECoG}	Neuroelectric	+++	++	++	+++	+	++
Positron Emission Tomography (PET)	Hemodynamic/ metabolic	+	+++	+++	++	+	+++
Functional Near-infrared Spectroscopy (fNIRS)	Hemodynamic/ metabolic	++	++	+	+	+++	+
Functional magnetic resonance imaging (fMRI)	Hemodynamic/ metabolic	+	+++	+++	+	+	+++

Remarks: ratings indicate highly advantageous (+ + +) to extremely disadvantageous (- - -), which reflect the characterizations of these neuroimaging modalities in the literature.

Neuroimaging methods are most frequently contrasted with respect to the temporal and spatial resolution they can provide to monitor functional brain activity. Figure 7 provides a summary diagram comparing the abovementioned neuroimaging modalities along these two dimensions (Uludag & Roebreck, 2014). The neuroelectric modalities such as ECoG, EEG and MEG monitor electrical activity induced by spiking neural populations, which provides a direct measurement of neural activity at the scale of milliseconds. However, due to the distortion induced by cortical tissue and the skull on the propogation of electric potentials, EEG electrodes located over the scalp can provide limited spatial resolution for pinpointing where the signal is originated from inside the brain. Since MEG is based on magnetic effects that are less influenced by cortical tissue, it can provide better spatial resolution, but since the detectable signals originate from particular geometric alignments of neurons there are still limitations in coverage. The ECoG method uses electrodes implanted over the cortex to mitigate these issues which improve the spatial resolution. However, this is an extremely invasive technique that can only be employed for cases that requires neurosurgery to treat a medical condition such as epilepsy, extreme depression, etc. Among the neuroelectric modalities, EEG provides better mobility as compared to MEG since MEG requires a specially shielded room with superconductors that can operate at certain temperatures so as to detect small magnetice disturbances originated from the brain. Nevertheless, MEG systems allow monitoring while the participants are sitting, so a range of experiments can be practically conducted in this environment.

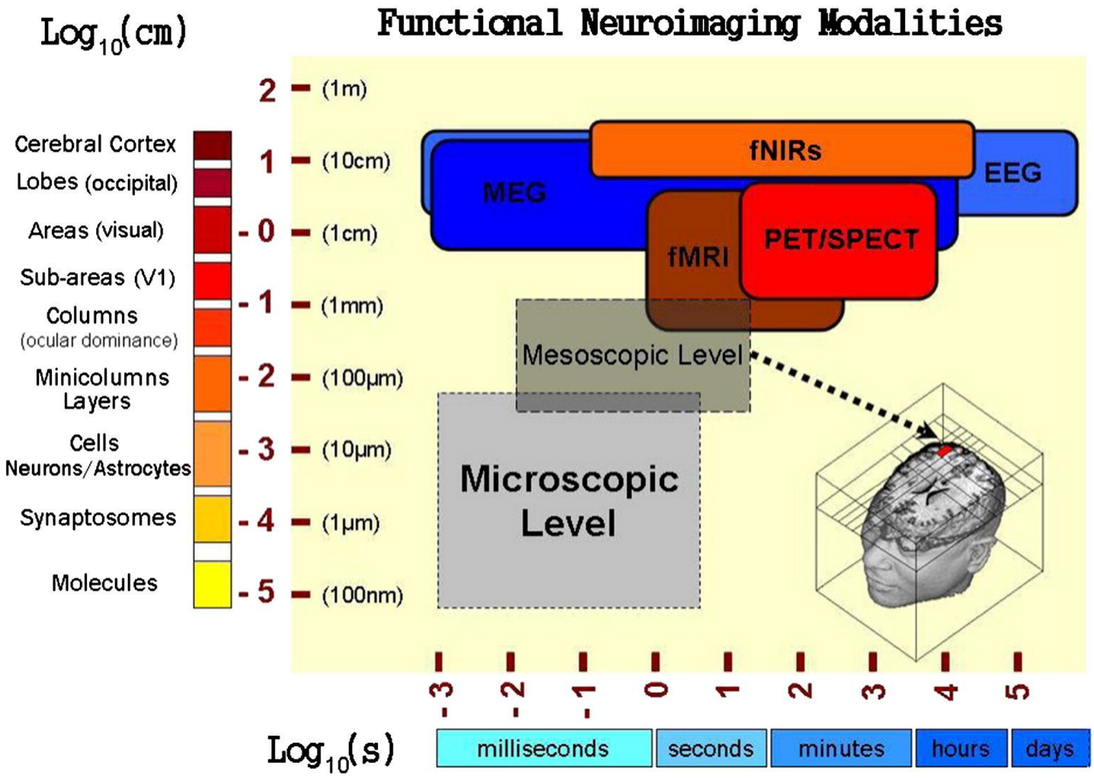

Figure 7: Temporal and spatial coverage of existing functional neuroimaging modalities (Uludag & Roebreck, 2014, p. 6)

The second group of methods focusing on hemodynamics have limited temporal resolution because of the delayed nature of the hemodynamic response induced by neural activity, which takes place in the order of seconds following neural spiking activity. However, methods such as fMRI and PET can provide millimeter and submillimeter scale for identifying the location of neural activity inside the entire brain. PET can be characterized as an invasive method since it requires the injection of special radioactive liquids to trace the cerebral bloodflow. fMRI and PET also require the participants to lie down in a confined position inside the scanner, which limit their portability and the range of experiments that can be run with these modalities.

Some review articles recently summarized the fundamental concepts of fNIRS, including its features, strengths, advantages, and limitations (2009, Minagawa-Kawai et al., Elwell Lloyd-Fox et al., 2008, Cooper, 2011, Gervain et al., 2011 and Quaresima et al., 2012). According to this literature, fNIRS is a non-invasive, portable and safe optical imaging technique that measures changes in human cerebral cortex oxygenation in response to various stimuli/tasks. As compared to other frequently used neuroimaging modalities, fNIRS provides a good balance of temporal and spatial resolution. Since it is based on hemodynamics, fNIRS lacks the temporal resolution of EEG/MEG, but can provide more specific information regarding the location of the monitored cortical region. In contrast to fMRI/PET, fNIRS is limited in terms of the depth and the spatial resolution of the images provided, but given its computational advantages fNIRS can provide much higher temporal resolution. fNIRS measurements can be taken in a natural setting, without restrictions, or in various postures. Since fNIRS measurements can be performed more naturally than other neuroimaging methods, changes in brain activities due to situations such as people whose brain activities are measured staying indoors, afraid, and disturbed by loud noise levels are prevented from affecting the results. Infrared rays are low in energy and have not been shown to cause cell damage (Meiri et al., 2012). It is not expected to adversely affect a person's health during repeated use, which is superior to techniques such as computerized tomography in which ionizing rays are used. The measurements can be obtained and processed in real-time if needed, and the functional near-infrared imaging method has a high temporal resolution as compared to other hemodynamics-based modalities such as fMRI and PET. The advantages of functional near-infrared imaging over other brain imaging are why it is widely preferred, especially in the field of research today (Ferrari and Quaresima, 2012).

Overall, the fNIRS method, which has been increasingly utilized in research in recent years, has some advantages and disadvantages compared to other neuroimaging methods. Among its advantages; fNIRS is easy to apply and has a high ecological validity because it can be applied in a natural environment, is relatively inexpensive, measurements can be made in a quiet environment, has good temporal resolution, and recording from people who have difficulty in adaptation or who are bedridden (Kumar et al., 2017). The most important disadvantages are low spatial resolution and limited cortex recordings. Some of these disadvantages can be mitigated through combined use of fNIRS with another modality like EEG.

2.4. Databases for Bibliometric Analysis

The bibliometric/scientometric analysis is widely performed using a variety of bibliographic databases. Among them are: PubMed, Microsoft Academic Research, Scopus, Google Scholar, and Web of Science. Among others, for Scientometric-based analysis, essential and popular bibliometric data sources include Web of Science, Scopus, PubMed, and Google Scholar. There are advantages and disadvantages to each of these databases.

The first citation databases for bibliometric studies were established by Eugene Garfield's 1955 article on citation indexing and pilot projects in the 1960s (Hood & Wilson, 2001). The scope, functionality, and timeliness of citation databases have all improved due to developments in computer and internet technologies. In today's world, citation databases keep track of millions of papers published in thousands of journals in hundreds of fields and domains across dozens of academic fields. They enable the searching, analyzing, and reporting of records. It is possible to include both the most recent and older recordings. Presently, some databases, such as PubMed are specialized over specific disciplines such as medicine, whereas databases like Web of Science and Scopus provide multidisciplinary. Table 2 below provides a comparison of the main properties of the most popular bibliometric databases.

Table 2: Characteristics of PubMed and WoS databases (adapted from Falagas et al, 2008)

Characteristic	Web of Science	Pub Med	Scopus	Google Scholar
Date of official inauguration	2004	1997	2004	2005
Content No. of journals	21,000	30,000	36,377	No data provided (theoretically all electronic resources)
Language	English (plus 45 other languages)	English (plus 56 other languages)	English (plus more than 30 other languages)	English (plus any language)
Focus (field)	Science, technology, social sciences, arts and humanities	Bioethics, space, life sciences, core clinical journals, dental journals, nursing journals, biomedicine, medicine, and history of medicine	Life sciences, physical sciences, health sciences, and social sciences	Business, administration, finance, and economics, chemistry and materials science, engineering, pharmacology, veterinary science, social sciences, and the arts and humanities are all included in this category.
Period covered	1900–presen	1950–present	1966–presen	Theoretically all available electronically
Databases covered	Expanded science citation index, arts and humanities citation index, social sciences citation index, chemistry citation index,	PubMed Central, which is linked to other NLM databases that are more specialized, Medline (1966–present), and the	100% Medline, Embase, Compendex, World textile index, Fluidex, Geobase, Biobase	PubMed, OCLC First Search

Table 2 (continued).

	and current chemical reactions citation index	older Medline (1950–1965)		
No. of keywords allowed	14	No limi	30	Theoretically no limit
Abstract	+	+	+	+
Author	+	+	+	+
Citation	+	-	+	+
Patent	+	-	+	-
Uses	Links to full-text, links to related articles	Links to related articles, links to full-text (5426 journals), links to free full text articles for a subset of journals (827 open access journals)	Links to full-text articles and other library resources	Links to full-text articles, free full-text articles, links to journals, links to related articles, links to libraries
Update Frequency	weekly	Dail	1–2 times weekly	Monthly on average
Citation analysis	As for Web of Science plus the total number of articles on a topic or by an individual author cited in other articles	None	Total number of articles citing work on a topic or by an individual author	Next to each paper listed is a “cited by” link; clicking on this link shows the citation analysis

Bibliographic databases like Scopus, Web of Science, and PubMed have literature review committees who select journals, book series and conference proceedings for inclusion based on specific scientific and quality criteria. Google Scholar, on the other hand, is not a human-curated database, which populates its database based on web searches narrowed down to those resources that are classified as "scientific" based on machine learning algorithms. Google Scholar contains additional types of resources covering a more comprehensive range of subject areas, including conference papers, books, and reports that are not included in Scopus, PubMed, or Web of Science. Google Scholar also provides a more comprehensive coverage of published materials in languages other than English. However, since papers are not curated into a taxonomy reflecting the type and the subject category of the articles, conducting a search focusing on a specific publication type such as review articles may not reveal accurate results in Google Scholar. For instance, Figure 8 presents a screen shot from the citation export interface of Scopus, which provides a summary of the information recorded in the database for each entry, including author, affiliation, source title, abstract, keywords, funding information, etc. Figure 8 represents a sample of the 60+ field codes available in Scopus to construct search queries. Figure 9 shows the advanced search interface of the Web of Science database, which provides 37 different field tags to search for entries in its database.

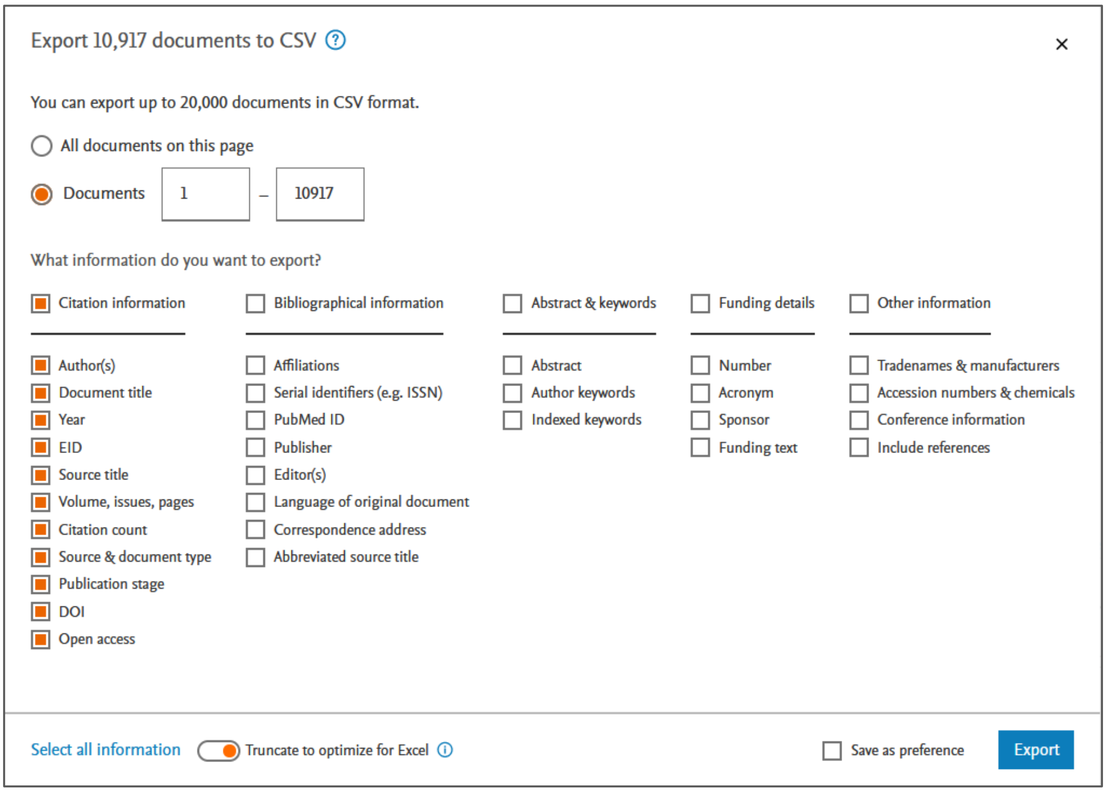

Figure 8: The field codes provided in the citation export utility interface of the Scopus database.

Overall, when the four most popular bibliometric databases are compared, the distinctive advantage provided by the Web of Science and Scopus databases is their taxonomy-based structure and the citation links among their records, which supports advanced bibliometric analysis techniques that will be covered in the subsequent sections. Although Pubmed and Google Scholar provides a broader coverage of the available literature, Pubmed provides very limited citation information, and the lack of structure in Google Scholar makes it difficult to develop bibliometric analyses over entities such as institutions, authors and countries. Web of Science and Scopus tend to be selective in their decisions to include specific journals, book series and conference proceedings, which inevitably brings limitations on the size of the available data when bibliometric analysis focuses on an emerging field such as fNIRS. Web of Science and Scopus are also critiqued for their lack of inclusion of non-English resources and under-representation of social sciences and humanities content. Since the focus of this study is in neuroimaging, Web of Science and Scopus provides an adequate and representative sample of fNIRS related publications for conducting bibliometric analysis (Figure 9).

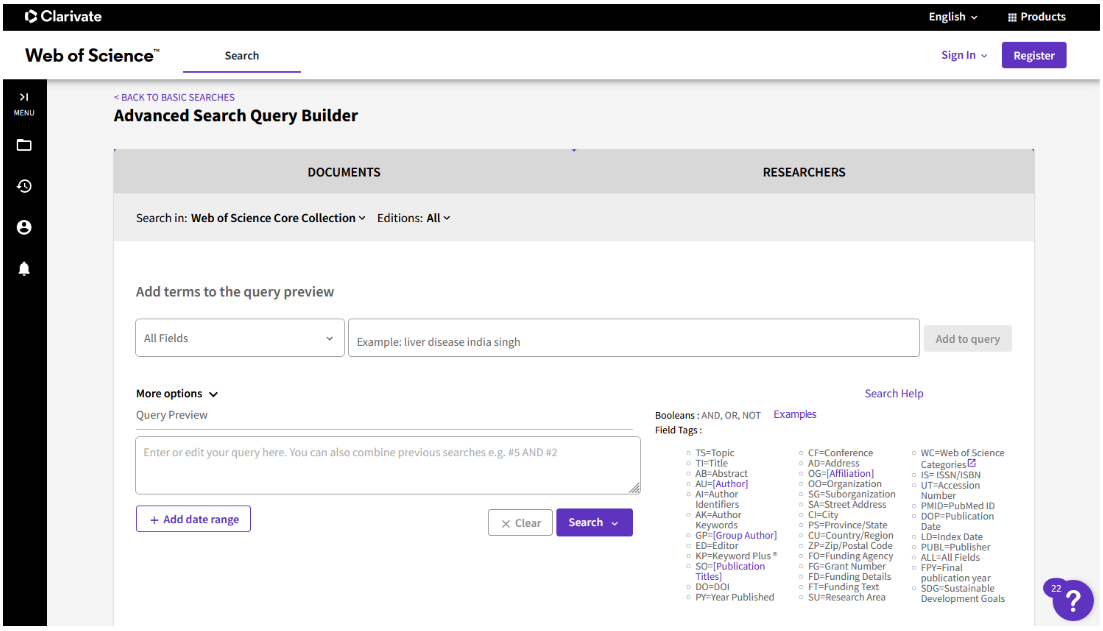

Figure 9: The field tags provided in the advanced search inteeface of the Web of Science database.

2.5. Bibliometric Indicators

This subsection provides a list of the fundamental bibliometric indicators and their definitions that will be utilized in the thesis to explore the fNIRS literature.

2.5.1. #Article: Number of Articles

The number of articles in the field of fNIRS between 1980-2020

2.5.2. #Citation: Number of Citations

The number of citations in the field of fNIRS between 1980-2020

2.5.3. #Disciplinary: Number of disciplinary

The number of articles with the same disciplines in address sections between 1980-2020

2.5.4. #Inter-Disciplinary: Number of Inter-disciplinary

The number of articles with different disciplines in address sections between 1980-2020

2.5.5. #University Collaboration:

The number of articles with different universities in address sections between 1980-2020

2.5.6. #Country Collaboration

The number of articles with different universities in address sections between 1980-2020

2.5.7. #Collaboration-None

The number of articles with the same universities in address sections between 1980-2020

2.5.8. CI: Citation Impact

Citation impact is defined as the ratio of the number of citations to the number of publications in a certain duration of time. In other words, the citation impact shows the number of citations a document has received.

2.5.9. #Occurrences

The total number of occurrences or co-occurrences of a given item, which can be used for weighting purposes.

2.5.10. #Links

The number of co-occurrence links of a given keyword with other keywords.

2.5.11. #Total link strength

The total link strength attribute shows the total strength of a researcher's co-occurence links with other keywords.

2.5.12. #Avg. pub. year:

The average publication of documents that contain a keyword or term, as well as the average year of publication of documents that are published by a source, author, organization, or nation.

2.5.13. #Avg. citations:

The average number of citations received by the documents containing a particular keyword or term and the average number of citations received by documents published by a source, author, organization, or nation.

2.5.14. Avg. norm. citations:

The citations received by documents containing a specific keyword or term, and the average citations received by documents authored by a source, individual author, organization, or country.

2.5.15. #Publication

Researchers share their findings and arguments with the rest of the scientific community through publications, the fundamental unit of scientific communication. A bibliometric database's definition of the term determines its scope. For example, articles, review articles, letters, conference proceedings, meeting summaries, editorial material, revision, biographical elements, news elements, and book reviews are included in Web of Science. The number of publications is typically used as an indicator of the output or productivity of an author, author group, or an institution.

2.5.16. #Citation

The relationship between cited works is defined by a citation link. A document's level of interest among other researchers is shown by the number of citations it has received. As a result, citations may be interpreted as a measure of impact or quality to some extent. The size of an institution can also impact the number of citations, as the likelihood of receiving citations increases with the number of publications. Additionally, review papers, among other documents, typically receive more citations.

2.5.17. Citation per Publication (CPP)

It is the average number of citations for a single scientific document. It is used as an indicator of impact to evaluate the average impact of documents published by a researcher or institution. A considerable percentage of articles in the scientific literature gets zero or a single citation. Thus, citations per publication aims to improve the straightforward metrics such as publication or citation count by controlling the case where an institution has several publications not cited.

2.5.18. #Collaboration

Collaboration is used to measure the publications produced jointly by researchers from different institutions in bibliometrics and scientometrics. Because they reveal which institutions tend to collaborate in which subject areas, co-authorship patterns captured by collaborative measures are essential to scientometric studies.

2.5.19. Co-Occurrence Analysis

The literature of a discipline such as fNIRS can also be analyzed by more common methods such as co-authoring or standard keyword analysis (Börrner et al. 2003). For this purpose, a list of all items (authors, keywords, addresses) is taken from the records to obtain the nodes of a graph, whose size is proportional to the number of articles in which they appear. Two nodes (items) i and j are linked whenever the number nij of articles in which they both appear is non-zero. More specifically, the co-occurrence normalized weight can be defined by the following formula:

$$w_{ij} = \frac{n_{ij}}{\sqrt{n_i n_j}}$$

2.5.20. Co-citation

It is a popular similarity measure that establishes a topic similarity between two items. If A and B are quoted by C, they can be related, even if they do not directly refer to each other. If many other clauses quote A and B, they have a stronger correlation. The more items they refer to, the stronger their relationship (Figure 10).

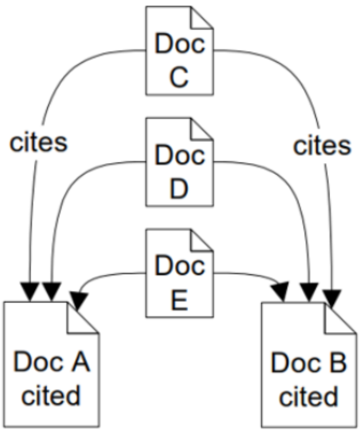

Figure 10: Co-citation relationship: (Gipp and Beel,2009)

2.5.21. Bibliographic Coupling

Bibliographic coupling can be a convenient and computationally inexpensive way to explore the thematic topology of a scientific literature. Meyer (1957) first published the bibliographic merge proposed by Kessler (1963) as a method for deciphering hidden topical affinities between research publications. If both articles refer to at least some of the same articles, then those two articles are combined bibliographically. The bibliographic unification analysis assumes that if two articles cite similar literature, they must be related topically in some way. That is, they are more likely related to each other than articles in which they share less number of cited references (Figure 11).

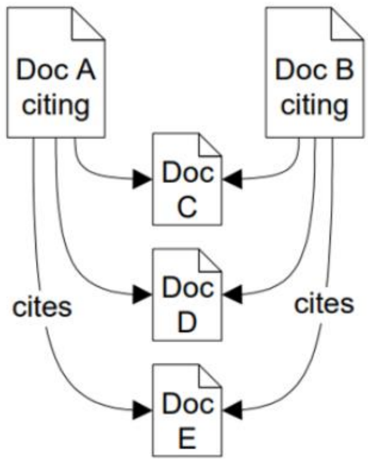

Figure 11: Bibliographic coupling relationship (Gipp and Beel,2009)

2.5.22. Impact Factor

It is the rate at which articles published in a scientific journal turn into information (Garfield, 1955). It is the ratio obtained by dividing the citations received by a scientific journal to articles from the previous two years by the number of articles published in the previous two years. The selection of a 2-year time period to measure impact is highly controversial given the diversity among fields in terms of the time it takes for a publication to attract citations.

2.5.23. Co-authorship networks

Co-authorship networks depict author collaborations, connecting nodes when individuals have jointly authored at least one publication.

2.5.24. Category Normalized Citation Index (CNCI)

It is computed by dividing the actual number of citing items by the expected citation rate for articles of publication year, and subject area.

2.5.25. Impact Relative to World (IREW).

It compares the impact of the research to the impact of worldwide research and serves as an indicator of relative research performance.

2.6. Bibliometric Networks

Bibliometric networks/graphs are concerned with examining patterns of engagement or interaction among publications. A network consists of nodes/vertices and weighted edges/connections (Newman, 2004). In a bibliometric network the nodes typically represent individuals of the population, such as countries, universities, authors, or organizations. The edges indicate relationships such as semantic links, professional relationships, communication patterns, or collaborative interactions. Bibliometric networks are mostly based on publication records obtained from citation databases such as Web of Science, Scopus and Google Scholar. Bibliometric networks are dynamic by nature, and they evolve over time. In recent years, "bibliometric networks" and "bibliometric network analysis" have received much attention from multidisciplinary fields such as medical sciences, behavioral sciences, marketing, physics, computer science, and economics.

Citation networks are a type of information flow network (Newman, 2004). Nodes in a citation network are typicaly articles. If paper A refers to paper B in its references, there will be a directed link from paper A to paper B. Academic publications include citations to refer to the previously published related work to possibly build upon, critique or extend the knowledge communicated in those publications. Price (1965) established one of the earliest citation networks in 1965 to investigate the relationships among publications. Since links are created from "cited article" to "cited article," citation networks are acyclic. In other words, because an article can only cite another already written article, citation networks do not include closed loops. These networks are said to represent the flow of information between the linked documents. According to Clough & Evans (2016), they produce causally structured directed acyclic graphs because they are constrained by time.

Co-authorship of a document occurs through collaboration between two or more authors. Collaboration of co-authors creates co-authoring networks. In this network, authors are nodes, and their cooperation creates edges. Cooperation can also be between institutions and countries. Institutions or countries will be nodes in this case, and the cooperation link between them will end (Newman, 2004).

Another type of network used in bibliometric research is created by the paired presence of terms within a given text unit. If terms A and B appear in the same document together, then the terms are said to co-occur together. In co-occurrence networks, terms are the nodes and co-occurrence frequencies form the edges. The words may be selected as keywords used by the authors to tag their papers, or category terms reflecting different levels of topic organization (Chen, 2016). Co-occurrence networks are typically used to explore the prominent topics covered within a scientific discipline.

If two documents are referred by a third document, then those two documents are said to be co-cited by that document (White & McCain, 1998). If those two papers are co-cited by several papers in a field, then one can infer that they are considered related by the community of authors in that field. In other words, the co-citation metric indicates the frequency of the cases where two documents have been cited together. Nodes in a co-citation network are typically articles, and the edges represent the strength of the co-citation relationship among the articles. Co-citation networks are symmetric, directionless graphs, in contrast to citation networks. In addition to article co-citation networks, journal and author-based co-citation networks are the other two types of co-citation networks frequently used in bibliometrics research. For instance, article co-citation information can be transformed into the number of cases where two authors are cited together by papers in a field.

Bibliographic coupling is another type of relationship that can be used to produce bibliometric networks. In this approach two articles are related to each other based on the percentage of shared citations in their reference list. Similar to co-citation networks, bibliographic coupling networks can be constructed over articles, authors, and journals.

Finding an appropriate topographic layout on 2D or 3D space to aid the interpretation of bibliometric networks is another important concern in bibliometrics research (McCain, 1990). The relationships established between entities such as publications, authors and journals through measures such as co-word or co-citation metrics can be transformed into distance matrices among the entities of interest, which can then be visualized over 2D/3D space with the help of multivariate analysis techniques such as multidimensional scaling. For instance, in such maps the authors that are co-cited together will be placed closeby, whereas authors that have low co-citation scores will be placed further away. This kind of mapping also brings the possibility of utilizing clustering algorithms to group the authors or articles based on the strength of the relationship among them. Once such a topographic layout is found, the nodes can be also presented in different ways to communicate additional information. For instance, the size of the nodes can be made to scale with the total number of publications or citations of a specific author. Such visualizations aid the interpretation of the bibliographic maps of a discipline in terms of central authors, prominent topics, cliques or schools within a discipline.

2.7. Bibliometric Analysis, Mapping, and Visualization Software

In the literature, there are several computer-based software programs to analyze citation-based bibliometric data to complete particular tasks such as conducting structural analysis of scholarly communication, the mapping of scientific publication, the creation of metrics-based social maps, the representation and organization of information, research visualization, and microlevel analysis. Other examples of such tasks include creating social maps based on metrics derived from co-word, co-authorship, bibliographic coupling, and co-citation statistics. Table 3 below summarizes the main features of leading bibliometric analysis and visualization software.

Table 3: Scientometric Analysis, Mapping and Visualisation Software.

Scientometric Tool	**VosViewer**	**CiteSpace**	**BibExcel**	**CitNet Explorer**	**BiblioTools**
Availability	Free	Free	Free	Free	Free
Platform	Java	Java	–	Java	Python
Operating System	Windows, Linux or Mac, Java Runtime (JRE)	Windows, Linux or Mac, Java Runtime (JRE)	Windows, Linux	Windows, any Java supporting OS	Unix, Mac, Windows
Data Import	WoS, Scopus,Pub Med	WoS, PubMed, arXiv, ADS, Scopus, NSF Award Abstracts	WoS, Scopus	WoS	WoS
Bibliometric Analysis	Bibliometric, Citation,Analysis, Co-Citation, Cluster Analysis, Bibliographic Coupling	Author, Institution, Countries Collaboration Networks, Document, Journal Map, Overlays; Interactive, Visualization	Bibliometric, Citation Analysis, Bibliographic Coupling, Cluster Analysis, Co-Citation,	Visualization, Citation Networks,	Data Parsing, Bibliographic Coupling, Authors, Co-Citations, Occurrence Maps
Export	CSV, Excel,Pajek	Pajek, Excel, SPSS	Pajek, NetDraw, Excel, SPSS	Pajek	Gephi, BiblioMaps
Documentation		Strong	Weak	Weak	Weak

The common features of these softwares can be summarized as;

- facilitate structural analysis of a subject discipline,
- facilitate and support the mapping of a discipline,
- able to import data from the data sources, editing and cleaning of raw data,
- help to construction of maps and networks for visualization.

Scientometric Analysis, Bibliometric Mapping and Visualisation Softwares can be used for the following purposes:

- to study structural analysis of information and dynamics of scholarly communication,
- bibliometric mapping of scientific research,
- facilitates application of modern science analysis, mapping and visualisation techniques and methods,
- Representation of information, organization, and visualization of networks.

Several software tools have been developed to perform scientific mapping analysis. There are many freely available science-mapping and visualization software tools for bibliometric and scientometric studies. Modern mathematical algorithms, statistical techniques, graph theory, sophisticated network theory, and visualization techniques, among other things, serve as the foundation for most of these software tools. Software developed for a more general purpose such as building social networls (e.g. Gephi, Pajek) can also be utilized for scientific mapping provided that the necessary data structures can be populated from bibliometric databases. This section provides a list of some of the popular tools used for conducting bibliometric analysis and visualization purposes.

2.7.1. BibExcel

BibExcel is designed by Olle Perrsson, BibExcel is a software program used to analyze bibliographic data. Through BibExcel, publication analyzes can be made according to years, countries, research topics, as well as citation, co-citation, co-authorship, clustering analysis (https://homepage.univie.ac.at/juan.gorraiz/bibexcel/).

2.7.2. VOSviewer

VOSviewer is a scientific mapping application for bibliometric network visualization. It can visualize citation networks and perform numerous bibliometric network analysis methods, including keyword co-occurrence, co-citation and co-authorship analyses (https://www.vosviewer.com/).

2.7.3. CiteSpace

Dr. Chaomei Chen, a Professor of Informatics at Drexel University in Philadelphia, USA, created CiteSpace for progressive knowledge domain visualization and analysis of scientific literature trends and patterns. It runs on Java Runtime for structural analyses of networks extracted from publication data, such as Collaboration Networks, Authors Co-citation Networks, and Document Co-citation Networks (http://cluster.cis.drexel.edu/~cchen/citespace/).

2.7.4. Gephi

Gephi is a free and open-source software used for visualizing and analyzing complex networks and graphs. It's commonly used in fields like social network analysis and data visualization to help people understand connections and relationships within data (https://gephi.org/).

2.7.5. HistCite

Eugene Garfield, who is the founder of the Science Citation Index, developed the HistCite software package. It is used for information visualization and bibliometric analysis. HistCite works with Internet Explorer on Windows computers; a free trial version is available. HistCite aims to locate the most influential (most cited) papers from topical Web of Science searches. HistCite works with Internet Explorer on Windows(https://en.wikipedia.org/wiki/Histcite).

2.7.6. NodeXL

NodeXL is open-source software that can be downloaded for free and used with Microsoft Excel 2007 and 2010. It makes it simple to explore network graphs. The network graphs created by the community can be accessed through the NodeXL graph gallery. NodeXL lets you set various fonts for labeling edges, vertex, and groups. Auto-update is built into NodeXL(https://nodexl.com/).

2.7.7. Pajek

Pajek was developed by Vladimir Batagelj and Andrej Mrvar, with Matjaz Zaversni contributing some procedures. Pajek is a Windows-based, non-commercial software program that can be downloaded for free. Pajek can carry out a wide range of network analyses and visualization tasks. Pajek's input data can be formatted with the Bibexcel software (http://mrvar.fdv.uni-lj.si/pajek/).

2.7.8. Publish or Perish

The free software program Publish or Perish (PoP) measures the impact of research by retrieving and analyzing academic citations from Google Scholar. PoP is capable of calculating a variety of metrics and indexes based on citations. It pulls publications' citations from Google Scholar Search for metrics-based citation analysis (https://harzing.com/resources/publish-or-perish).

2.7.9. R-Project

R is a statistical computing programming language. It is free software supported by the R Foundation. R is a GNU project that can do much statistical computing, like linear and nonlinear data modeling, time-series analysis, data classification, and clustering, among other things. And techniques for graphical formation are highly adaptable (https://www.r-project.org/).

2.7.10. Bibliotools

A set of Python scripts called BiblioTools can be used to analyze bibliographic data. The scripts take bibliographic data files from Scopus or Web of Science as input and create formatted output files that can be used in Gephi, the graph visualization tool, or BiblioMaps, the web interactive visualization platform (http://www.sebastian-grauwin.com/bibliomaps/).

2.7.11. CitNetExplorer

CitNetExplorer, like Bibliotools, is a free Java-based software tool created by Nees Jan van Eck and Ludo Waltman. It is used to better understand the structure and dynamics of science communication by analyzing citation networks of scientific publications. Creating citation networks enables direct data import from the Web of Science. Interactive exploration of citation networks is possible (https://www.citnetexplorer.nl/).

2.7.12. SciMAT

SciMAT is a Java-based open-source bibliometric science mapping software tool developed by the research group Sci2. It stands for Science Mapping Analysis software Tool. The Project of the Spanish Ministry of Education and Science has helped SciMAT (https://sci2s.ugr.es/scimat/).

2.7.13. UCINET

A software package for bibliometric network analysis is called UCINET 6 for Windows (https://sites.google.com/site/ucinetsoftware/home).

2.8. Bibliometric Studies on the Neuroimaging Literature

The recent proliferation of the Neurosciences and the Neuroimaging literature have also attracted interest from the bibliometric research. An early study by Schwechheimer & Winterhager (2001) investigated the bibliometric properties of the neuroscience literature focusing on a medical condition called retrograde amnesia. By using records obtained from the WoS databases the authors identified the most active countries and authors on this topic, and evaluated the content validity of their author co-citation map with the help of a domain expert. The authors highlighted the interdisciplinary nature of research on this topic and concluded that the co-citation map provided an accurate representation of the prominent authors in this topic. The authors also provided a diagram visualizing the relationship among different scientific disciplines and related topics from the neuroscience field, which highlights the interdisciplinary nature of the studies in this domain (Figure 12).

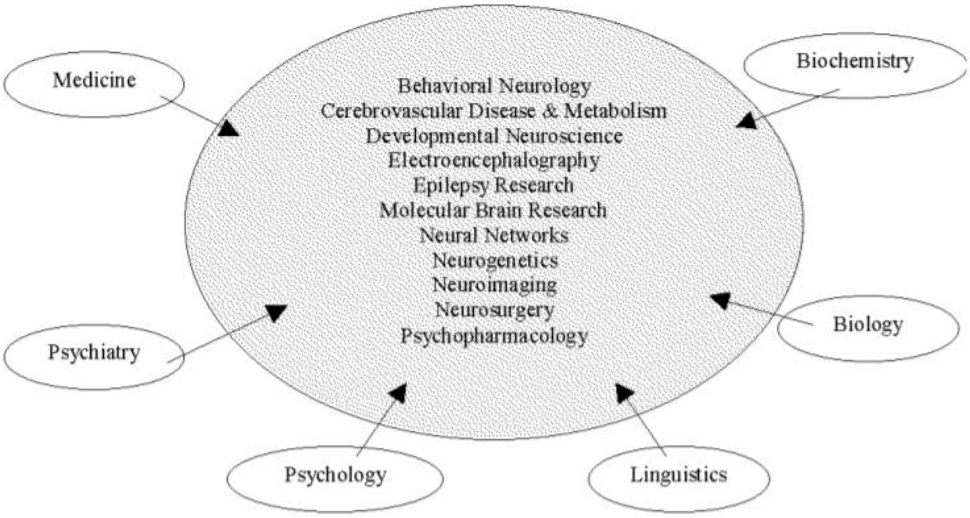

Figure 12: Neuroscience topics and their relationships to other disciplines in the context of retrograde amnesia studies (Schwechheimer & Winterhager, 2001, p. 312).

Yeung et al. (2017) conducted one of the first bibliometric studies focusing on the broader Neurorimaging literature. The authors searched for the publications indexed under the subject category Neuroimaging by the WoS database for the years 2003-2014. The authors identified USA, Germany and England as the top contributing countries, Harvard University, University of Dusseldorf and UCL as the institutions with the highest number of co-authorship counts (i.e. institutions with the highest international collaboration). They also observed that collaborations were predominantly within the same country/region. The authors also provided a journal co-citation map where Neuroimage was located at a central position, and journals with clinical (e.g. Neurology, Stroke, Lancet), engineering (e.g. IEEE Transactions in Biomedical Engineering), radiology (e.g. Magentic Resonance in Medicine) psychiatry (e.g. Biological Psychiatry, American Journal of Psychiatry), and multidisciplinary (e.g. Nature, Science) focus tended to be clustered together. A term-map of the keywords based on their co-occurrence in the articles produced clusters with a clinical focus (e.g. neurysm, haemorrhage, stenosis) in the periphery and basic research (e.g. emotion, empathy, memory) in the center, indicating that the basic research terms are tended to be associated with those articles with higher impact. The keyword analysis also showed the prominence of MRI as the neuroimaging modality that is associated with the highest impact studies. In a separate article focusing on the Neuroimaging literature, Yeung et al. (2017) indentified the increasing impact associated with articles focusing on the keywords brain connectivity, meta analysis, Alzheimer’s disease, and autism. The authors interpreted this shift in termmap patterns as a shift towards health care priorities and translational research in Neuroimaging.

2.9. The Notion of Disciplinarity in Science

The study of disciplinarity in scientific knowledge production has emerged as a main topic in science and technology studies in recent decades (Wagner et al. 2011). The initial bibliometric studies focusing on the broader Neuroimaging literature effectively identified the multidisciplinary landscape of this field, including contributions from basic sciences and engineering in the development of imaging instrumentation and software, as well as their applications in several clinical and social science domains.

In the Science & Tecnology Studies literature several different types of disciplinarity has been proposed, distinguishing disciplinary, multidisciplinary and interdisciplinary approaches (Tress et al., 2004). These distinctions are typically made in terms of the pursued goals, affiliations of the researchers, and the level of conceptual exchange and integration among groups (Figure 13).

Disciplinary research is typically conducted within the boundaries of recognized, well established disciplines, where the goal is typically to advance the current knowledge in the discipline by using the conceptual framework and methods within the discipline. There is no explicit effort in terms of utilizing another discipline's methods or to establish conceptual connections among the knowledge structures of other disciplines.

In the case of multidisciplinary efforts, there is a shared goal or a problem structure, where each discipline contributes within their own disciplinary methods and concepts, without the explicit aim to develop a joint framework or theory. In contrast, interdisciplinary research aims to force participating disciplines to cross subject boundaries to create new knowledge and theory to achieve a common research goal. Integration of knowledge across disciplines is a key aspect in this case. The inception of new departments or specialized journals could be considered as further evidence of the emergence and establishment of such interdisciplinary efforts.

Finally, transdisciplinary research can be characterized based on its participatory structure, spanning across academic and non-academic disciplines working towards goals impacting the society at large. The term is also used as an intensified version of interdisciplinary research, indicating a set of concepts and methods that transcend the partitipating disciplines, bringing new knowledge paradigms (Moran, 2002). However, such characterizations are critiqued for their rather mystic characterization of scientific progress, and are difficult to define in operational terms.

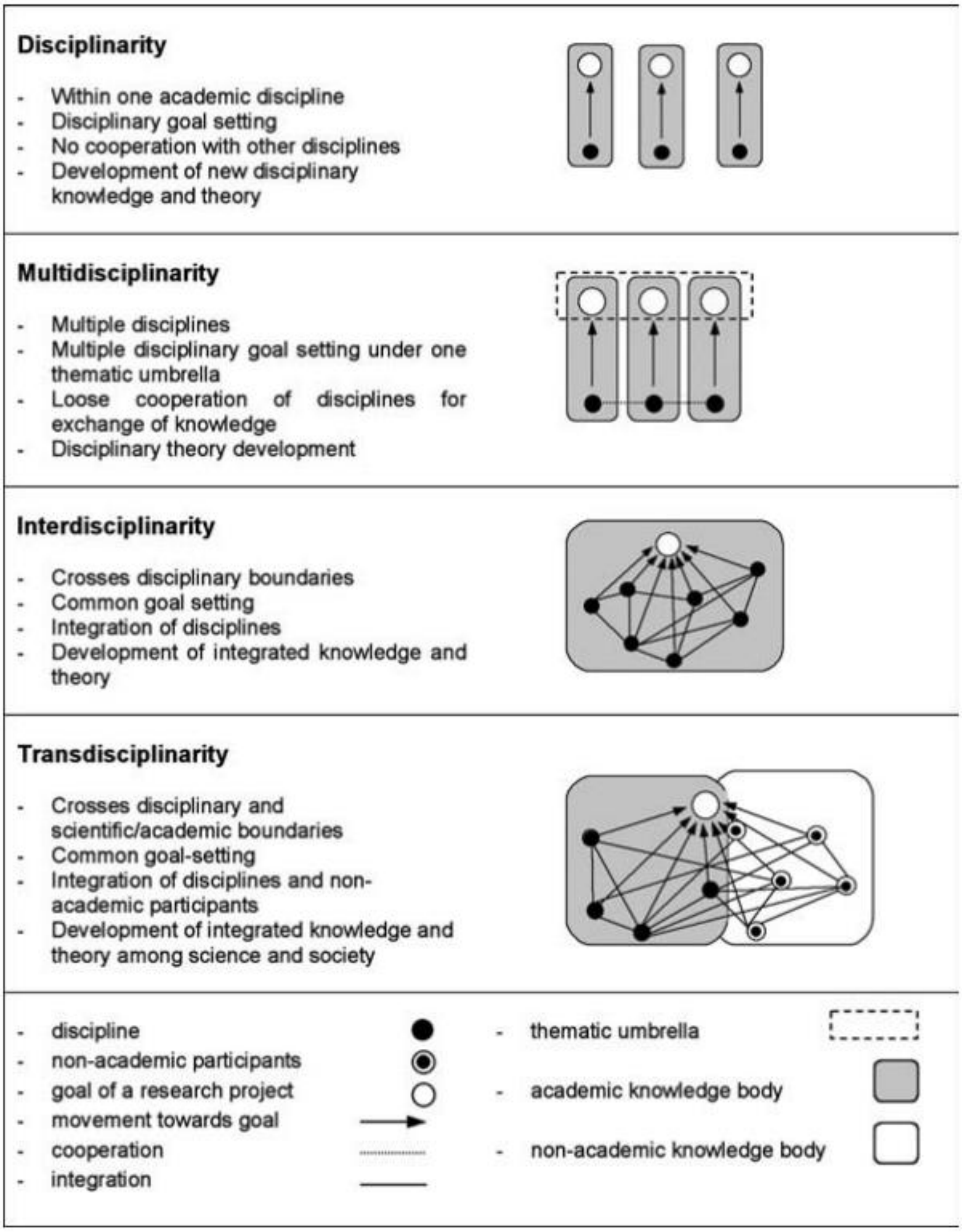

Figure 13: Overview of scientific disciplinarity definitions proposed by Tress et al. (2004, p. 484).

Neuoroimaging, as a subdiscipline within Neurosciences, is concerned with developing novel methods and techniques to probe into the details of the nervous system to improve our understanding of its structure and function. The contributions of several disciplines to this overall goal is recognized by the existing bibliometric studies of this field, but to the best of our knowledge, the nature of this interdisciplinarity has not been subjected to systematic investigation with respect to existing taxonomies proposed in Science & Technology Studies.

2.10. Bibliometric Studies on the fNIRS Literature

Given the recent popularity of fNIRS as a neuroimaging modality, there are not many bibliometric studies focusing on this literature before the year 2020. Yan et al. (2020), Dezevas (2021) and Ye et al. (2023) utilized bibliometric methods to explore the trends and most prominent authors/institutions in the last 20 years of this growing literature.

Yan et al. (2020) focused on a collection of 1727 fNIRS related publications indexed in the SCI-Expanded list of the WoS database covering the years 2000-2019, and used the CiteSpace software to explore the trends represented in this sample. Yan et al. (2020) reported an exponentially increasing trend in the number of publications utilizing the fNIRS method in this time range. Neuroimage, Frontiers in Human Neuroscience, Neurophotonics, Journal of Biolmedical Optics and Scientific Reports were reported as the top 5 journals where fNIRS related articles most frequently appeared. The authors reported that there was no significant correlation between the impact factors and the number of publications in these journals, suggesting that fNIRS related papers do not have a strong presence in higher impact journals in the neurosciences. United States, Japan, China, Germany, and England were listed as the countries that produced the highest number of fNIRS related articles. University of Tubingen in Germany, Drexel University in USA, UCL in England, Beijing Normal University in China, and Busan National University in Korea were the top 5 institutions ranked by publication output.

In addition to basic descriptive statistics, Yan et al. (2020) also utilized keyword and citation burst statistics they obtained from CiteSpace. CiteSpace can detect sudden increasing trends in specific time periods in the frequency of use of specific keywords and citations accrued by specific articles. Yan et al. (2020) identified infant (2012-2019), social interaction (2015-2019), and older adult (2017-2019) as the keywords that showed recent bursts, indicating their increasing prominence in the fNIRS literature. The authors also identified articles that exhibited citation bursts, two of which were review papers by Boas et al. (2014) and Ferrari & Quaresima (2012) reflecting on the progress in fNIRS research in the past 20 years as part of a special issue, another article was by Scholkmann et al. (2014) that provided an overview of fNIRS equipment and methodological issues, and finally an article by Kirilina et al. (2012) focusing on an important methodological breakthrough for cleaning fNIRS signals from superficial confounding physiological effects.

In another recent study, Devezas (2021) focused on a similar data set covering 2153 fNIRS related journal articles and reviews indexed by the WoS database for the years 2000-2020. The results regarding the eminent authors, institutions and countries in the fNIRS literature are consistent with Yan et al.'s (2020) findings. Devezas also provided a cluster map of keywords based on a similarity measurement derived from co-word statistics and argued that cognitive functions and motor impairment, development and languages, social and emotional engagement, brain-computer interfaces, and rehabilitation are becoming prominent topics within fNIRS research.

Finally, Ye et al. (2023) focused on the last 10 years (i.e., 2011-2022) of fNIRS research based on the publications retrieved from the WoS database with a focus on clinical applications. The authors focused on 467 articles which were narrowed down from 5612 records after the removal of reviews, meeting abstracts, case reports, book chapters, corrections, letters, patents and data papers. The authors also excluded animal studies, methodology paper and non-medical sciences content. The influential authors, institutions and countries were consistent with Yan et al.'s and Devezas' findings. The explicit clinical focus emphasized additional journals as source of fNIRS studies, such as Neuroimage-Clinical, Neurorehabilitation and Neural Repair, IEEE Transactions on Neural Systems and Rehabilitation Engineering, and Schizophrenia Research.

2.11. Motivation & Significance

Although earlier articles identified the interdisciplinary nature of neuroimaging studies, none of the bibliometric analyses explicitly focused on the articles role of interdisciplinarity feature and collaboration perspective. In addition, existing analyses of disciplinary links are not based on authors' departmental affiliations and existing bibliometric studies on fNIRS tended to focus on a data set covering recent work (e.g. the last 10 years), without explicitly focusing on the shifts in these trends since the inception of fNIRS

Therefore, our thesis aims to address these gaps by utilizing bibliometric methods over sliding time windows to identify temporal shifts in fNIRS research, as well as exploring the role of interdisciplinarity and collaboration over the impact of fNIRS studies.

2.12. Summary and Objectives

Previous related studies that employ bibliometric analysis methods to explore the fNIRS literature in particular, and the Neuroimaging literature in general, have made important observations regarding the influential authors, publications, institutions, and countries in this growing literature, as well as the trends related to prominent research topics via co-word and term-map analysis. However, existing studies tended to focus on a data set covering a specific year range (e.g. the last 10 years), without explicitly focusing on the shifts in these trends since the inception of fNIRS as a new neuroimaging modality, throughout the time period in which it gained prominence. In addition to this, although earlier work identified the interdisciplinary nature of neuroimaging studies, none of the bibliometric analyses explicitly focused on the role of interdisciplinarity on the impact generated by the publications in this research area. The current thesis aims to address these gaps by utilizing bibliometric methods over sliding time windows to identify temporal shifts in fNIRS research as well as exploring the role of interdisciplinarity over the impact of fNIRS studies.

In order to test if there is a relationship between the level of interdisciplinarity in co-authorship and the impact generated, we focused on the address sections of fNIRS-related articles retrieved from the WoS database as an indication of disciplinary diversity, and examined the impact of those articles via bibliometric measures such as the number of citations, Journal Impact Factor (JIF) quartile distributions, Category

Normalized Citation Index (CNCI), and Impact Relative to World (IREW). In particular, we aimed to observe whether being a product of a disciplinary - or inter-disciplinary approach and/or a university/country collaboration will positively influence the impact generated by those publications. At the same time, we also aimed to identify which disciplines and departments are the prominent contributors of fNIRS research.

In short, this dissertation will aim to address the following research questions by utilizing bibliometric analysis methods:

> **RQ1:** Is there a relationship between the impact generated by fNIRS publications and the degree of disciplinarity in their authorship?
>
> **RQ2:** Which disciplines are the most frequent contributors to the fNIRS literature and what is the level of interaction among those disciplines?
>
> **RQ3**: How does the prominent research topics and author groups as evidenced in co-authorship, co-citation and keyword co-occurrence patterns change in time in the fNIRS literature?

CHAPTER III

METHODOLOGY

3.1. Materials

A two-step cross-sectional bibliometric analysis of disciplinary and collaborative studies, including the mapping of authors, sources, countries and keywords in the fNIRS literature was conducted in this thesis study. During the first step, the documents that will be subjected to bibliometric analysis were collected. For this purpose, the Clarivate Web of Science (WoS) database was used to access bibliographic records, and the Clarivate InCites service to calculate impact statistics that are not readily available in WoS. Next, Rstudio-Biblioshiny, VOSviewer, and Citespace software packages were used to merge and clean the dataset, as well as to carry out several bibliometric analysis techniques. Tables and graphics were prepared using MS Excel and MS Word programs. The data collection and analysis stages followed in this study is summarized in Figure 13.

3.2. Why we chose the fNIRS modality to be the focus of this thesis study?

Although fNIRS is an emerging neuroimaging modality, the number of publications and application areas are growing. Compared to other neuroimaging modalities such as MRI and PET, the size of the literature is relatively manageable. Access to local researchers active in fNIRS research who can aid the interpretation of the findings of this study.

Therefore, fNIRS provides a suitable case for this study to explore the utility of bilbiometric methods for identifying useful trends and developments in the fNIRS literature.

3.3. Data Extraction

The keywords and search criteria were identified with the aim to cover the broad spectrum of research works in fNIRS. Firstly, a sample of fNIRS studies were reviewed to identify some of the frequently used keywords by the authors to indicate the fNIRS related methodology they employed in their studies. We used the advanced search interface of WoS database to compose a query for retrieving fNIRS-related publications: TI=(("optical imaging" AND "brain") OR ("optical spectroscopy" AND "brain") OR "optical brain imaging" OR "functional near-infrared spectroscopy" OR ("near-infrared spectroscopy" AND "brain") OR ("optical tomography" AND "brain") OR ("NIRS" AND "brain") OR fNIRS OR FNIR OR neurophotonic) (Table 5).

Publications and journals were searched apart from keywords, references, authors, and institutions. We focused on articles in the Science Citation Index-Expanded covering the years 1980-2020. We did not include conference proceeding articles because the citation network structure was not sufficiently established. Our search conducted on

11.10.2022 returned 1673 fNIRS articles from the WoS database. By using the WoS data export interface, we saved “full records + cited references” and data download format “tab-delimited (Win, UTF-8)” to download the retrieved set of publications. The records containing the year of publication, journal, authors, title, and keywords from the Clarivate-Web of Science database (WoS) constituted our dataset. All articles were collected online from the WoS Science Citation Index-Expanded database. WoS database was used in this study due to its adequate coverage of the target literature including the most significant journals in this field (Boyack et al., 2005).

Figure 14 summarizes the data extraction process:

- The first stage was the database selection.
- The second stage was the preliminary data retrieval.
- The third stage was data cleaning and sample selection. English was chosen as the language.
- We chose “articles” as the literature type.
- The fourth stage was data pruning where articles with a valid address were selected.
- The fifth stage was data parsing. In this stage, articles were separated according to their address information, discipline, and collaboration data.
- The sixth stage was bibliometric analysis. We analyzed publication trends from 1980 to 2020 to acquire fNIRS's research status and frontier progress. The current disciplinarity research status of fNIRS and the path of knowledge evolution on fNIRS were presented by bibliometric analysis.

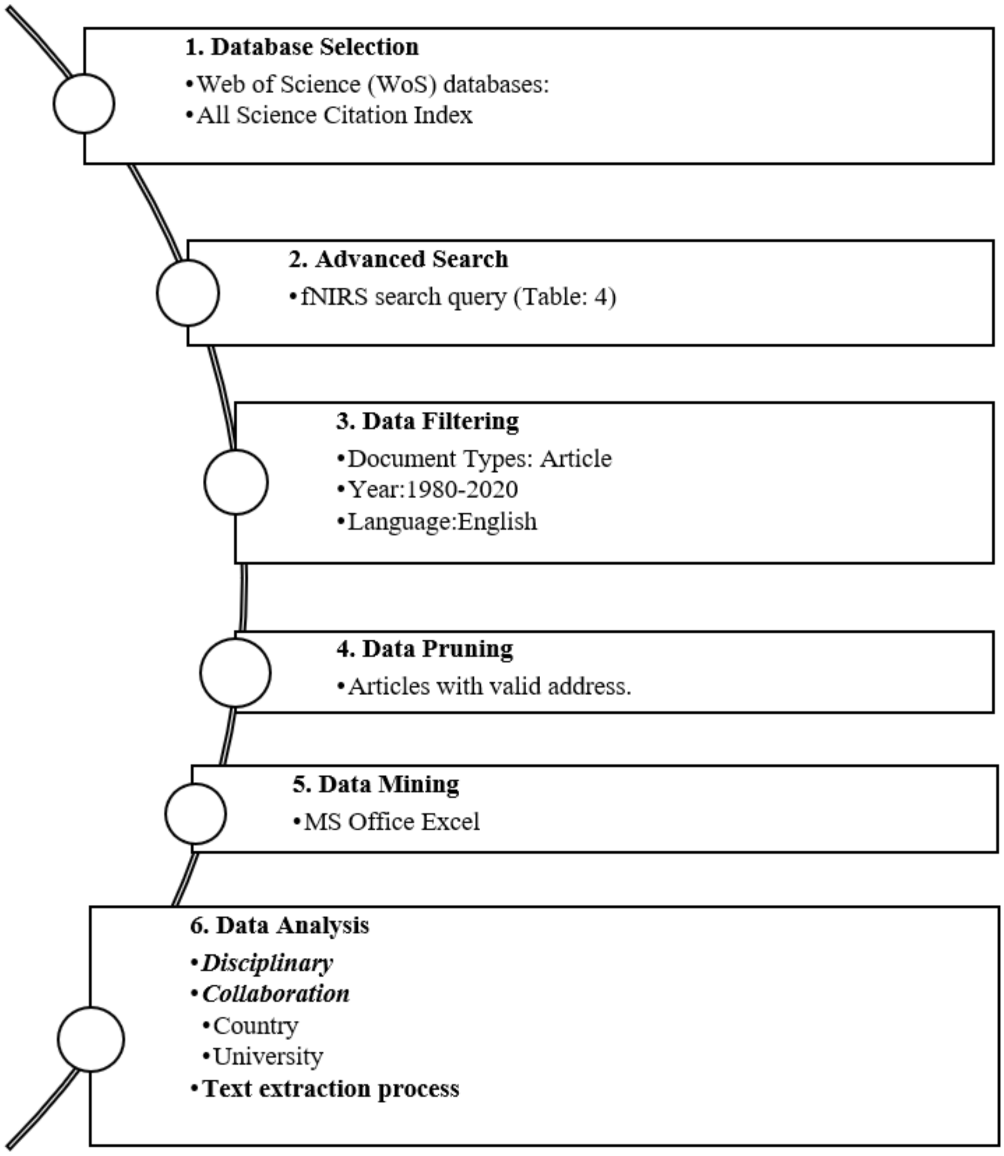

Figure 14: Data extraction and analysis process

Table 4: Query phrase and the search field code definitions used to retrieve articles in the field of fNIRS from the WoS Database

Web of Science Advanced Search Query
(TI=(("optical imaging" AND "brain") OR ("optical spectroscopy" AND "brain") OR "optical brain imaging" OR "functional near-infrared spectroscopy" OR ("near-infrared spectroscopy" AND "brain") OR ("optical tomography" AND "brain") OR ("NIRS" AND "brain") OR fnirs OR fnir OR neurophotonic)) AND FPY=1980-2020 AND DT=Article

Booleans: AND, OR, NOT, SAME, NEAR

Field Tags:
TS=Topic
TI=Title
PY= Year Published
SU= Research Area
WC= Web of Science Category
IS= ISSN/ISBN
PMID= PubMed ID
ALL= All Fields

3.4. Disciplinarity and Impact Analysis

For the impact measures, the number of articles in the Q1, Q2, Q3, and Q4 JIF quartiles as well as the number of highly cited, hot, early access, and open access papers in the fields of fNIRS were assessed (Table 4). For this purpose, the search results obtained from the WoS database were exported into InCites. The impact statistics calculated over this dataset were then used for further analysis.

According to our search results, a total of 1673 articles on fNIRS were published in journals with JIF quartiles in the WoS database (Table 5). The number of articles in the field of fNIRS was higher in the range of 2011 and 2020. Q1 JIF Quartile category articles were the highest at 733 (%44), followed by Q2 (433, %26), indicating that %70 of the fNIRS articles appeared in the top two quartiles. The number of highly cited articles also increased in the last 10 years to 6, indicative of the recent growing impact of this literature. Further analysis of this data is provided in the results section.

Table 5: Distribution of articles in the field of fNIRS in the WoS Database.

Category	1980-2000	2001-2010	2011-2020	Total
All Open Access Documents	13	76	913	1002
Non-Open Access Documents	40	135	495	670
Highly Cited Papers	0	0	6	6
Documents in Q1 Journals	13	107	613	733
Documents in Q2 Journals	3	35	395	433
Documents in Q3 Journals	5	36	173	214
Documents in Q4 Journals	0	7	91	98

In order to explore the relationship between impact measures and the disciplinary/collaborative attributes of fNIRS articles, the articles in our dataset were annoted based on the author affiliation information. Table 6 provides a sample of 4 articles to illustrate the annotation scheme employed in this thesis. The annotation procedure focuses on the address section to identify the department, university, and country affiliations of the authors of each article.

Table 6: Multi-disciplinary and collaborative studies Analysis Sample

Adress	**Inter-Disciplinary**	**Disciplinary**	**University Collaboration**	**Country Collaboration**	**Collaboration-None**
[Einalou, Zahra] Islamic Azad Univ, North Tehran Branch, Dept Biomed Engn, Tehran, Iran; [Maghooli, Keivan] Islamic Azad Univ, Sci & Res Branch, Dept Biomed Engn, Tehran, Iran; [Akin, Ata] Acibadem Univ, Dept Biomed Engn, Istanbul, Turkey		1	1	1	
[Dolu, Nazan] Baskent Univ, Med Fac, Dept Physiol, TR-06790 Ankara, Turkey; [Altinkaynak, Miray; Guven, Aysegul] Erciyes Univ, Engn Fac, Dept Biomed Engn, Kayseri, Turkey; [Ozmen, Sevgi; Demirci, Esra] Erciyes Univ, Med Fac, Dept Child Psychiat, Kayseri, Turkey; [Izzetoglu, Meltem] Villanova Univ, Elect & Comp Engn Dept, Villanova, PA 19085 USA; [Pektas, Ferhat] Altinbas Univ, Med Fac, Dept Physiol, Istanbul, Turkey	1		1	1	
[Eken, Aykut] Duzce Univ, Biomed Engn Dept, Fac Engn, Duzce, Turkey; [Kara, Murat] Hacettepe Univ, Dept Phys & Rehabil Med, Med Sch, Ankara, Turkey; [Baskak, Bora] Ankara Univ, Med Sch, Dept Psychiat, Ankara, Turkey; [Baskak, Bora] Ankara Univ, Brain Res & Applicat Ctr, Ankara, Turkey; [Baltaci, Aysegul] Yenimahalle Educ & Res Hosp, Dept Phys & Rehabil Med, Ankara, Turkey; [Gokcay, Didem] Middle East Tech Univ, Informat Inst, Dept Hlth Informat, Ankara, Turkey	1		1		
[Quaresima, Valentina; Giosue, Patricia; Roncone, Rita; Casacchia, Massimo; Ferrari, Marco] Univ Aquila, Dept Hlth Sci, I-67100 Laquila, Italy					1

Given the challenges involved with operationalizing different levels of disciplinarity, we employed a simple distinction based on the reported departmental affiliations in the bibliographic record. An article is tagged disciplinary if all authors are from the same department (e.g. Dept of Biomed Eng). If there are at least two authors from different departments, then the article is tagged as interdisciplinary. For instance, the second article in Table 6 brings together authors from Biomedical Engineering, Child Psychiatry, Electrical & Electronics Engineering and Physiology. Since there are more than two departments listed, this article is considered to be inter-disciplinary. In the scope of this thesis we don't make a technical distinction between degree of disciplinary type of research due to the lack of agreement in the literature regarding the proposed definitions.

The annotation scheme also encodes the participation structure based on the location of the authors. If an article has a single author or all auhors are affiliated with the same institution, then the article is tagged with the label Collaboration-None. If two of the co-authors are from different institutions, then the article is tagged wih the label University Collaboration. Finally, if at least two co-authors are affiliated with institiutions from different countries, then the article is tagged with the label Country Collaboration. Although they are closely related concepts, we decided to implement a two-step annotation scheme that distinguish disciplinariy and collaboration tags, so as to distinguish collaborations of disciplinary or multi/inter-disciplinary nature.

3.5. Text Extraction

We used data and text mining methods provided by Leximancer to analyze the similarities of the collected datasets. Leximancer is a text mining tool based on machine learning that is used to analyze discipline data. It enables quick visualization and interpretation of large, complex corpora of natural language text data.

The text mining step involves applying traditional data mining algorithms such as data collecting, parsing, filtering, and transformation. Text mining is an iterative process involving repeated analysis steps using different settings and including/excluding terms for better results. The outcome of this process can be clusters of departments, universities, and countries. (Chakraborty, Pagolu, and Garla, 2013).

Figure 15 shows the text extraction process. At this stage, the process is started over the data obtained from the extraction process. Text parsing is performed for qualitative data as in the data mining process after the data is collected. Necessary filtering processes are applied after the parsing process is completed—for example, department, country, and university. After the filtering process, a coloring scheme reflecting the similarities of the data was employed to visualize disciplinary/interdisciplinary and country/university collaboration information.

The bibliometric data obtained from the WoS citation database do not readily provide the disciplinary composition of the articles since affiliation addresses are not unified into distinct department name categories in the WoS database as opposed to University names unified under the organizations-enhanced feature. For this reason, the data used in the disciplinary and collaboration analysis could not be readily retrieved from the citation database. To process department information, first the author affiliation sections of the articles were manually extracted from the citation records one by one. Then the co-occurance matrix was obtained by automatic extraction of departments and cleaning with the help of the leximancer software.

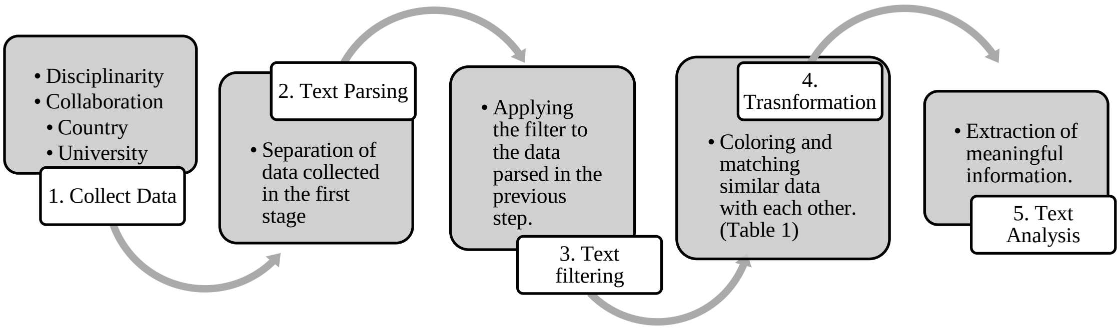

Figure 15: Text extraction Process (Chakraborty & Pagolu and Garla., 2013)

3.6. Bibliometrics and Scientific Mapping Method

Bibliometric methods are based on obtaining bibliographic data from databases and obtaining an image of the field of interest (Zupic, 2015) and are generally performed for two purposes. These are performance analysis and scientific mapping. On the other hand, scientific mapping tries to reveal the dynamics and structure of a scientific field (Cobo et al., 2011), while performance analysis expresses the institution's or country's scientific publication performance.

Inferences are obtained with the help of various patterns of authors, documents, and countries (Martinez et al., 2015). Scientific mapping or bibliometric mapping; represents a spatial representation of the interrelationship of disciplines, fields, specialties, documents, and authors. The scientific mapping method is expressed as discovering valuable information from data (Cobo et al., 2011). There are eight essential steps in the analysis. These include:

(1) data from WoS, Scopus, Pubmed, etc. databases,
(2) preprocessing the data,
(3) net extraction from the data,
(4) normalizing the data to get meaningful results from the data,
(5) mapping,
(6) analysis,
(7) visualization, and
(8) interpretation (Martinez et al., 2015; Chen, 2017).

A large number of software has been developed to perform scientific mapping analysis. Software developed for some general purposes can also be used for scientific mapping. This software includes Pajek, Gephi, UCINET, Cytoscape, Bibexcel, CiteSpace II, CoPalRed, IN-SPIRE, VantagePoint, VOSviewer and Science of Science Tool (Cobo et al., 2012).

We analyzed each article's bibliographic record (title, keywords, author, cited references and summary). We created a network of bibliographic links to link articles that share at least two standard references.

The next step was to use an algorithm to find groups of articles with many shared links. Topics are collections of articles that are all in the same group and arranged in knots or circles. The number of items in an apartment is proportional to its size. The degree to which the subjects are decoupled is indicated by the thickness of the separate lines. The articles within each topic were then subdivided using the same algorithm.

We use an implementation of the Louvain algorithm to divide the publications into clusters using a modularity optimization-based community detection algorithm. The Louvain algorithm is one of the quickest modularity-based algorithms and is effective when working with large graphs. Additionally, it reveals a hierarchy of communities at various scales, which helps comprehend a network's global operation.

We must first examine modularity as a whole in order to comprehend the Louvain modularity algorithm. (Figure 16).

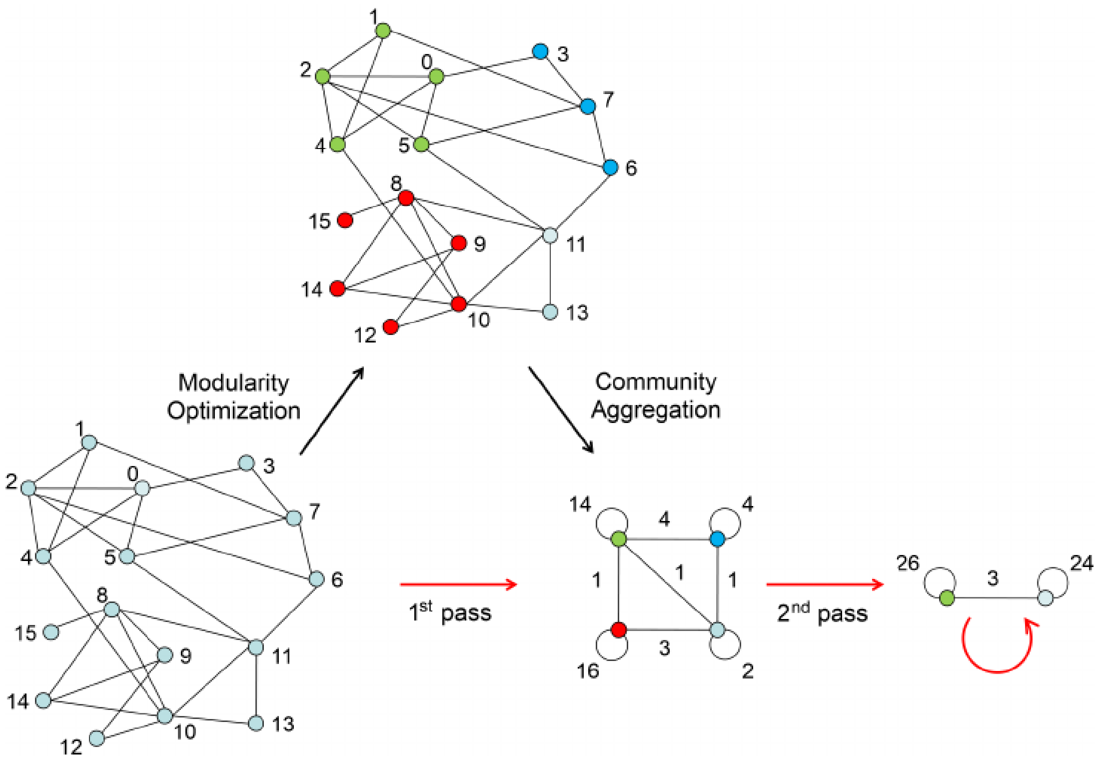

Figure 16: Louvain algorithm overview

A measure of modularity is how well groups have been divided into clusters. It compares the relationships in a cluster to the expected number of connections from a random (or another baseline) source.

The algorithm groups publications belonging to the same "dense" region of the BC network in terms of links. The modularity Q, a number between -1 and 1, can be used to measure the quality of the cluster partitioning. The partitioning becomes more significant the higher it is. Using the so-called Louvain modularity algorithm, the obtained network can be divided into "groups of cohesive articles" or clusters:

$$\sigma = \sqrt{N}\frac{f - f_0}{\sqrt{f_0(1 - f_0)}}$$

Publications belonging to the same set are grouped into a single node or circle, the size of which is proportional to the number of publications it contains. Then, more frequent/essential items can be used as automatic tags (keywords, references, authors, etc.) with which a standard frequency analysis is performed to characterize each cluster.

The Louvain algorithm performs hierarchical clustering on condensed graphs, a hierarchical clustering technique that recursively combines communities into a single node. Each detected set's subsets of publications can be divided into subsets using the same approach. Then, the following three network and cluster analyses were carried out using Bibliometrix R Package, Gephi, CiteSpace, and Vosviewer to produce network and visualization.

To sum up, after the map was built, which represented the relationships and computed clusters, we reviewed the most cited and representative papers in each topic and subtopic to create labels and descriptions. Gephi, CiteSpace, Vosviewer, and the Bibliometrix R Package were used to complete the data analysis and visualization.

CHAPTER IV

RESULTS

4.1. Disciplinarity Analysis Results

In this section, we focus on whether fNIRS publications that employ an inter-disciplinary approach and/or establishing university and country collaborations have a higher overall impact as quantified by the number of citations, CI, and CNCI values in the year range 1980-2020.

1673 fNIRS articles in the World met our search criteria from 1980 to 2020 (Table 8). Publication and citation trends increased from 1 article in 1982 to 261 articles in 2020. The status of the articles published in the field of fNIRS between 1980-2020 in the World according to their disciplinarity and institutional/international collaboration status are summarized in Table 7.

Table 7: The status of the articles published in the field of fNIRS between 1980-2020 in the World

Year	#Article	#Citation	#Disciplinary	#Inter-Disciplinary	#University Collaboration	#Country Collaboration	#Collaboration-None	CI	CNCI	IREW
1982	1	33					1	33.0	0.86	2.18
1983	1	20	1				1	20.0	0.57	1.33
1984	1	136			1			136.0	2.82	8.87
1991	1	188		1	1			188.0	3.53	9.75
1992	3	64		1	1		2	21.3	0.45	1.06
1993	5	1335	1		1		4	267.0	5.64	12.83
1994	2	126		1	1	1	1	63.0	1.05	3.07
1995	5	245			1		4	49.0	1.13	2.27
1996	5	520	2	1	3		2	104.0	2.71	4.84
1997	8	1483		3	3	1	5	185.4	3.51	8.34
1998	6	266		4	4	3	2	44.3	0.98	1.87
1999	8	286	2	3	5	1	3	35.8	1.00	1.44
2000	7	715		5	4	1	3	102.1	2.83	3.80
2001	10	1395	1	6	7	1	3	139.5	3.12	5.05
2002	4	1473	1	1	1		2	368.3	6.32	13.16
2003	12	898		5	4		8	74.8	1.67	2.68
2004	11	1801	1	5	3	2	7	163.7	3.48	5.98
2005	21	1410	3	10	8	2	13	67.1	1.56	2.69

Table 7 (continued).

2006	21	1397	9	7	10	2	10	66.5	1.69	2.76
2007	24	2180	4	11	7	3	14	90.8	2.40	4.15
2008	30	1287	10	12	14	2	16	42.9	1.11	1.97
2009	35	2266	4	23	21	5	14	64.7	2.15	3.12
2010	44	2071	9	22	24	4	19	47.1	1.25	2.31
2011	47	2029	8	31	27	8	20	43.2	1.26	2.25
2012	75	3410	10	50	48	14	26	45.5	1.41	2.54
2013	99	3112	20	52	52	21	46	31.4	1.10	1.85
2014	141	5623	27	89	89	29	51	39.9	1.51	2.52
2015	120	3773	26	81	88	23	30	31.4	1.37	2.13
2016	123	3644	37	73	86	38	37	29.6	1.50	2.26
2017	168	3565	44	105	125	49	43	21.2	1.18	1.78
2018	195	3379	32	135	135	58	60	17.3	1.20	1.65
2019	179	2392	33	130	135	58	44	13.4	1.20	1.55
2020	261	2114	42	186	185	81	76	8.1	1.01	1.17
Total	1673	54636	327	1053	1094	407	567			

#Article
Number of articles in the field of fNIRS between 1980-2020
#Citation
Number of citations in the field of fNIRS between 1980-2020
#Disciplinary
Number of articles with the same disciplines in address sections between 1980-2020
#Inter-Disciplinary
Number of articles with different disciplines in address sections between 1980-2020
#University Collaboration
Number of articles with different universities in address sections between 1980-2020
#Country Collaboration
Number of articles with different universities in address sections between 1980-2020
#Collaboration-None
Number of articles with the same universities in address sections between 1980-2020
CI: Citation Impact
Divide the number of citations by the number of publications to get the citation impact of a set of documents. The citation impact section shows the average number of citations a document has received.
IREW: Impact Relative to World
Impact of the set of publications on citations concerning the global average.
CNCI: Category Normalized Citation Impact
The expected rate of citations for documents of the same type, publication year, and subject matter is divided by the actual number of citations for a document to determine its Category Normalized Citation Impact (CNCI). When a document is assigned to more than one subject, the average of the ratios of actual citations to expected citations is used.

Firstly, we focus on comparing the impact generated by fNIRS articles that have a disciplinary and interdisciplinary composition in terms of their author affiliations. Our annotation of the fNIRS articles revealed that of the 1671 articles, 1053 of them were classified as interdisciplinary, and 618 of them were classified as disciplinary. Figure 17 below shows the number of articles published in each category between 1980 and 2020. There is an overall increasing trend in the number of articles published, and the growth is larger in the case of interdisciplinary studies, especially from 2014 to 2020. There is a slight decrease in 2019, which may be partly due to the Covid-19 pandemic.

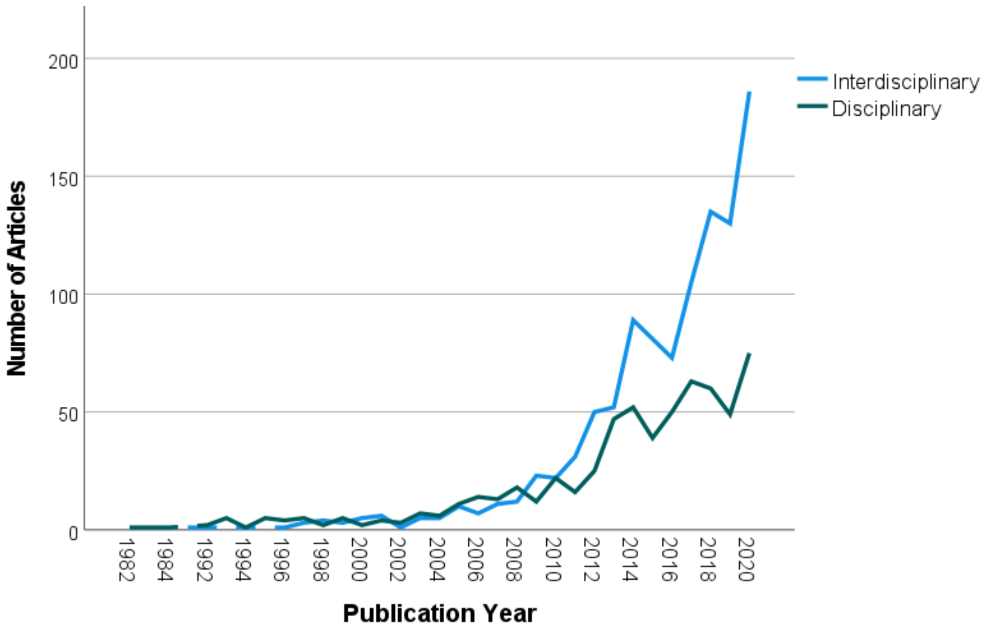

Figure 17: The number of disciplinary and interdisciplinary fNIRS related articles published between 1980 and 2020.

Figure 18 below compares the two groups of fNIRS articles in terms of the total number of citations accrued in each year between 1980 and 2020. Especially in the last 10 years interdisciplinary studies tended to generate more citations, whereas during the inception of fNIRS as a new field within Neuroimaging, studies of disciplinary nature tended to have a larger share of citations.

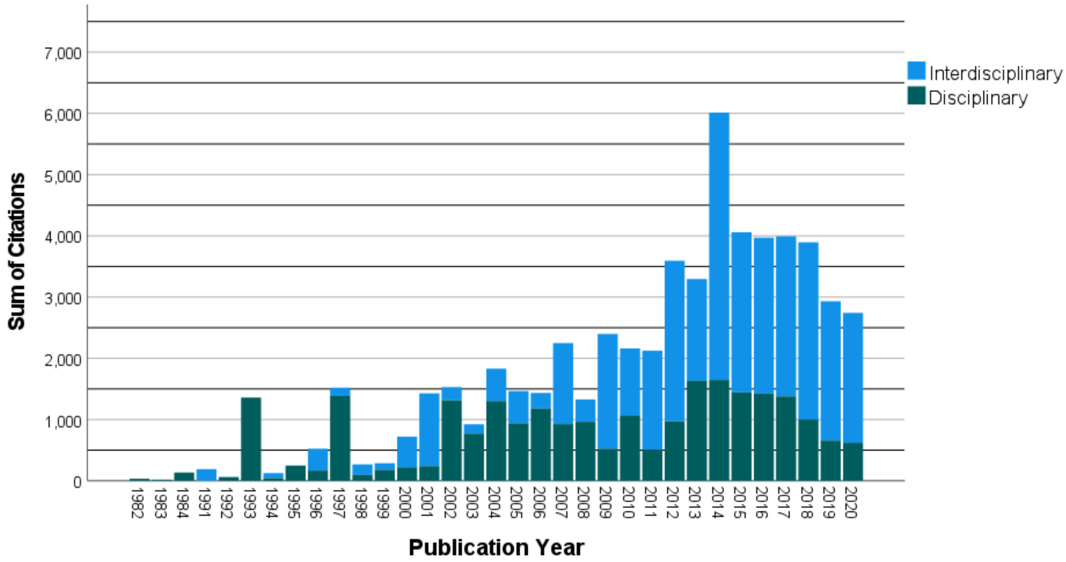

Figure 18. Number of citations accrued by interdisciplinary and disciplinary fNIRS studies.

Figure 19 below shows the yearly changes in citation per publication (CPP) or the citation impact (CI) for the disciplinary and interdisciplinary fNIRS articles. CPP is another impact indicator which normalizes with respect to the total number of publications. The terms CI and CPP are used interchangeably in the bibliometrics literature. During the early years there is considerable variability with spikes in 1996, 1998, and 2002, which is due to the publication of seminal studies that attracted significant number of citations, when the number of total publications were still small. The variability decreased after the year 2010 as there are considerably more fNIRS studies getting published after this year. Figure 20 zooms into the time period 2010-2020, where one can observe that interdisciplinary studies tend to generate more citation impact. The decreasing trend in citation impact can be expected since the newly published studies tend to have much lower number of citations as compared to older articles.

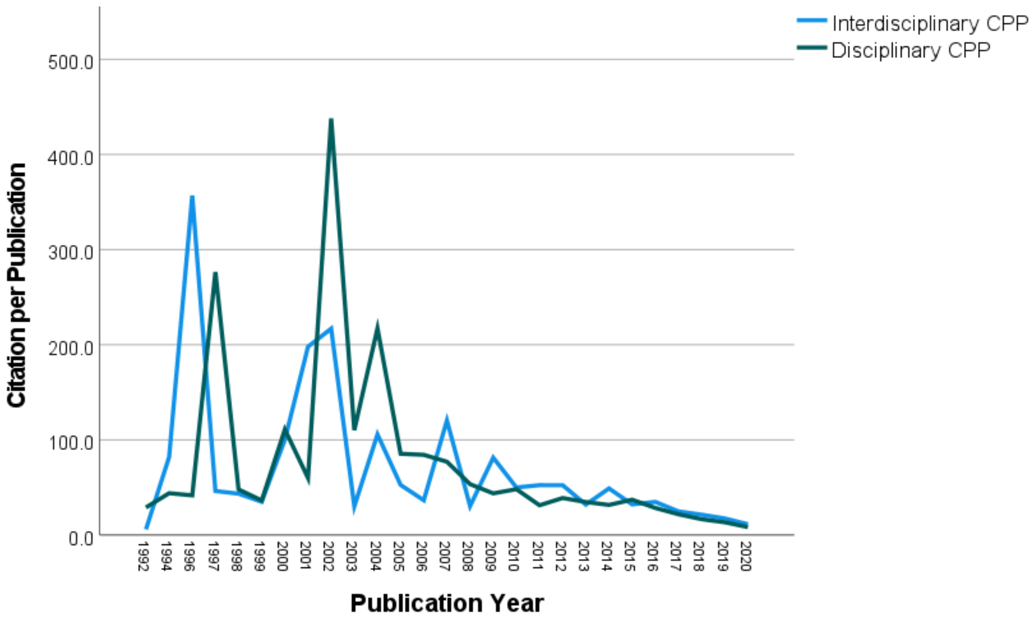

Figure 19: Citation per publication ratios for interdisciplinary and disciplinary fNIRS studies.

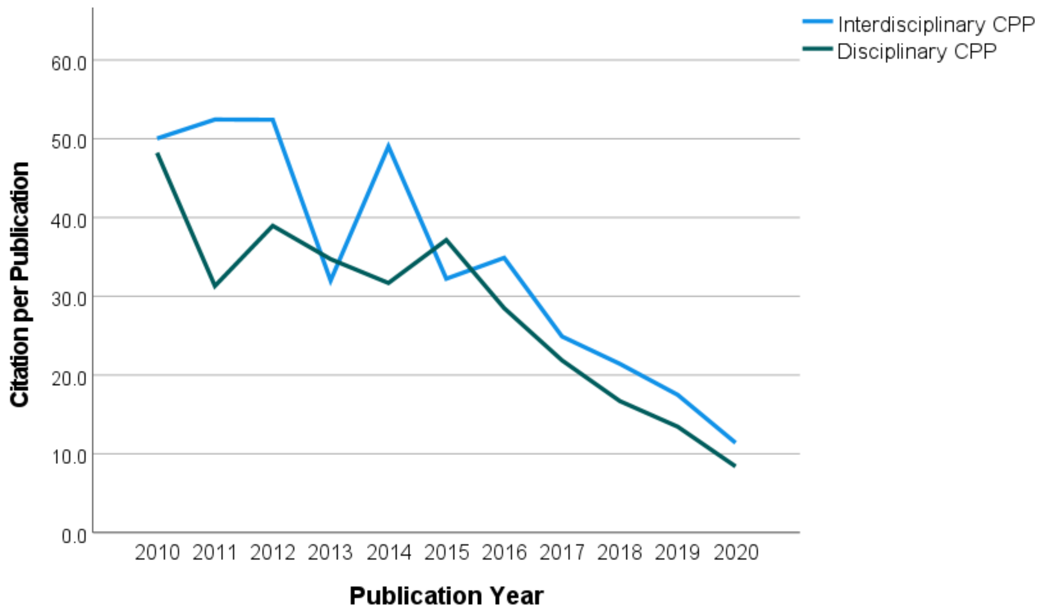

Figure 20: Citation per publication ratios for interdisciplinary and disciplinary fNIRS studies in the past 10 years.

Category Normalized Citation Impact (CNCI) is a measure provided by InCites which normalizes the CPP or CI ratio with respect to the world average in the cooresponding subject area. CNCI values above 1 indicates that the citation impact performance of the selected articles is above the global average in that subject category. Figure 21 shows the yearly average of CNCI measures for interdisciplinary and disciplinary fNIRS articles. The seminal studies prior to 2002 that established fNIRS as a viable neuroimaging modality tended to have high CNCI values as well, indicating the global significance of their impact. Figure 22 shows the CNCI values for the last 10 years where interdisciplinary studies tended to generate higher citation impact above the world average.

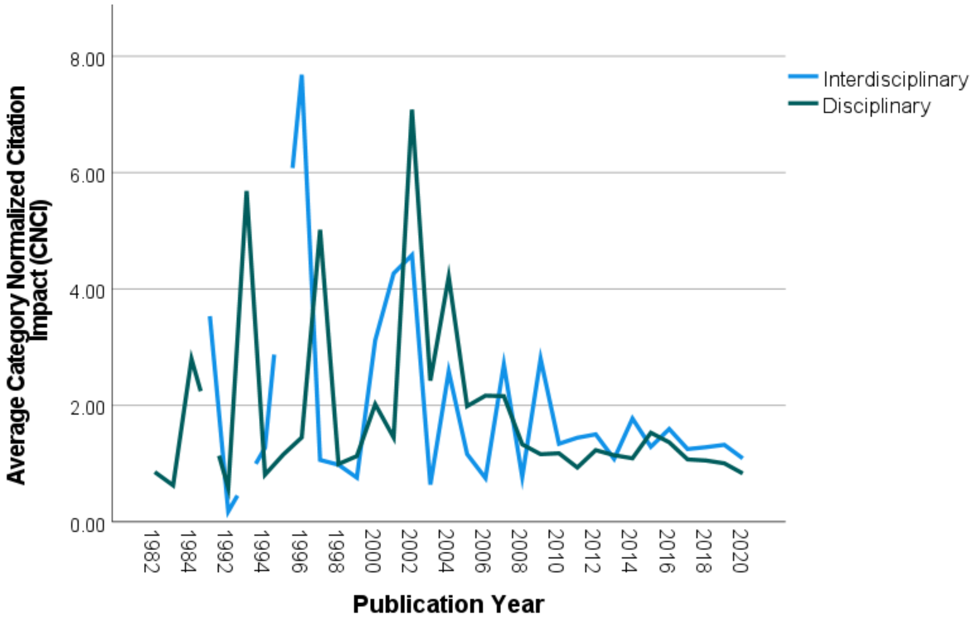

Figure 21: Category normalized citation impact (CNCI) values for the interdisciplinary and disciplinary fNIRS studies.

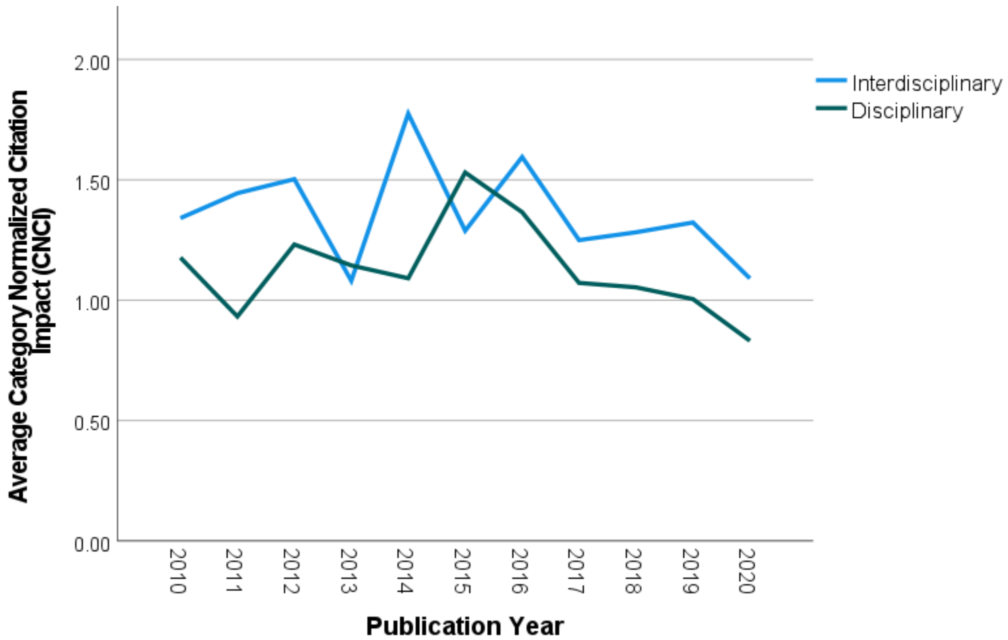

Figure 22: Category normalized citation impact (CNCI) values for the interdisciplinary and disciplinary fNIRS studies in the past 10 years.

In order to test the statistical significance of these trends, we pooled the data into 5 year-long segments and conducted three two-way mixed ANOVA tests where disciplinarity type and time-period were the independent variables and the impact measures citation, CPP and CNCI were the dependent measures. We considered articles between 1995-2020 since earlier years did not have sufficient data points for a statistical analysis.

In terms of average citations, we found that interdisciplinary articles have a significantly higher average citations than disciplinary articles, $F(1,20)=5.86$, $p<.05$, $\eta^2=.23$. We also found a significant interaction effect, $F(1,20)=5.15$, $p<.01$, $\eta^2=.51$, which is due to the increasing separation between the two groups in the last two 5-year long segments. The main effect of time was also significant, $F(4,20)=11.56$, $p<.01$, $\eta^2=.69$, indicating the significant growth in the citation trends of both groups (Figure 23).

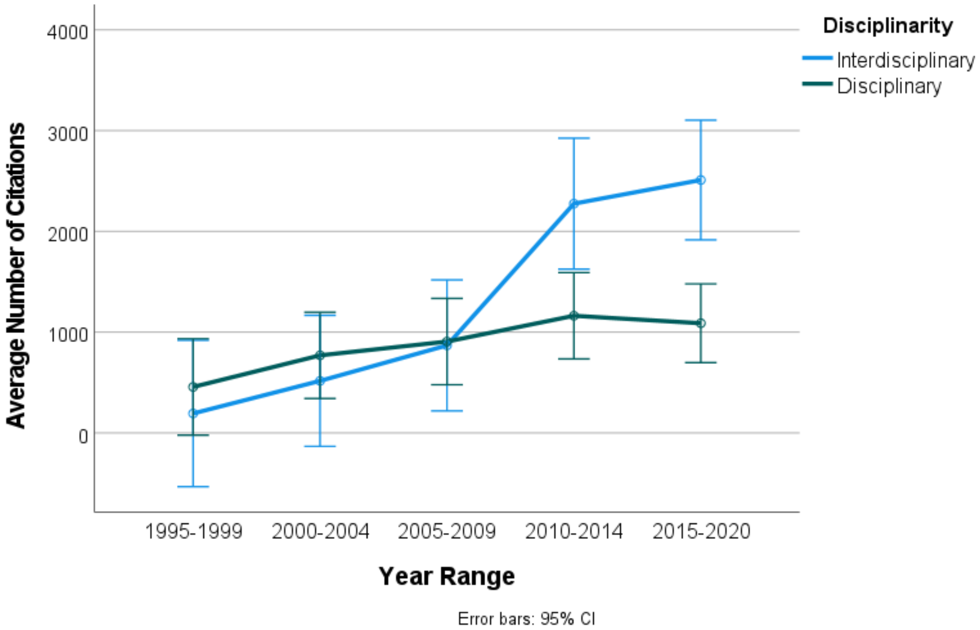

Figure 23: Change in average citations in 5-year long segments for disciplinary and interdisciplinary fNIRS articles.

In terms of CPP and CNCI measures, there was no significant difference between disciplinary and interdisciplinary articles. The interaction effects were also not significant. The only significant effect was due to time, indicating significant changes in time for the CPP ($F(4,20)=4.99$, $p<.01$, $\eta^2=.50$) and CNCI ($F(4,20)=7.41$, $p<.05$, $\eta^2=.42$) measures (Figures 24 and 25).

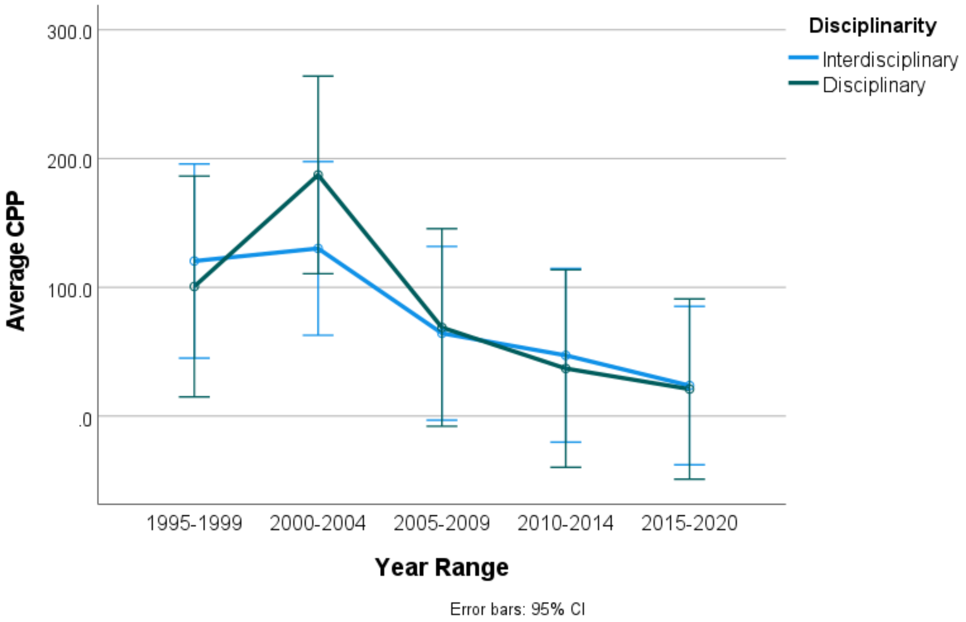

Figure 24: Change in average CPP values in 5-year long segments for disciplinary and inter-disciplinary fNIRS articles

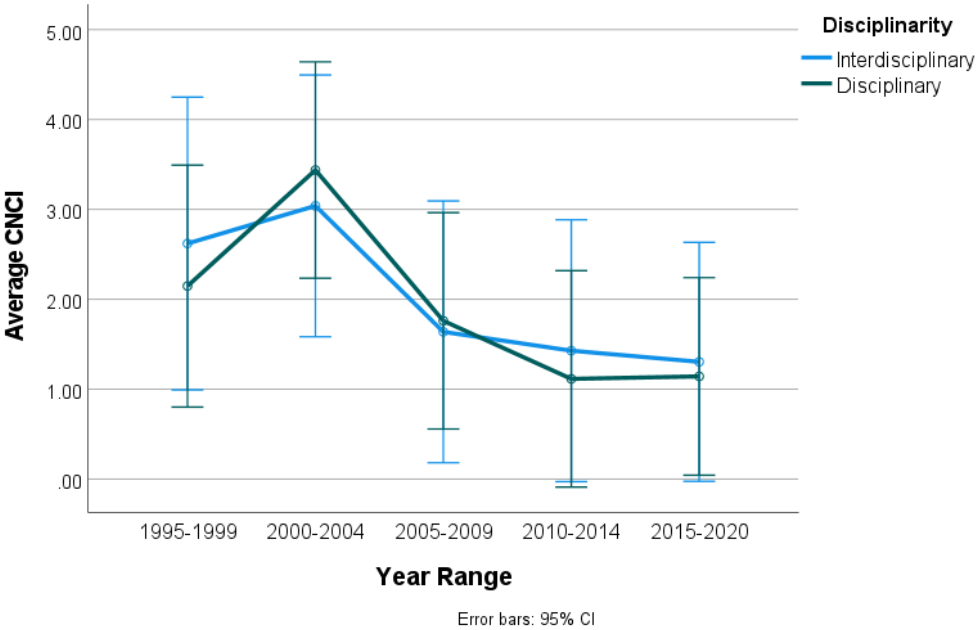

Figure 25: Change in average CNCI values in 5-year long segments for disciplinary and interdisciplinary fNIRS articles.

4.2. Collaboration Analysis Results

In this section, we focus on whether fNIRS publications that are a product of institutional collaboration have a higher overall impact as quantified by the number of citations, the CI, and CNCI values in the year range 1980-2020. Our annotation of the fNIRS articles revealed that 577, 687, and 407 articles were classified as no-collaboration, institutional collaboration and international collaboration categories, respectively. All international collaboration category articles also fit into the institutional collaboration category (i.e. there were no articles with international co-authors from the same type of department). Therefore, one can consider a binary category indicating whether the article was a product of collaboration across different institutions or not. No collaboration category does not suggest that the articles in this category were all single author publications. There were only 31 single-authored articles in our sample, which suggests that the %98 of the articles were product of collaboration among multiple co-authors. Our collaboration category only distinguishes the involvement of different departments/institutions.

Figure 26 below shows the number of articles published in each collaboration category between 1980 and 2020. There is an overall increasing trend in the number of articles published, and the growth is larger in the case of studies in the institutional collaboration group, especially from 2014 to 2020.

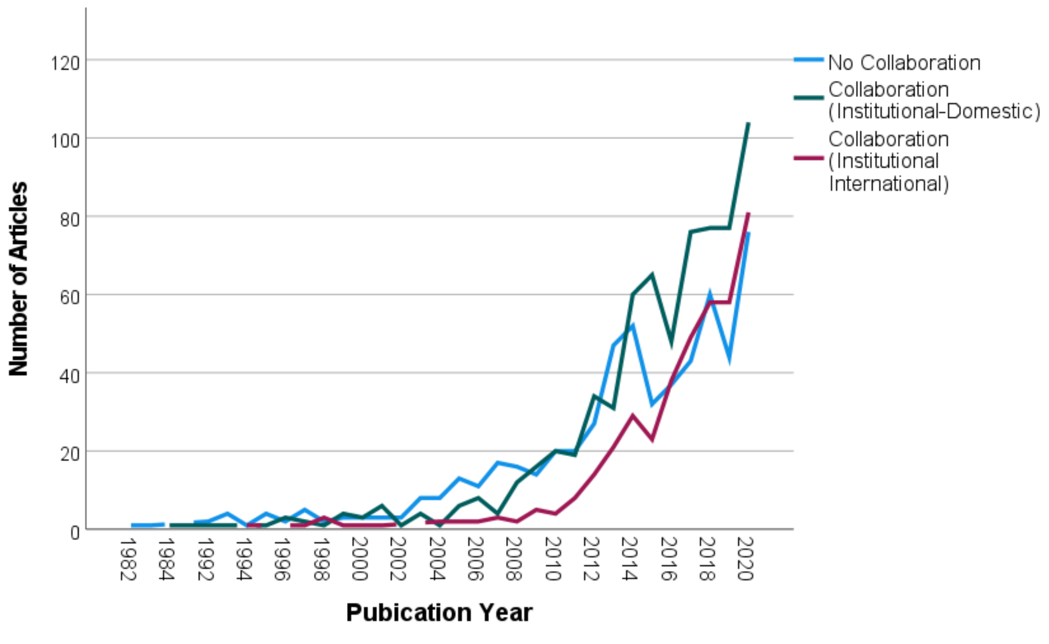

Figure 26: The number of fNIRS related articles in each institutional collaboration group published between 1980 and 2020.

Figure 27 below compares the three institutional collaboration groups of fNIRS articles in terms of the total number of citations accrued in each year between 1980 and 2020. Especially in the last 10 years studies that are a product of institutional collaboration tended to generate more citations, whereas during the inception of fNIRS as a new field within Neuroimaging, studies with no-institutional collaboration tended to have a larger share of citations.

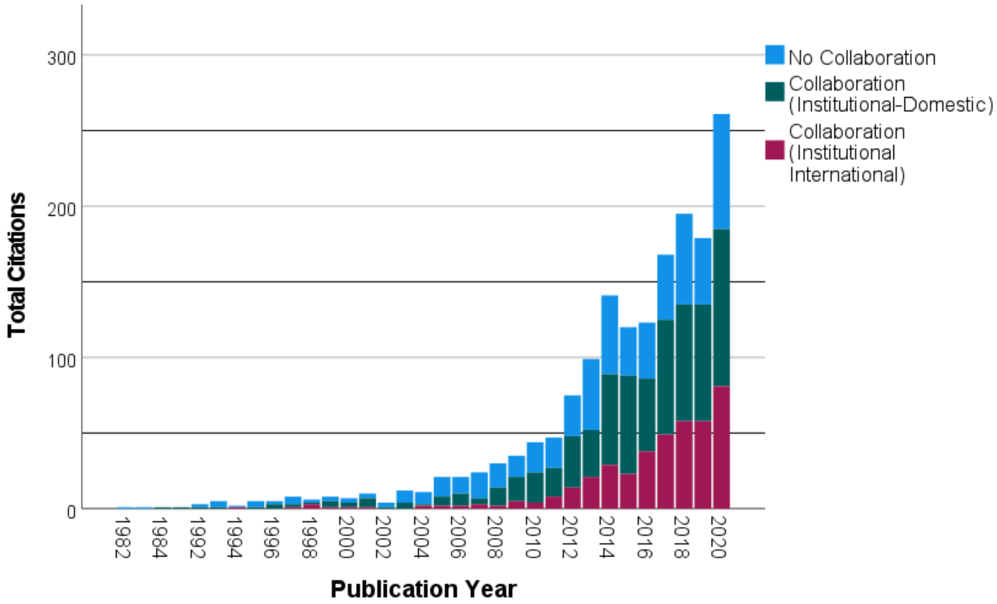

Figure 27: Number of citations accrued by fNIRS studies in different institutional collaboration groups.

Figure 28 below shows the CPP values for each collaboration group. During the early years there is considerable variability when the number of total publications were still small. The variability decreased after the year 2010 as there are considerably more fNIRS studies getting published after this year. Figure 29 zooms into the time period 2010-2020, where one can observe that studies with international collaboration tend to generate more citation impact. The decreasing trend in citation impact can be expected since the newly published studies tend to have much lower number of citations as compared to older articles.

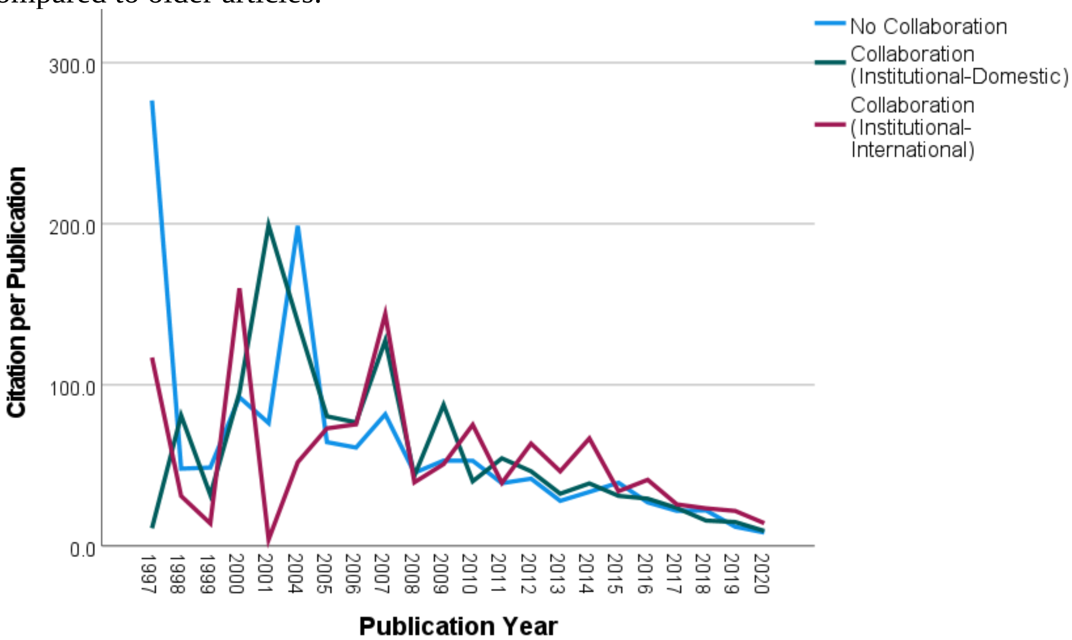

Figure 28: Citation per publication ratios for the three collaboration groups.

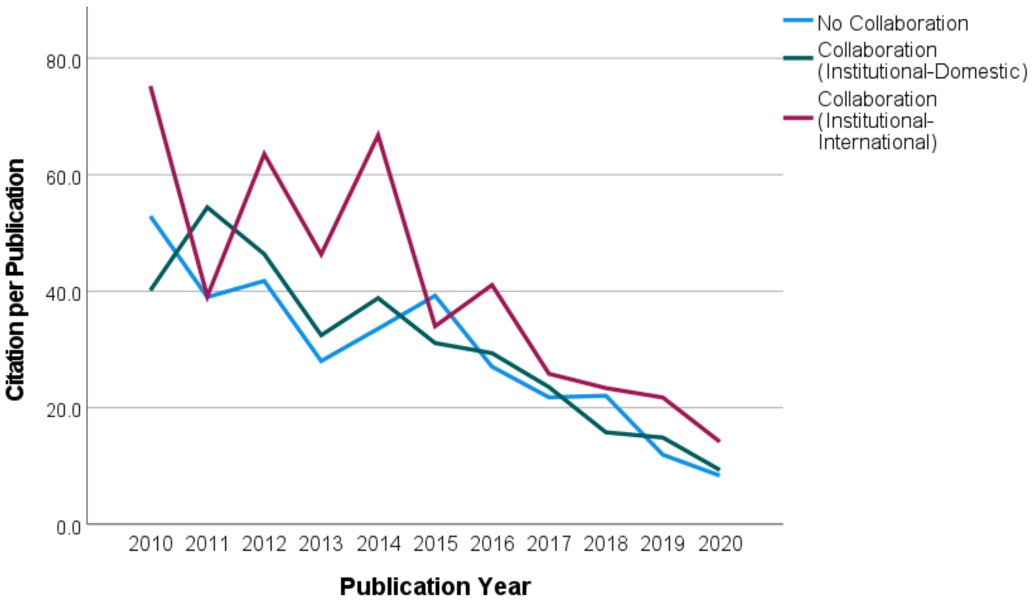

Figure 29: Citation per publication ratios for the collaboration groups in the past 10 years.

Figure 30 shows the yearly average of CNCI measures for the three collaboration groups. The seminal studies prior to 2002 that established fNIRS as a viable neuroimaging modality tended to have high CNCI values as well, indicating the global significance of their impact. Figure 31 shows the CNCI values for the last 10 years where studies with international collaboration tended to generate higher citation impact above the world average.

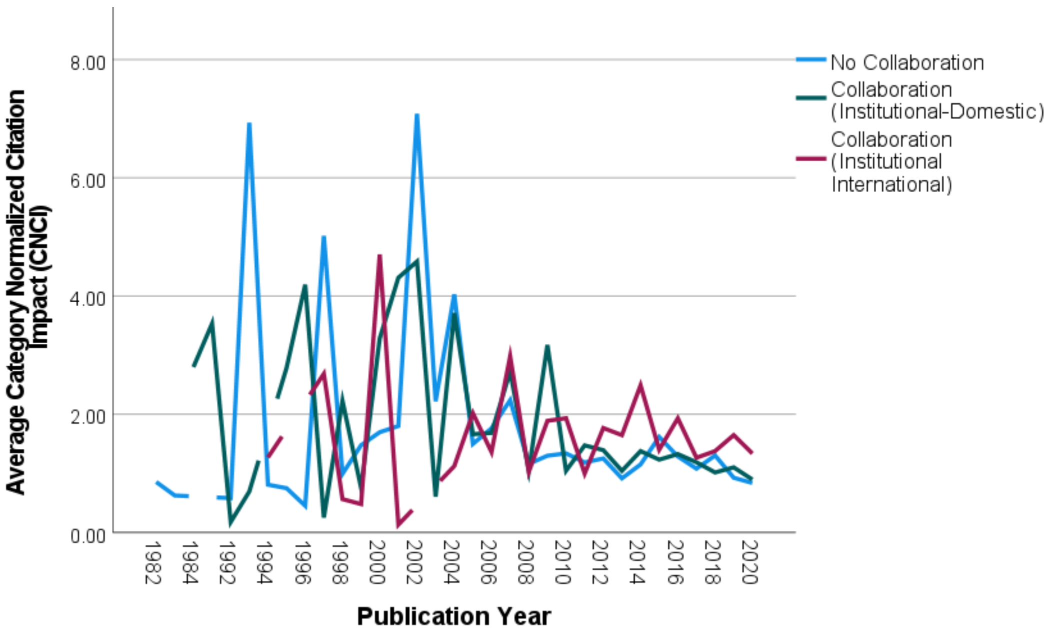

Figure 30: Category normalized citation impact (CNCI) values for the collaboration groups.

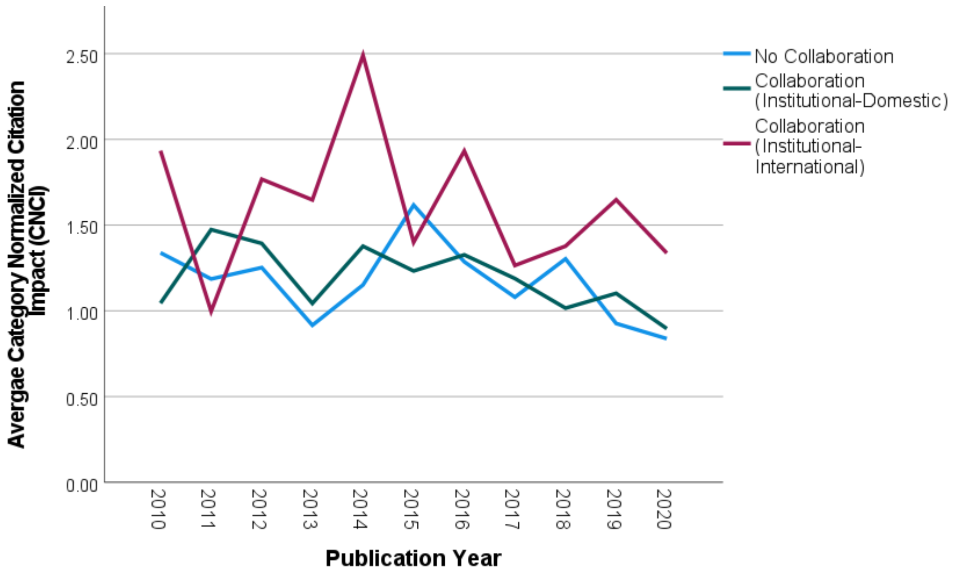

Figure 31: Category normalized citation impact (CNCI) values for the collaboration groups in the past 10 years.

In order to test the statistical significance of these trends, we pooled the data into 5 year-long segments and conducted three two-way mixed ANOVA tests where collaboration type and time-period were the independent variables and the impact measures citation, CPP and CNCI were the dependent measures. We considered articles between 1995-2020 since earlier years did not have sufficient data points for a statistical analysis.

In terms of average citations, we found a significant difference among collaboration groups, $F(2,34)=5.75$, $p<.05$, $\eta^2=.25$. The interaction effect was not significant, $F(8,34)=1.86$, $p>.05$. The main effect of time was also significant, $F(4,17)=8.25$, $p<.01$, $\eta^2=.66$, indicating the significant growth in the citation trends of both groups (Figure 32).

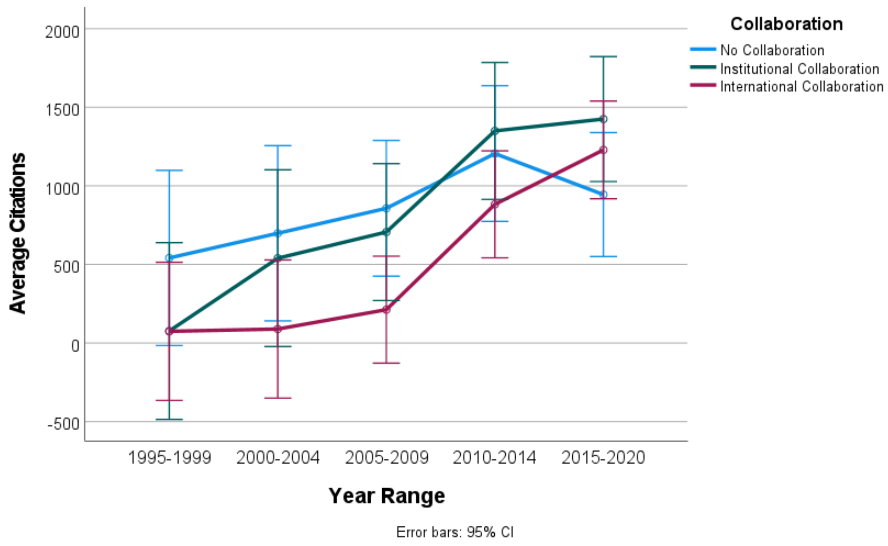

Figure 32: Change in average citations during 5-year long segments for the collaboration categories.

In terms of CPP and CNCI measures, there was no significant difference between collaboration categories. The interaction effects were also not significant. The only significant effect was due to time, indicating significant changes in time for the CPP (F(4,17)=7.83, p<.01, η^2=.65) and CNCI (F(4,17)=3.70, p<.05, η^2=.48) measures (Figures 33 and 34).

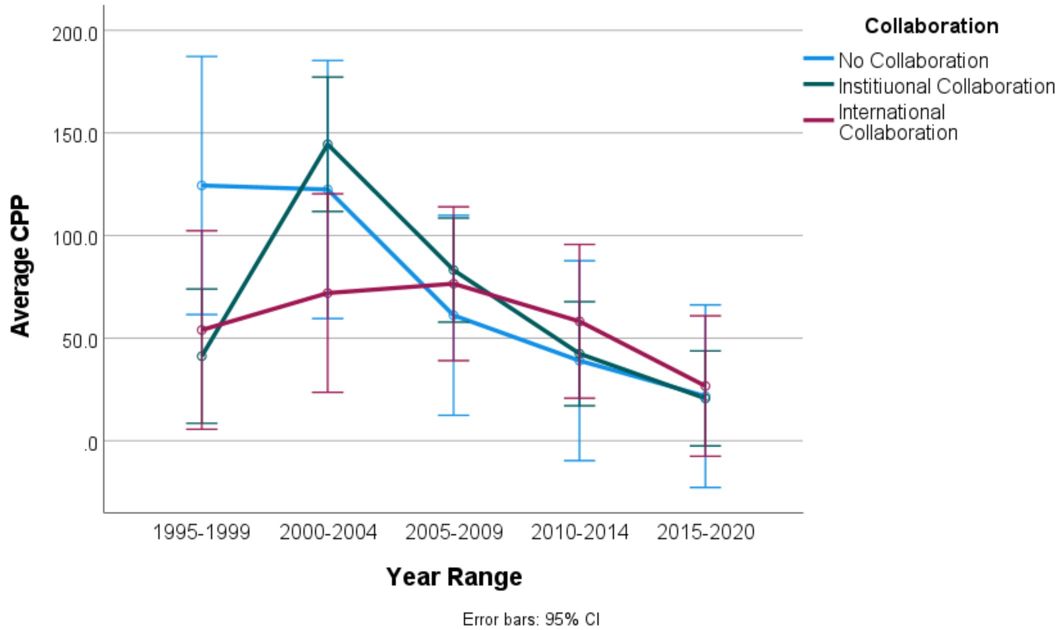

Figure 33: Change in average CPP values in 5-year long segments for the collaboration categories.

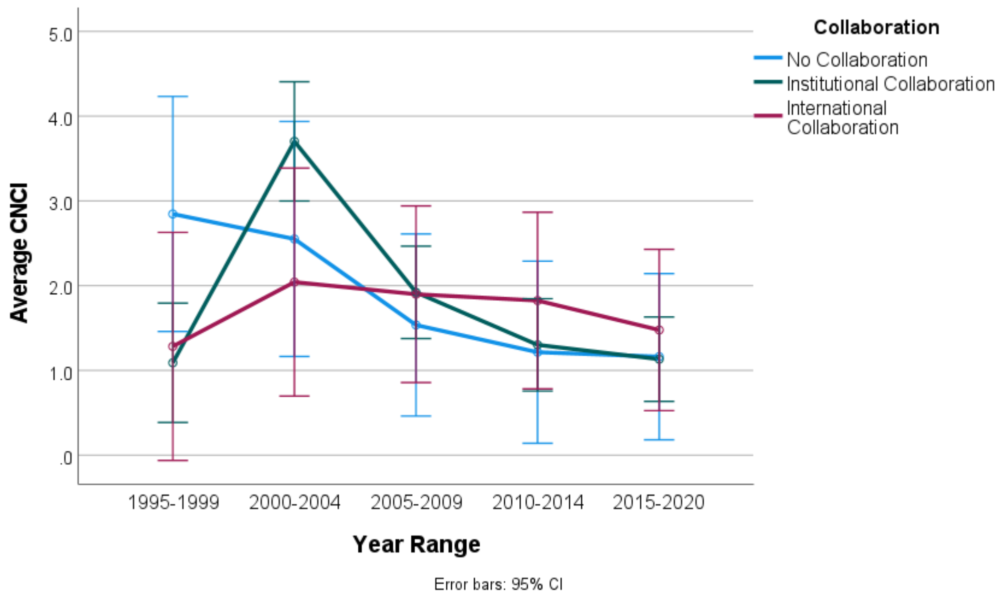

Figure 34: Change in average CNCI values in 5-year long segments for the collaboration categories.

4.3. JIF Quartile Analysis Results

In this section, we focus on whether fNIRS articles that differ in terms of their disciplinary and collaboration properties show different trends in terms of their distribution over Journal Impact Factor (JIF) quartiles. For that purpose, we used the InCites software to obtain the number of articles in each JIF quartile, as well as the total citations, citation impact values of those articles (Table 9).

Table 8: Distribution of the articles in the field of fNIRS in World according to their Q1, Q2, Q3 and Q4 quartiles.

JIF Quartile	#Article	#Citation	CI	#Disciplinary	#Inter-Disciplinary	#University Collaboration	#Country Collaboration	#Collaboration-None
Q1	464	22923	49,40	97	303	330	137	130
Q2	691	21223	30,71	119	481	481	170	208
Q3	250	7690	30,76	50	144	145	52	104
Q4	98	836	8,53	22	50	51	17	45
#N/A	170	1964	11,55	39	75	87	31	80
Total	1673	54636	32,66	327	1053	1094	407	567

The majority of fNIRS articles were found to be published in Q1 and Q2 JIF quartile category journals (Figure 35). In parallel, it was seen that the articles in Q1 and Q2 received more citations as expected. In addition, interdisciplinary articles have a larger share of the articles in Q1 and Q2 as compared to disciplinary articles.

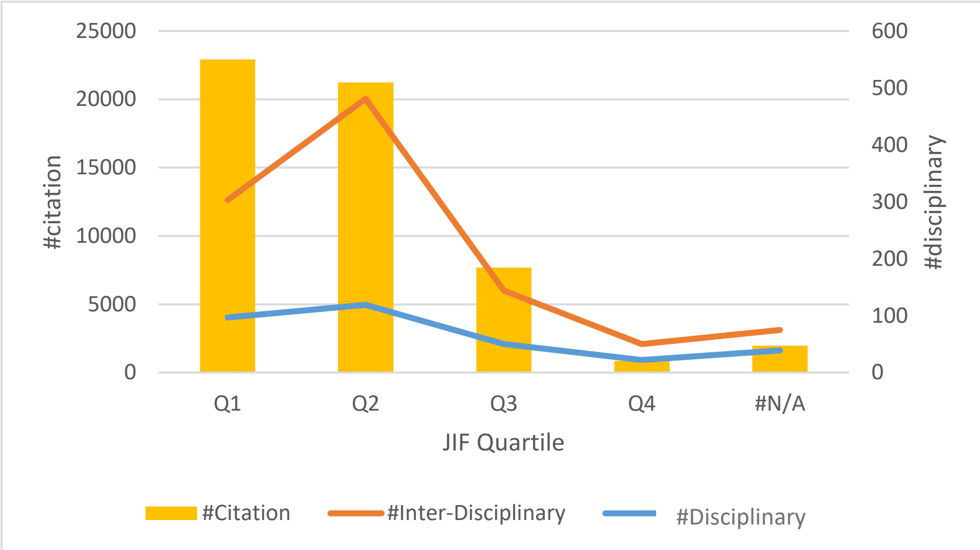

Figure 35: JIF Quartile distribution of disciplinary approach according to #citations.

As seen in Figure 36, the CI (Citation Impact) value of the articles produced in the Q1 category is higher, and interdisciplinary articles have a larger share in that quartile category. Interdisciplinary articles in the Q2 category produced even more citation impact as compared to Q1 publications.

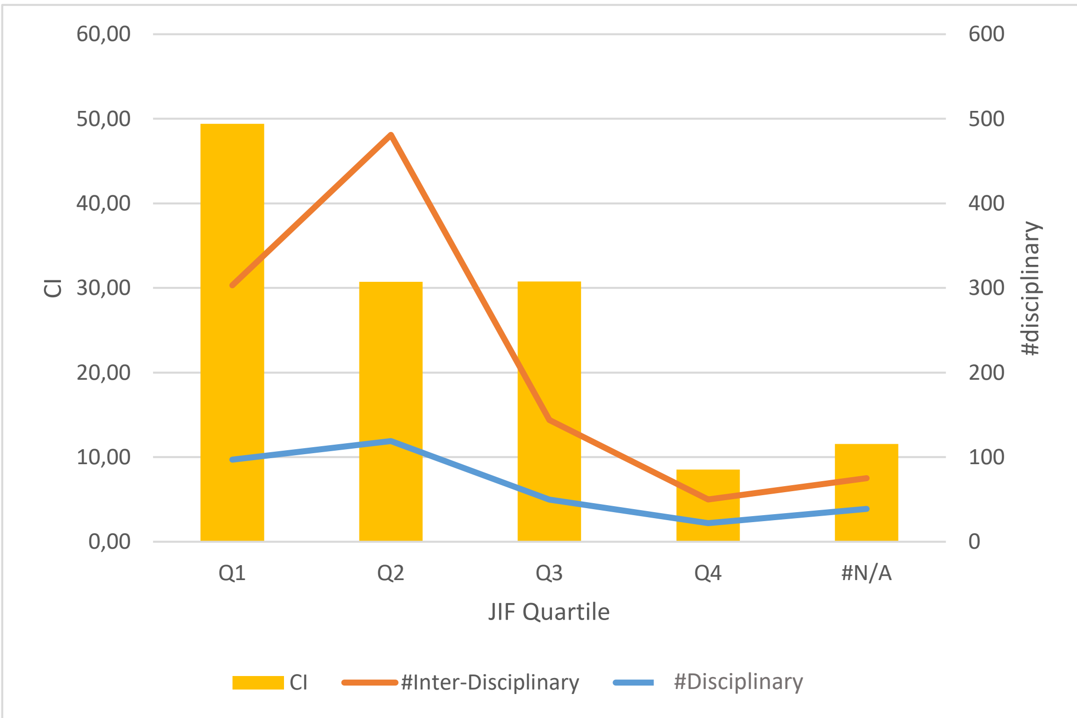

Figure 36: JIF Quartile distribution of disciplinary approach according to CI (Citation Impact)

When we focus on the quartile distribution from the collaboration perspective, we observed that the largest share of Q1-Q2 articles originate from articles with institutional collaboration (Figure 37). International collaboration has a slightly larger presence in the top quartile categories as compared to single institution authored articles.

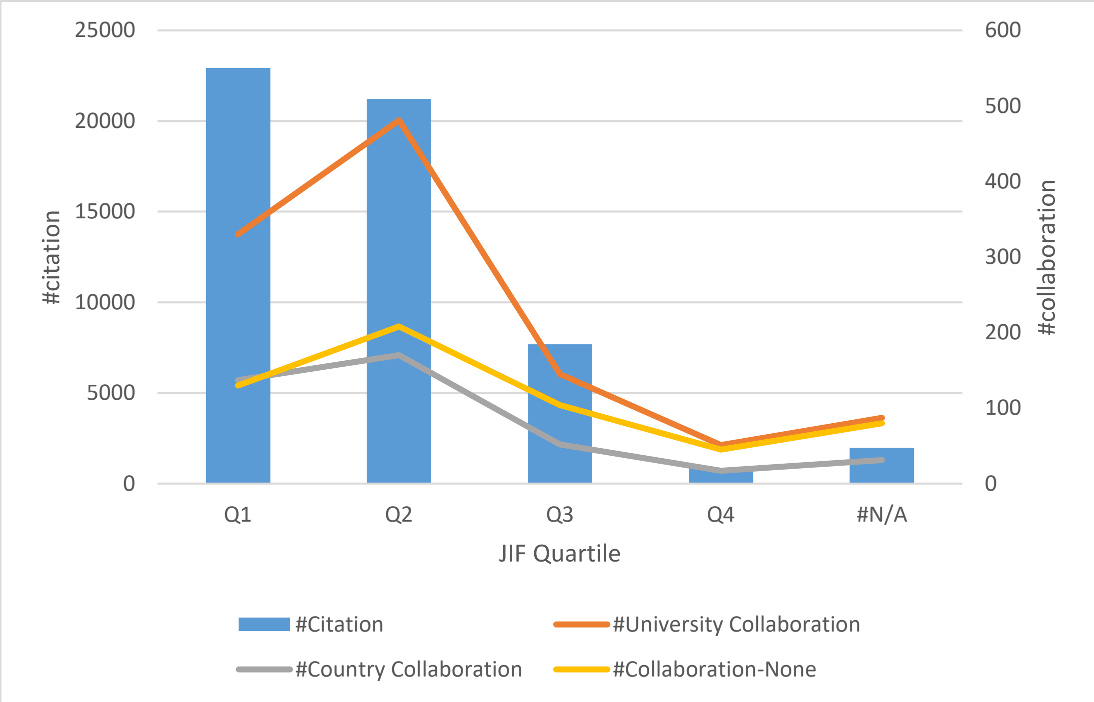

Figure 37: JIF Quartile distribution of collaboration approach according to #Citation

As seen in Figure 38, the CI (Citation Impact) values show a similar pattern where the articles with institutional collaboration has the largest share of the citation impact in Q1.

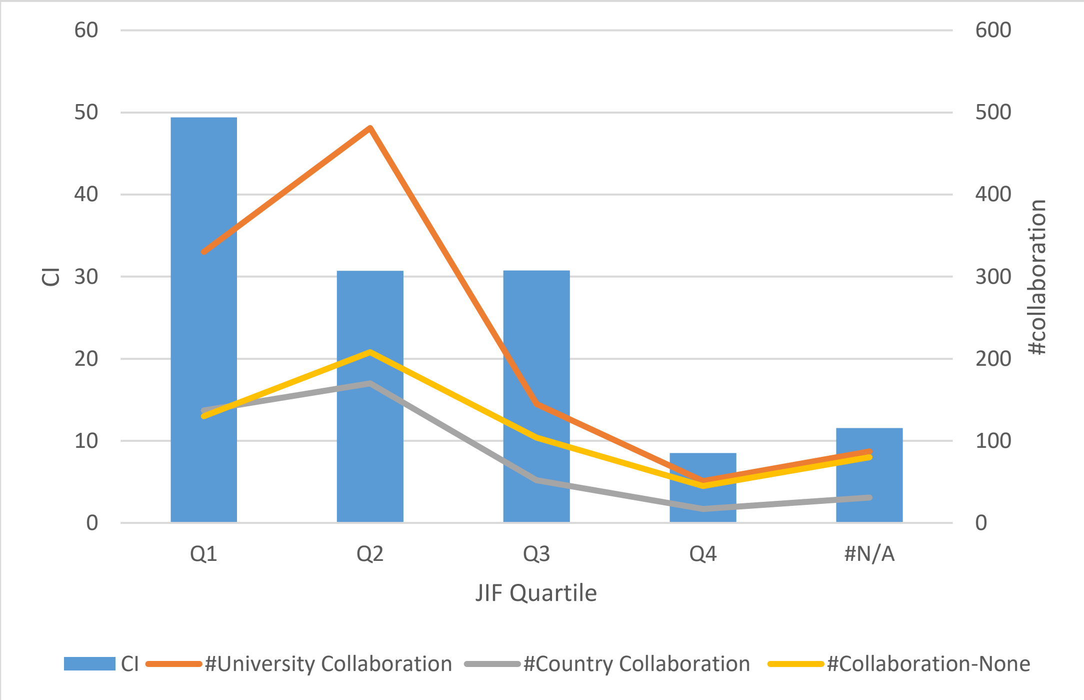

Figure 38: JIF Quartile distribution of collaboration approach according to CI (Citation Impact)

Table 9: Distribution of the articles in the field of fNIRS in World according to their Q1-Q2 and Q3-Q4 quartiles.

Year	**#disciplinary**	**#inter-disciplinary**	**#university collaboration**	**#country collaboration**	**#collaboration -None**	**Documents in Q1-Q2**	**Documents in Q3-Q4**
1982					1	0	0
1983	1				1	0	0
1984			1			0	0
1991		1	1			0	0
1992		1	1		2	0	0
1993	1		1		4	0	0
1994		1	1	1	1	0	0
1995			1		4	0	0
1996	2	1	3		2	0	0
1997		3	3	1	5	4	1
1998		4	4	3	2	3	1
1999	2	3	5	1	3	3	3
2000		5	4	1	3	6	0
2001	1	6	7	1	3	8	1

Table 9 (continued).

2002	1	1	1		2	4	0
2003		5	4		8	7	3
2004	1	5	3	2	7	9	2
2005	3	10	8	2	13	16	2
2006	9	7	10	2	10	13	7
2007	4	11	7	3	14	15	6
2008	10	12	14	2	16	19	8
2009	4	23	21	5	14	25	7
2010	9	22	24	4	19	26	7
2011	8	31	27	8	20	31	6
2012	10	50	48	14	26	48	18
2013	20	52	52	21	46	61	21
2014	27	89	89	29	51	89	30
2015	26	81	88	23	30	87	23
2016	37	73	86	38	37	99	15
2017	44	105	125	49	43	127	28
2018	32	135	135	58	60	142	36
2019	33	130	135	58	44	140	32
2020	42	186	185	81	76	184	55

Figure 39 shows the annual changes in the sum of citations accrued by fNIRS articles that are categorized as interdisciplinary and disciplinary for each quartile. The trends suggest that interdisciplinary fNIRS articles tended to have a larger share in Q1-Q2 journal and also produce a larger share of the total citations. In the early years of fNIRS research, the disciplinary fNIRS studies tended to generate more impact, based on their more frequent appearance in Q1 journals and larger share of citations.

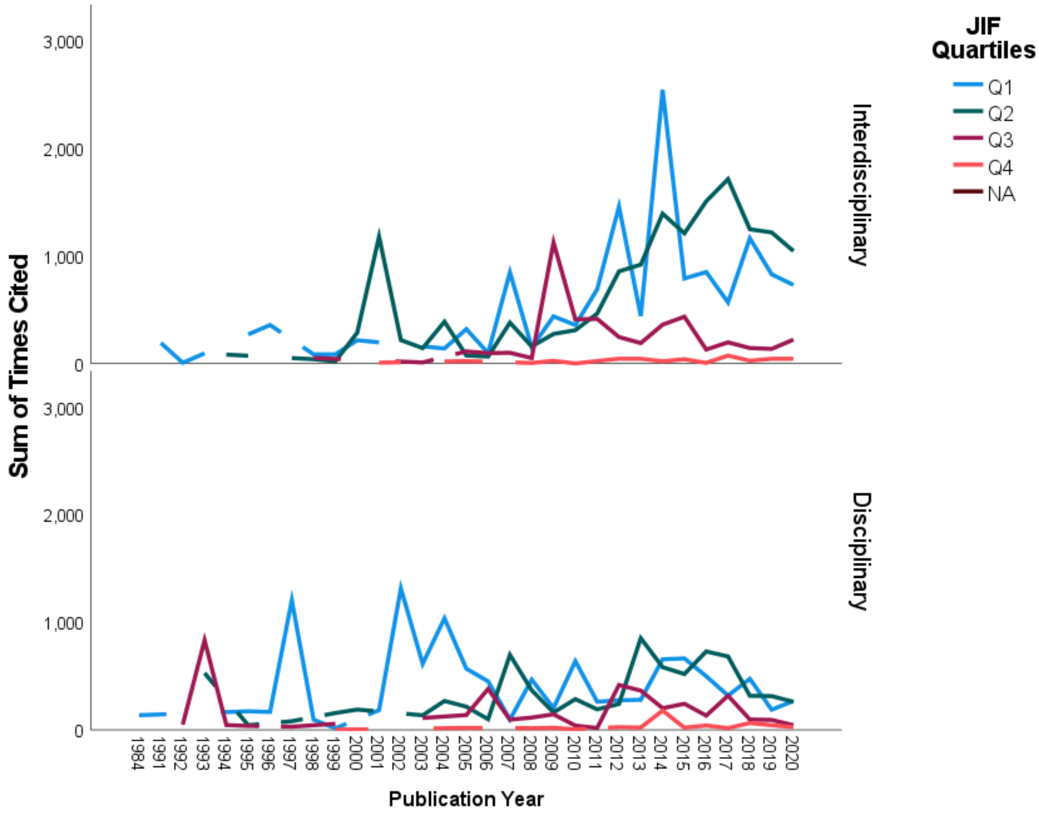

Figure 39: JIF Quartile distribution of interdisciplinary and disciplinary fNIRS articles over time.

Figure 40 shows the annual changes in the sum of citations accrued by fNIRS articles that belong to different collaboration categories for each quartile. The trends suggest that fNIRS articles that are a product of institutional or international collaboration tended to have a larger share in Q1-Q2 journals and also produce a larger share of the total citations. In the early years of fNIRS research, fNIRS studies conducted without institutional or international collaboration tended to generate greater impact, based on their more frequent appearance in Q1 journals and larger share of citations.

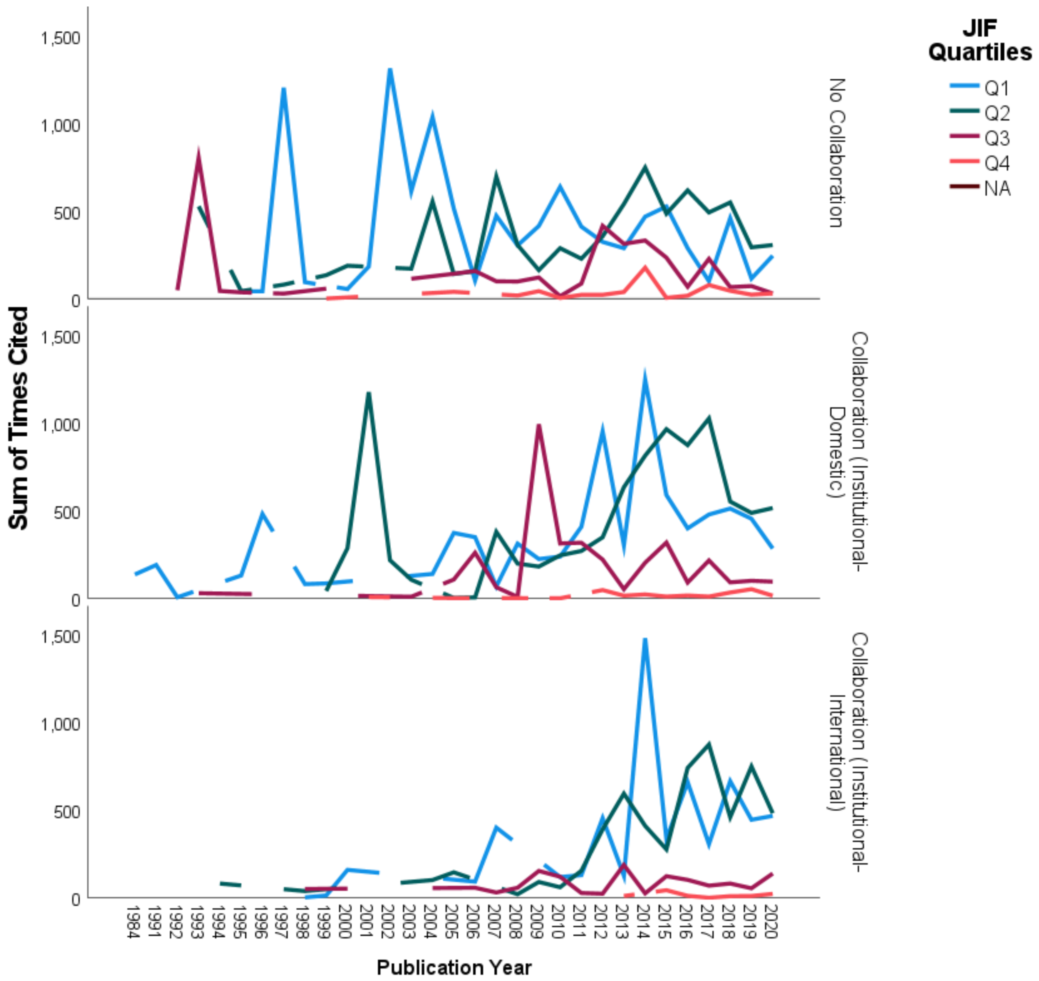

Figure 40: JIF Quartile distribution of fNIRS articles over time.

In order to test whether there is a statistical difference among collaboration and disciplinary categories in terms of their JIF quartile distributions, we conducted chi square tests over the contingency tables indicating the joint frequency distributions of disciplinary and Q categories. The chi-square test indicated significant difference between the quartile distributions of interdisciplinary and disciplinary articles, $\chi^2(3)=20.92$, $p<.01$, which is due to the higher percentage of interdisciplinary articles in Q1 and Q2 categories (Figure 41).

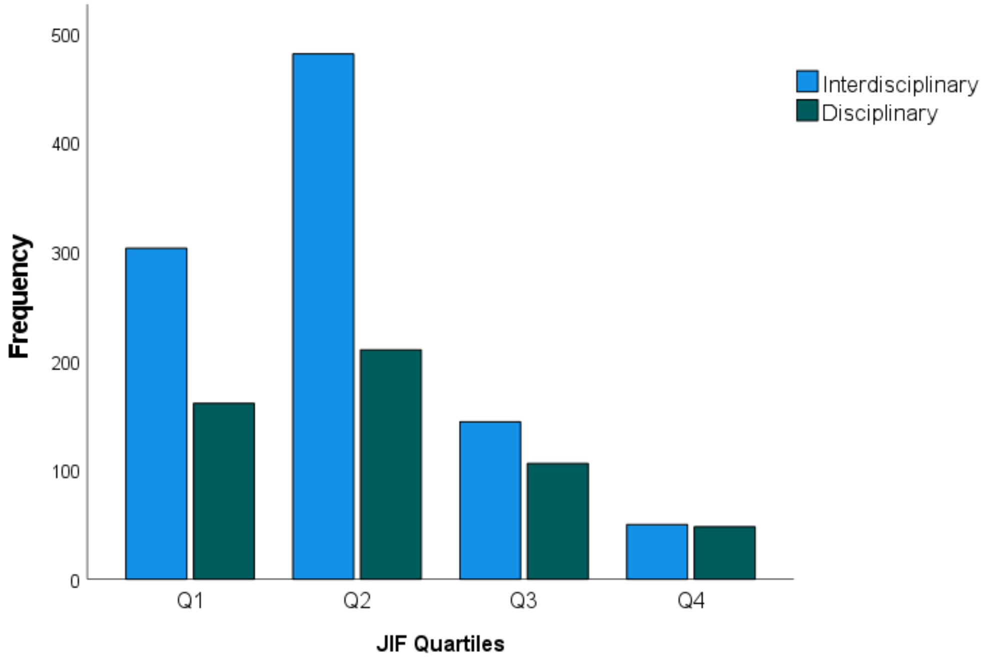

Figure 41: Frequency distributions of disciplinarity and JFI quartile categories.

The chi-square test conducted over collaboration categories and their quartile distributions were also significant, $\chi^2(6)=28.62$, $p<.01$. This difference is largely due to the more frequent appearance of institutional collaboration and international collaboration articles in Q1 and Q2 categories as compared to Q3-Q4 (Figure 42).

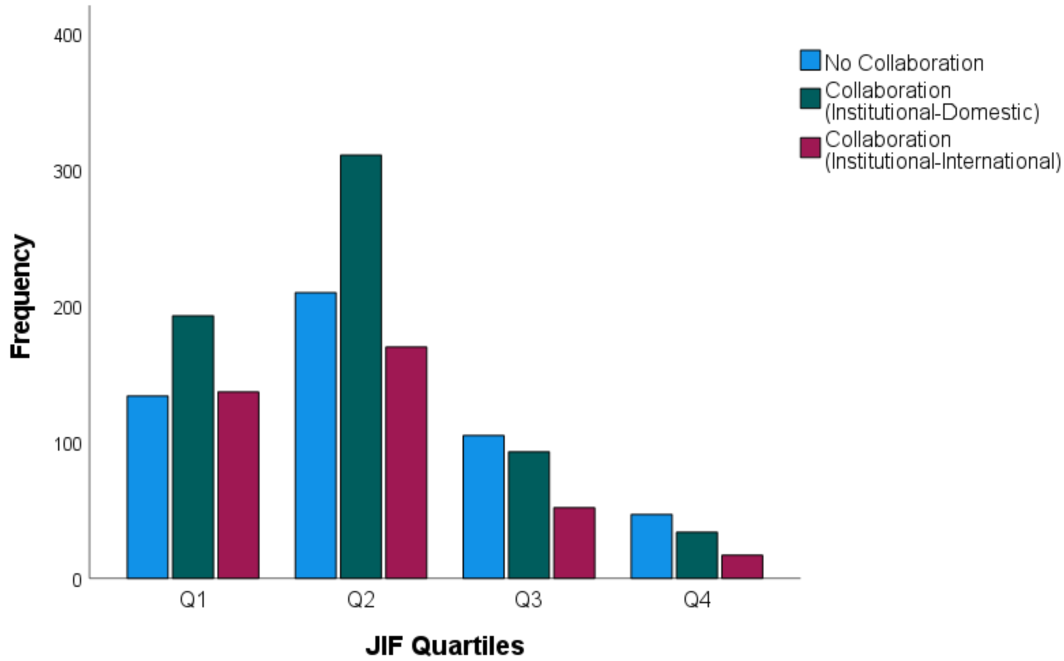

Figure 42: Frequency distributions of collaboration and JFI quartile categories.

4.4. Bibliometric Mapping Analysis of Institutional Collaboration

Given our findings regarding the impact generated by fNIRS publications that are a product of interdisciplinary institutional collaboration, we explored further the nature of these relationships by using bibliometric maps constructed over co-authorship links. Firstly, we used the Biblioshiny tool to identify the most actively contributing institutions to fNIRS literature. The ranking of universities with the most articles in fNIRS studies is shown in Figure 43. According to these results, University of Pittsburgh (USA), Drexel University (USA), University of Tubingen (Germany), Beijing Normal University (China), and Pusan National University (South Korea) form the top 5 most productive institutions.

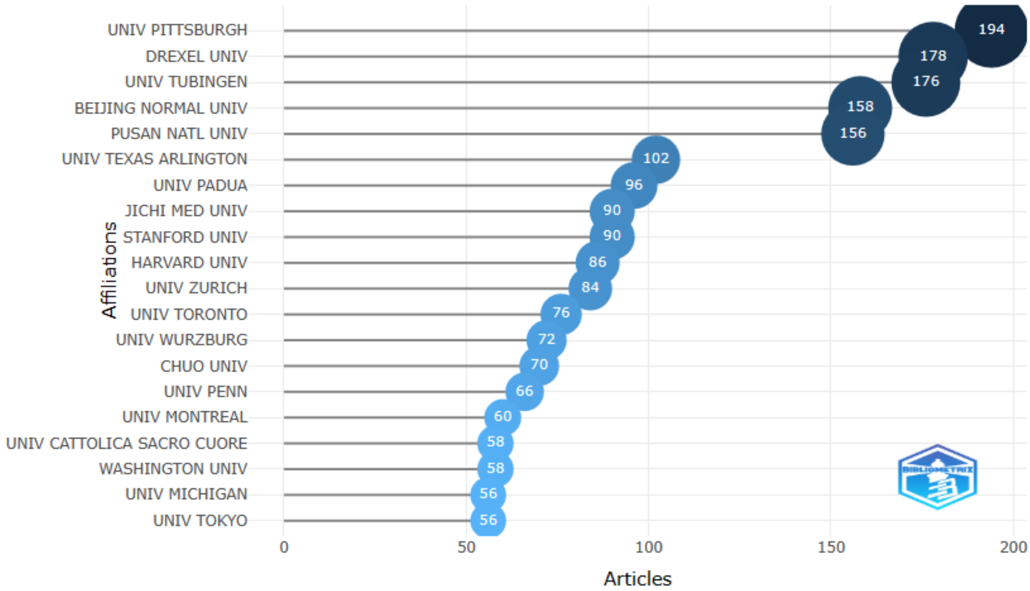

Figure 43: Most actively contributing institutions obtained via Biblioshiny.

Next, we explored the degree of collaborative relationships between these institutions based on co-authorship information. The VOSViewer software allows researchers to build such maps from a collection of articles by visualizing co-authorship links at the author, institution and country levels (Van Eck & Waltmam 2014). For instance, Figure 44 shows the bibliometric mapping of institutions computed over our fNIRS document collection with the VOSViewer software. In this map the nodes represent the institutions, and the lines represent collaboration links based on co-authors' affiliations. The size of each node increases in proportion to the number of articles contributed by that institution. The lines between the nodes represent the collaborative relationship, and the thickness of the connecting lines represents the strength of the cooperation based on the number of co-authored documents involving those institutions. Nodes that are similar to each other based on their co-authorship profiles are positioned nearby whereas dissimilar institutions are positioned further away. The color coding represents the clusters automatically found by VOSViewer based on its clustering algorithm which groups nodes within a certain range of similarity based on two parameters called attraction and repulsion (Waltman et al., 2010). According to the map institutions such as Harvard, Tubingen, Drexel, UCL, Beijing Normal and

Pusan Universities stand out in terms of the number of fNIRS related contributions. However, the co-citation relationships also highlight the role of Harvard, UCL and Stanford as major hubs connecting the rest of the community together. The clusters identified by the VOS algorithm highlight three European clusters based around Zurich, Tubingen and Italy (Padua & Milan), a Japanese cluster around Keio and Chuo Universities, a US cluster around Drexel and Penn, an asian cluster including institutions from Korea and China, as well as a more central cluster including UCL, Harvard and their collaborators in China,

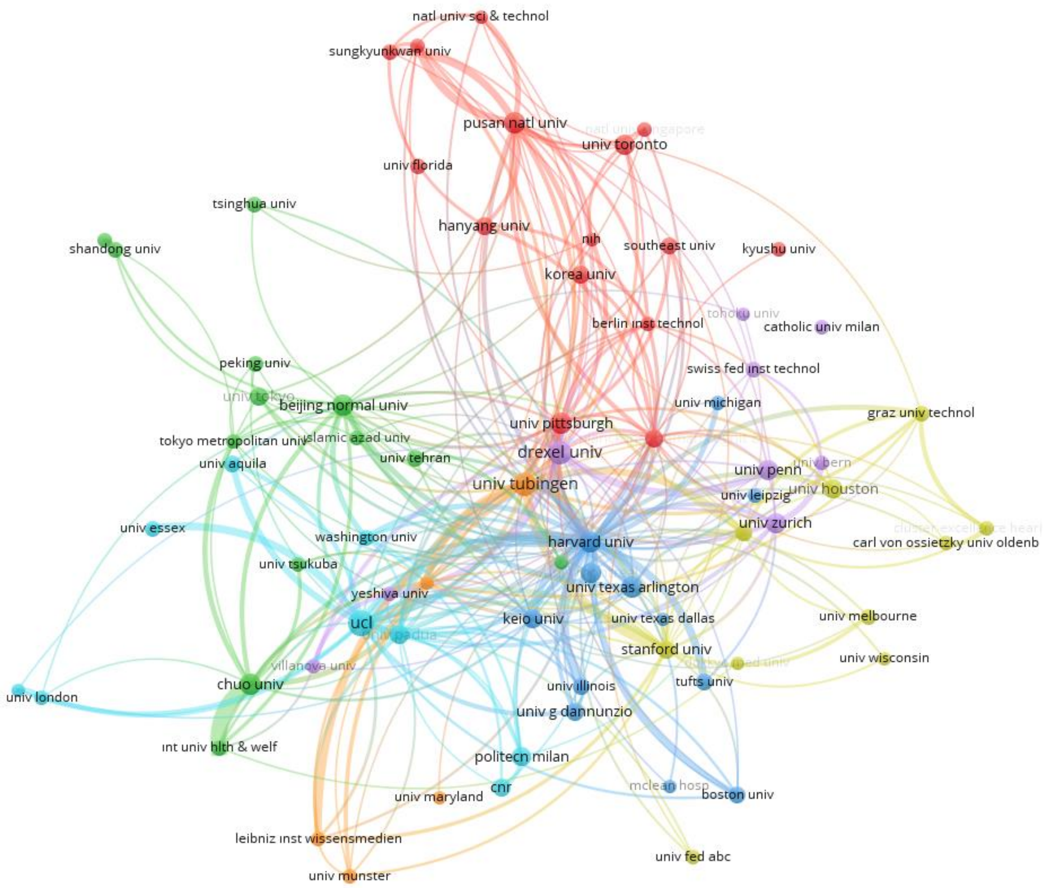

Figure 44: University Collaboration Network in fNIRS articles (Source: VOSviewer).

Figure 45 shows the mapping of collaboration ties among countries/regions associated with fNIRS research, which was produced in VOSViewer over the same dataset. In this case, the nodes represent countries and the size of the nodes grows proportionally to the number of publications originating from that country. The relationship of cooperation is depicted by the presence of edges that connect the nodes, and the thickness of the connecting lines indicates the strength of their cooperation. USA, Japan, Germany, China, England, South Korea and Italy are the top countries for producing fNIRS studies. USA has a high degree of centrality with connections to almost all other countries, particularly with Canada, Japan, England, South Korea, China and Israel. Studies conducted in Turkey appear to be related to the USA, Netherlands, England, Iran and Spain.

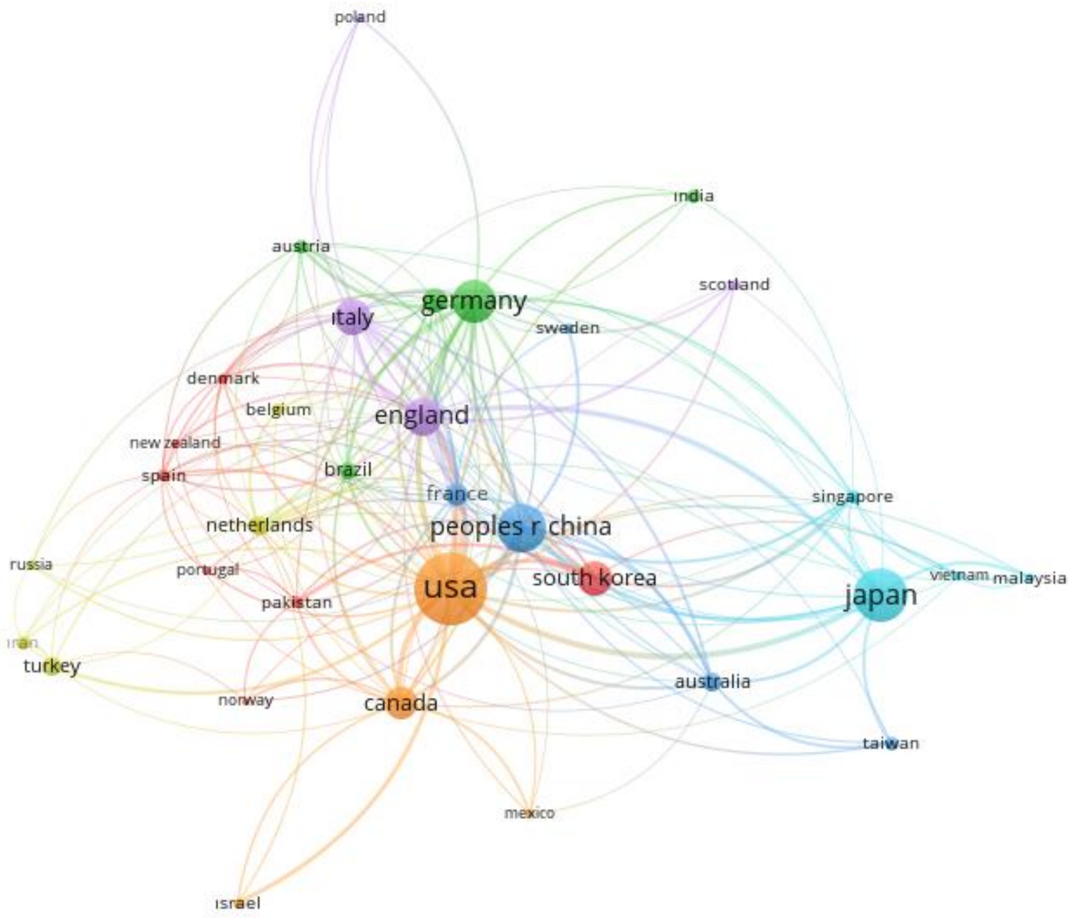

Figure 45: Country Collaborations Network in fNIRS (Source: VOSviewer).

The VOSViewer software does not support the production of co-authorship maps based on address information, which is where the departmental affiliations (e.g. Dept. of Biomedical Eng., Neurology, etc.) of the authors are stated. In an effort to explore institutional collaboration and the nature of interdisciplinarity in fNIRS, we utilized the Leximancer software's text mining features to build a similar bibliometric map showing the relationships at the department level, which is indicative of the disciplinary roots of the contributing institutions.

Table 10 shows the co-occurrence matrix for the mentioned sections were obtained thanks to the text mining made in the address sections of the articles with the Leximancer program. The weight column provides information about how many times each department name is mentioned in the address sections of this dataset. The table includes the first 30 disciplines ranked with respect to weight. Departments of Neurology, Radiology, Biomedical Eng., Pediatrics, Psychiatry and Psychology are the most frequently mentioned departments/disciplines. The rest of the table shows the co-occurrence frequencies of the top 30 most frequent department names. The cells of the co-occurrence matrix indicates the number of times the corresponding pair of department names appeared in the address list of the same article.

Table 10: Discipline (department) co-occurrence matrix

Concept	weight	Dept Neurol	Dept Radiol	Dept Biomed Engn	Dept Pediat	Dept Psychiat	Dept Psychol	Dept Neurosurg	Dept Anesthesiol	Dept Phys	Dept Neurosci	Dept Surg	Dept Physiol	Dept Bioengn	Dept Pathol	Dept Med Phys	Dept Elect Engn	Dept Neonatol	Dept Neurol Surg	Dept Comp Sci	Dept Biostat	Dept Chem	Dept Anesthesia	Dept Neurobiol	Dept Neuropsychiat	Dept Paediat	Dept Pharmacol	Dept Cardiol	Dept Clin Neurosci	Dept Mech Engn	Dept Brain & Cog
Dept Neurol	706	547	89	44	51	36	36	61	50	45	22	21	14	17	18	4	10	4	7	4	12	4	5	4	2	1	7	9	6	4	3
Dept Radiol	695	89	484	86	49	60	26	35	24	50	17	17	19	36	19	10	16	11	10	1	11	9	1	6	3	0	3	3	8	5	2
Dept Biomed Engn	545	44	86	508	28	26	25	24	16	34	16	16	18	5	23	5	28	3	13	13	4	12	3	8	0	0	3	1	2	8	6
Dept Pediat	495	51	49	28	398	18	34	19	42	17	14	20	15	16	12	1	9	30	4	0	7	2	7	6	2	16	4	6	1	4	0
Dept Psychiat	455	36	60	26	18	503	82	12	8	8	38	4	6	15	3	20	3	0	0	4	1	3	0	3	35	0	1	0	1	3	6
Dept Psychol	402	36	26	25	34	82	728	6	1	14	15	2	10	18	0	18	8	3	9	5	3	1	1	6	5	0	6	0	2	3	7
Dept Neurosurg	370	61	35	24	19	12	6	324	32	14	7	16	8	10	20	2	8	1	8	3	2	3	6	4	0	0	2	1	5	4	0
Dept Anesthesiol	345	50	24	16	42	8	1	32	289	17	4	25	11	7	6	0	2	6	3	0	9	1	13	2	2	1	3	5	4	0	0
Dept Phys	311	45	50	34	17	8	14	14	17	214	10	7	8	9	7	2	5	3	0	0	12	6	1	0	2	0	1	0	0	2	0
Dept Neurosci	249	22	17	16	14	38	15	7	4	10	152	1	9	7	4	19	3	0	2	3	0	2	1	3	3	2	4	0	2	3	1
Dept Surg	239	21	17	16	20	4	2	16	25	7	1	148	5	8	13	2	7	0	2	3	4	4	8	4	0	1	2	2	1	0	0
Dept Physiol	229	14	19	18	15	6	10	8	11	8	9	5	211	1	5	5	3	1	2	1	1	4	3	1	2	2	6	5	3	1	1
Dept Bioengn	222	17	36	5	16	15	18	10	7	9	7	8	1	152	2	1	8	0	5	3	2	1	1	5	0	0	5	0	0	2	0
Dept Pathol	188	18	19	23	12	3	0	20	6	7	4	13	5	2	104	0	3	2	7	1	4	6	5	4	0	0	0	0	0	1	0
Dept Med Phys	175	4	10	5	1	20	18	2	0	2	19	2	5	1	0	212	2	7	2	23	0	1	0	1	0	12	0	2	1	0	1
Dept Elect Engn	172	10	16	28	9	3	8	8	2	5	3	7	3	8	3	2	162	1	5	10	1	1	1	0	3	2	2	0	1	3	2
Dept Neonatol	108	4	11	3	30	0	3	1	6	3	0	0	1	0	2	7	1	158	0	0	2	0	0	1	0	12	0	4	0	0	0
Dept Neurol Surg	103	7	10	13	4	0	9	8	3	0	2	2	2	5	7	2	5	0	80	1	2	2	1	1	0	0	0	1	0	1	0
Dept Comp Sci	100	4	1	13	0	4	5	3	0	0	3	3	1	3	1	23	10	0	1	101	1	0	0	0	0	4	0	0	0	1	6
Dept Biostat	97	12	11	4	7	1	3	2	9	12	0	4	1	2	4	0	1	2	2	1	52	1	2	0	0	0	0	4	0	0	0
Dept Chem	81	4	9	12	2	3	1	3	1	6	2	4	4	1	6	1	1	0	2	0	1	72	0	1	0	1	1	0	0	3	0

Table 10 (continued).

Dept Anesthesia	75	5	1	3	7	0	1	6	13	1	1	8	3	1	5	0	1	0	1	0	2	0	79	0	0	0	0	2	1	0	0
Dept Neurobiol	73	4	6	8	6	3	6	4	2	0	3	4	1	5	4	1	0	1	1	0	0	1	0	64	0	0	2	0	0	0	0
Dept Neuropsychiat	67	2	3	0	2	35	5	0	2	2	3	0	2	0	0	0	3	0	0	0	0	0	0	0	96	0	0	0	0	0	3
Dept Paediat	65	1	0	0	16	0	0	0	1	0	2	1	2	0	0	12	2	12	0	4	0	1	0	0	0	58	1	2	0	0	0
Dept Pharmacol	64	7	3	3	4	1	6	2	3	1	4	2	6	5	0	0	2	0	0	0	0	1	0	2	0	1	60	0	0	0	0
Dept Cardiol	60	9	3	1	6	0	0	1	5	0	0	2	5	0	0	2	0	4	1	0	4	0	2	0	0	2	0	36	0	0	0
Dept Clin Neurosci	53	6	8	2	1	1	2	5	4	0	2	1	3	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	48	1	0
Dept Mech Engn	53	4	5	8	4	3	3	4	0	2	3	0	1	2	1	0	3	0	1	1	0	3	0	0	0	0	0	0	1	45	1
Dept Brain &Cog	46	3	2	6	0	6	7	0	0	0	1	0	1	0	0	1	2	0	0	6	0	0	0	0	3	0	0	0	0	1	61

Weight is the sum of the co-occurrence count values of the concept with all the other concepts (these values should be integers, but there is a small precision loss - just round the value to get the integer back).

The co-occurrence matrix is then transformed into a graph in the Leximancer program which computes a spatial layout for the 30 department names over 2D space based on their similarities in terms of their co-occurrence vectors, and also clustered based on their similarity. In this visualization, circles represent themes, which are collections of relevant concepts, and dots represent concepts, which are collections of words with related meanings. The color of the circles (brighter circles indicate greater importance) and their size (larger sizes indicate that more concepts have been grouped to form a particular theme) demonstrate the significance of the themes. In this particular representation, dots represent the department names, and the themes are abstractions that can be named based on the groupings of the departments. The degree to which two concepts are related is indicated by the distance between them. The results obtained with the Leximancer program were analyzed in 9 main groups, which highlight the modular organization of the discipline terms (Figure 46).

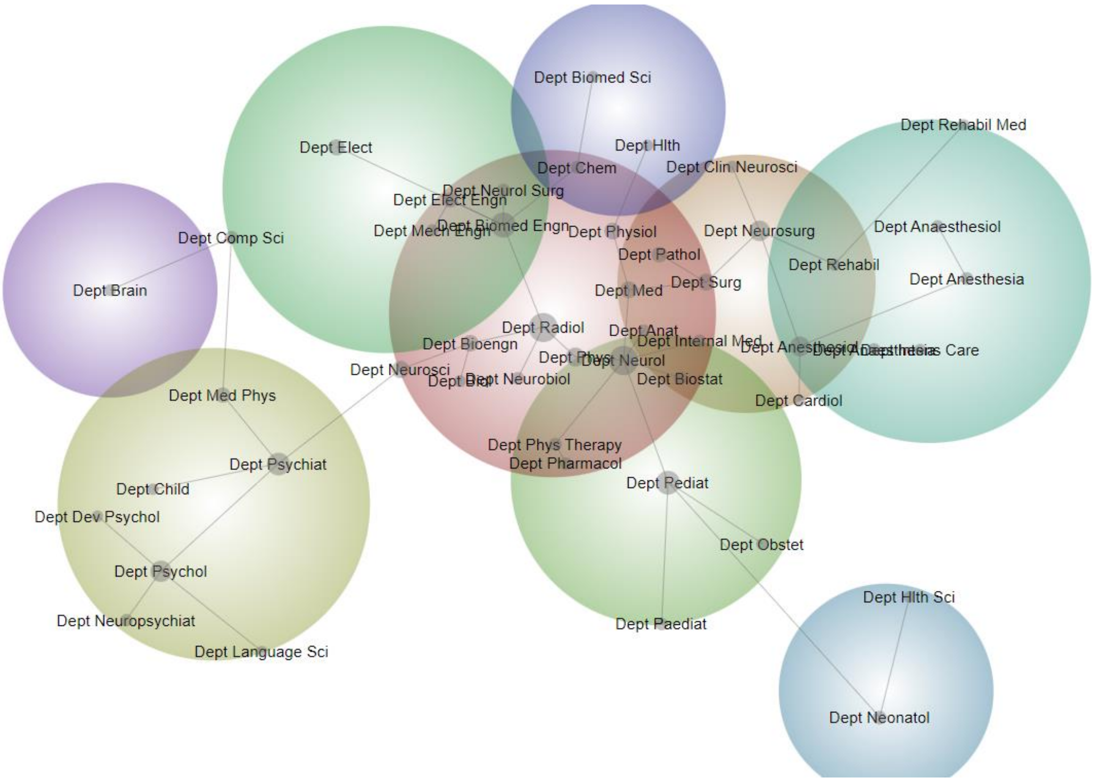

Figure 46: Modularity Analysis of Disciplines (Department) in the fNIRS between 1980-2020 (Source: Leximancer).

Figure 46 shows that there are recognizable disciplinary clusters or modules centered around the theme populated by Radiology, Neuroscience and Physiology with strong connections to Biomedical and Electrical/Electronics Engineering. A cluster including Developmental Psychology, Language Development and Psychiatry is connected to the central cluster via Neuroscience. Clinical clusters including Anesthesiology, Neonatal Medicine, Pediatrics, and Surgery can be also recognized.

4.5 Keyword Mapping Analysis

In an effort to explore research topics/themes in fNIRS we conducted a bibliometric mapping of keywords (also called as a termmap) extracted from the title, author selected keywords and the abstracts of the articles in our dataset. We used the VOSviewer software to extract and map the keywords.

Our initial review of the frequently used keywords in the fNIRS literature suggested that the keywords can be grouped under 6 main dimensions (the full list is provided in Appendix C):

1. Imaging Method/Analysis Methodology/Physical Phenomenon (light, optics etc.)
2. Physiological Phenomena
3. Cognitive Processes/Abnormalities
4. Application Area
5. Brain Regions
6. Population

A review of the top 50 frequently occurring keywords across these dimensions provide a quick overview of fNIRS research in the past 40 years (Table 11). For instance, under the third dimension working memory, attention, Alzheimer’s disease, traumatic brain injury, verbal fluency task, perception, executive functions, language appear as some of the topics classified under cognitive processes and/or abnormalities investigated with fNIRS. Application areas such as brain-computer interfaces, exercise, gait, surgery, aging, movement, recovery (from anesthesia), walking, stress, rehabilitation and pain illustrate some of the areas where fNIRS is frequently utilized, especially in activity/rehabilitation setups due to its portability. Moreover, some of the frequently referenced brain regions are prefrontal cortex, premotor/motor cortex, auditory cortex, somatosensory cortex, parietal cortex, hemispheric lateralization, and visual cortex, indicating the variety of the regions investigated with existing fNIRS systems. Due to fNIRS’ limitation in monitoring deep structures, the anatomical keywords tend to focus on the cortex. The population dimension suggests that fNIRS is most frequently used with a diverse human population including newborns, infants, children, adolescents, adults, and older adults as well as animal populations including piglets/swine, rats/mice and monkeys.

Table 11: Top 50 keywords each group network

Imaging Method/Analysis Methodology/Physical Phenomenon (light, optics etc.)		Physiological Phenomena		Cognitive Processes/Abnormalities		Application Area		Brain Regions		Population	
Keywords	**#occurrences**	**Keywords**	**#occurrences**	**Keywords**	**#occurrences**	**Keywords**	**#occurrences**	**Keywords**	**#occurrences**	**Keywords**	**#occurrences**
fMRI	514	oxygenation	319	working memory	324	bci	223	prefrontal cortex	652	infant	227
EEG	253	hemodynamic response	263	attention	170	exercise	105	cortex	480	children	211
stimulation	158	cerebral oxygenation	183	Alzheimer's disease	140	gait	103	human brain	264	motor imagery	127
diffuse optical tomography	151	functional connectivity	183	traumatic brain injury	132	surgery	93	motor cortex	105	humans	112
MRI	148	stroke	174	schizophrenia	131	cardiopulmonary bypass	90	visual cortex	100	older adults	101
tomography	119	cerebral hemodynamics	159	verbal fluency task	126	aging	89	frontal cortex	77	rat	95
metaanalysis	98	network	150	perception	115	cardiac surgery	88	auditory cortex	59	preterm infants	92
oximetry	86	saturation	131	executive function	114	movement	71	dorsolateral prefrontal cortex	59	adult	86
sensitivity	86	autoregulation	125	cognition	105	recovery	67	default mode	50	newborn	67
fluorescence	84	connectivity	115	brain injury	105	therapy	65	somatosensory cortex	50	cells	62
positron-emission-tomography	78	metabolism	110	language	104	walking	64	anterior cingulate cortex	43	individual-differences	57
resolution	77	tissue oxygenation	107	motor	95	injury	62	lateralization	40	neonate	52
functional mri	73	perfusion	106	time	93	stress	61	parietal cortex	37	newborn-infants	52
optical topography	72	hemoglobin	101	recognition	86	rehabilitation	60	cerebral-cortex	35	adult head	46
scattering	72	oxygen-saturation	87	memory	83	reconstruction	57	frontal lobe	33	mice	41
light-propagation	70	intracranial pressure	77	emotion	83	pain	54	premotor cortex	33	rat-brain	38

Table 11 (continued).

microscopy	68	ischemia	77	depression	82	diagnosis	52	barrel cortex	32	preterm	37
interference	67	neurovascular coupling	77	behavior	73	anesthesia	52	orbitofrontal cortex	30	premature-infants	34
validation	66	flow	76	speech	68	cooperation	45	prefrontal activation	29	infancy	32
optical-properties	64	communication	73	dysfunction	63	sex-differences	41	asymmetry	27	birth-weight infants	27
modulation	63	oscillations	65	Parkinson disease	60	development	38	primary motor cortex	26	mouse	24
spatial registration	63	plasticity	65	cognitive control	59	sleep	36	amygdala	25	mouse-brain	24
bold	57	hypoxia	64	dementia	51	glioma	36	inferior frontal gyrus	25	adolescents	23
coherence	57	cerebral autoregulation	63	executive functions	50	balance	36	temporal cortex	24	childhood	23
diffuse correlation spectroscopy	57	neural activity	63	resting state	49	cancer	34	hemispheric-asymmetry	20	mouse model	23
bold signal	55	low-frequency oscillations	57	mild cognitive impairment	49	motion	32	human visual-cortex	20	neonatal encephalopa thy	19
transcranial magnetic stimulation	54	cortical activation	56	decision-making	49	glioblastoma	32	resting-state functional connectivity	20	awake infants	17
independent component analysis	53	heart rate variability	53	response inhibition	46	virtual reality	31	state functional connectivity	20	gender	17
photon migration	52	reactivity	52	bipolar disorder	46	physical-activity	30	dlpfc	19	transgenic mice	17
topography	51	cerebrovascular autoregulation	50	mental workload	44	subarachnoid hemorrhage	29	prefrontal cortex activity	19	young	16
hyperscanning	50	inhibition	50	epilepsy	41	neurofeedback	29	resting-state	19	young-children	16
optical pathlength	50	cerebral blood volume	48	risk	40	breast	27	primary somatosensory cortex	18	infant brain	15
false discovery rate	48	absorption	47	speech perception	39	age-related-changes	27	functional architecture	17	women	15
transcranial doppler	48	cerebral oxygen saturation	47	impairment	35	resection	25	mirror neuron system	17	newborn piglets	14
optical tomography	46	heart rate	43	imagery	35	therapeutic hypothermia	24	primary visual-cortex	17	neonatal	13

Table 11 (continued).

cerebral oximetry	43	delivery	40	visual-stimulation	34	motor control	24	sensorimotor cortex	17	swine model	13
turbid media	42	blood-volume	39	fatigue	34	feedback	24	ventrolateral prefrontal cortex	17	adult brain	12
indocyanine green	41	hypothermia	39	anxiety	33	brain-development	24	frontal activation	16	gender-differences	12
resuscitation	41	hypoxic-ischemic encephalopathy	38	verbal fluency	32	neuroprotection	23	medial prefrontal cortex	16	handedness	12
artifacts	39	muscle	38	stroop task	32	neuroergonomics	23	reduced frontopolar activation	16	sheep	12
event-related fmri	39	blood-pressure	35	dual task	32	drug-delivery	23	white-matter	16	monkey	11
optical spectroscopy	39	oxyhemoglobin	35	cognitive impairment	31	imitation	22	resting-state networks	15	elderly	10
simulation	39	hypercapnia	34	attention-deficit/hyperactivity disorder	31	locomotion	20	supplementary motor area	15	healthy	10
functional magnetic resonance imaging	35	perfusion-pressure	34	abnormalities	31	carotid-endarterectomy	20	basal ganglia	14	prematurity	10
monte carlo simulation	35	arterial	33	emotion regulation	30	breast-cancer	20	cortex activity	14	child	9
nanoparticles	35	intraventricular hemorrhage	33	deficits	30	neurodevelopmental outcomes	19	default mode network	14	elderly subjects	9
synchronization	35	cardiac arrest	31	cognitive performance	29	maximal exercise	19	parietal	14	elderly-patients	9
reflectance	34	excitability	31	sustained attention	28	incremental exercise	19	lateral prefrontal cortex	13	patient	9
in-vitro	33	oxygenated hemoglobin	29	social cognition	28	cardiopulmonary-resuscitation	19	human cerebral-cortex	12	sex	9
cerebral perfusion	32	oxygenation changes	29	major depressive disorder	28	neurorehabilitation	18	human motor cortex	12	age-related differences	8

Pure frequency counts do not reveal how the keywords are related and how their prominence and relationship structure change over time. In an effort to explore the prominence and the mutual relationships among topics, we produced keyword co-occurrence maps by using the VOSviewer software for 10 year-long overlapping durations of time.

Figure 47 shows the keyword co-occurrence map computed by the VOSviewer software for the fNIRS publications between 1995-2005. The VOS similarity-based clustering algorithm suggested 4 clusters that are represented in different colors. This time period mainly marked the emergence of fNIRS as a neuroimaging modality focusing on hemodynamic response effects, so its not surprising to observe keywords such as hemoglobin, cerebral oxygenation, hemodynamics, cerebral blood volume as prominent keywords since they constitute what is aimed to be measured with fNIRS and more generally with optical biomedical imaging methods. Light scattering properties of cellular structures such as mitochondria, cytochrome oxidase, and hemoglobin can be considered as part of the initial attempts to understand the relationship between optical measurements and the presence of these targeted molecules in tissue. Time resolved spectroscopy, monte carlo simulations of photon migration paths, tissue oxygen saturation are also related concepts to these efforts. Another related effort in quantifying blood flow involves methodology concepts such as laser doppler flowmetry, as well as their use in cases where blood flow is disrupted such as hypoxia, ischemia/stroke, hypercapnia (i.e. too much carbondioxide saturation) and surgical processes like carotid endarterectomy. Another related set of concepts cluster around the concept of voltage sensitive dyes, which can be used together with optical microscobic/spectroscopic techniques to probe into more fine-grained processes such as monitoring neurotransmitter dynamics, such as GABA. Animal models with rats and newborn piglets also appear in the map, albeit closer to different sets of keywords, possibly because piglets are mainly used as models for sensor testing due to its close resemblance to human skull and tissue as a model, whereas rats primarily served as models for more fine grained processes like neurotransmitter release patterns and for validating the fNIRS method with the combined use of invasive, single cell recording techniques to explore the relationship between neural activity and hemodynamic responses.

Overall, this landscape indicate that the primary focus is on basic science studies that aim to establish the veridicality of the fNIRS method for monitoring brain activity related phenomenon. There are a few application oriented prominent keywords such as neonates/newborns and aging, which are one of the earliest adopters of fNIRS for monitoring cerebral oxygenation trends in these delicate populations, and cognitive processes such as language processing and working memory. However, these topics are not as prominent as the methodology-oriented topics, where the focus seems to establish fNIRS as a veridical neuroimaging modality.

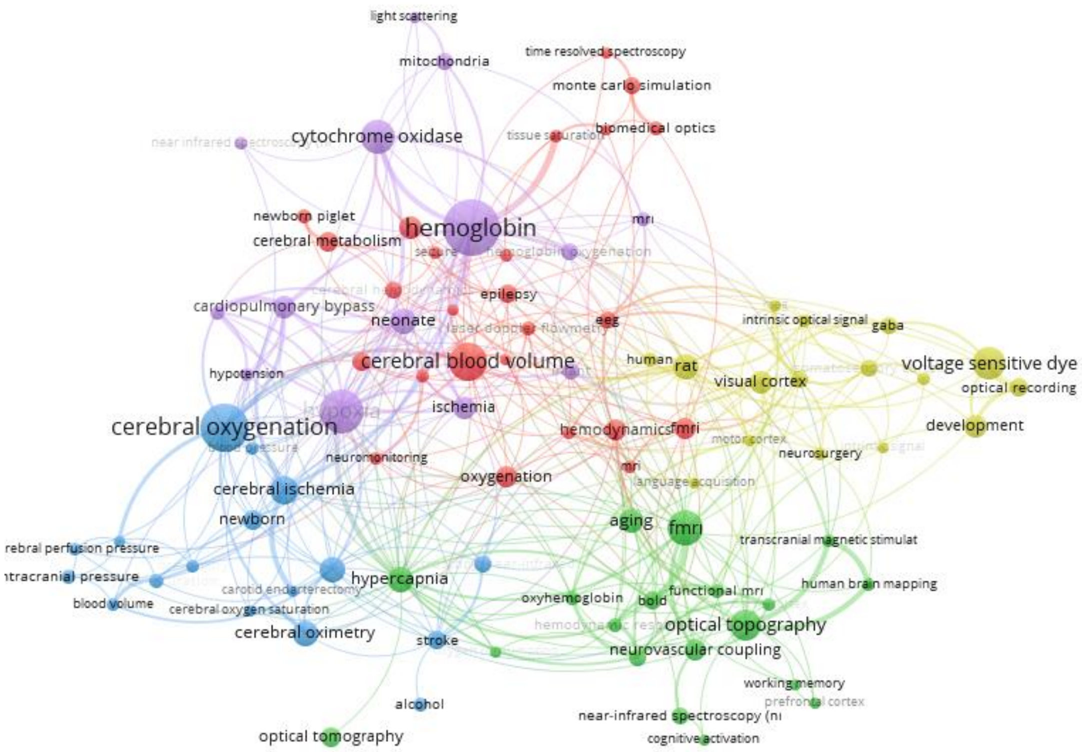

Figure 47: VOSviewer visualization of keywords in the field of fNIRS between 1995-2005

Figure 48 shows the keyword co-occurrence map for the period 2000-2010. In addition to the methodology-oriented themes summarized for the previous time period, there are application areas such as exercise and cognitive processes recruiting prefrontal cortex resources in the context of tasks such as verbal fluency and Stroop tasks. Cognitive processes such as attention and emotion begin to gain prominence, in tandem with related disorders such as depression. There is also an increasing presence of other modalities such as EEG and fMRI, where EEG is primarily utilized in obtaining multimodal measures of brain activity together with fNIRS, whereas fMRI is mainly utilized to cross validate the hemodynamic responses reported by fNIRS. The name of a new NIRS technique called diffuse optical tomography seems to have gained prominence in this time-period as a novel design to enable fNIRS recordings at multiple depths to provide 3D images up to a certain depth in cerebral cortex.

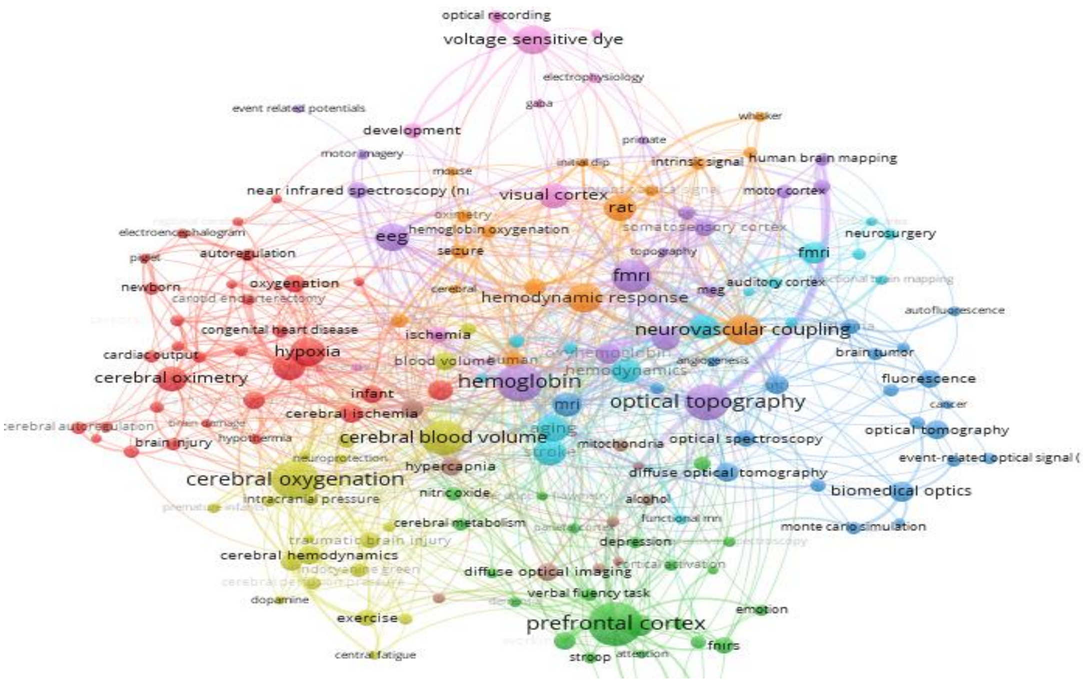

Figure 48: VOSviewer visualization of keywords in the field of fNIRS between 2000-2010

Next, Figure 49 shows the keyword distribution in the time period 2005-2015. Application areas of fNIRS seem to be gaining further prominence and diversity. For instance, brain computer-interfaces (BCI) and associated themes such as motor imagery and motor execution have become more visible in this time period. Applications over sensitive populations such as neonates, children and elderly have also become more prominent, along with themes around cognitive processes such as language acquisition, speech perception, emotion, emotion regulation, and disorders such as depression, schizophrenia, and dementia. Functional connectivity has emerged as a new methodological theme indicating the gradual shift of emphasis from regional brain responses to connectivity patterns. Diffuse correlation spectroscopy also gained prominence in this period as a new method within NIRS for monitoring blood flow in cortical tissue. Another emerging theme around fluorescence also mark the improving prominence of these techniques in so-called wet lab uses of NIRS techniques in the lab for imaging purposes at molecular levels.

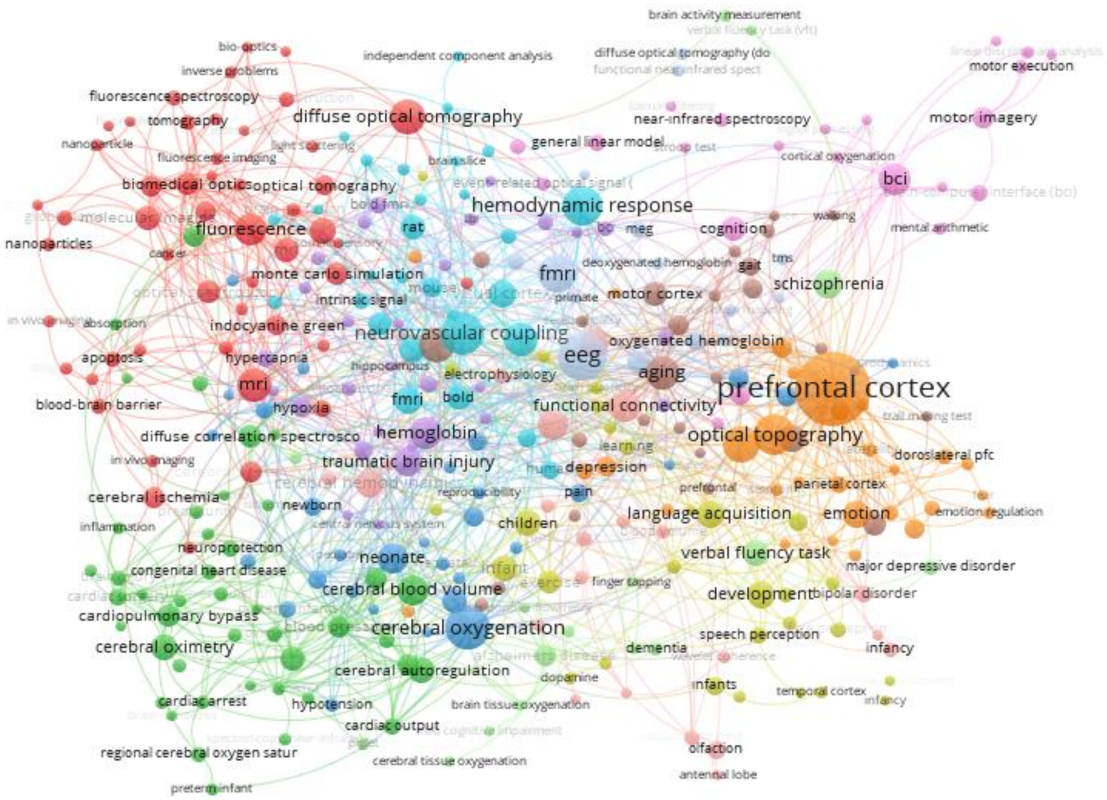

Figure 49: VOSviewer visualization of keywords in the field of fNIRS between 2005-2015

Figure 50 shows the co-ocurrance map for the last 10 years of fNIRS research. One can observe the emergence of new themes around the most prominent term prefrontal cortex, such as hyperscanning that involves simultaneous fNIRS recordings obtained from two or more subjects, focusing on social cognition related themes like eye contact, cooperation, and mirror neurons. BCI also improved its prominence with the addition of neurofeedback, motor imagery, and mental workload as related themes. Keywords related to functional connectivity methods such as resting state and wavelet coherence also exhibited increased prominence. The use of biophotonics methods on detecting brain tumor and glioma also gained some prominence in relation to progress in in-vivo fleuroscence imaging methods.

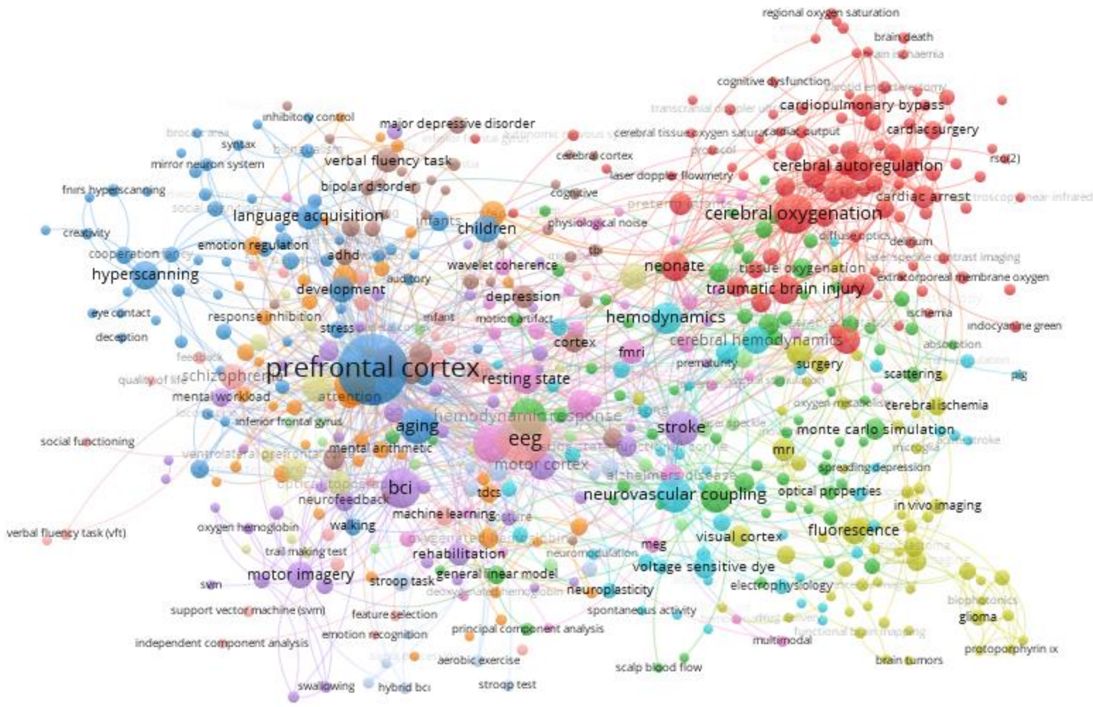

Figure 50: VOSviewer visualization of keywords in the field of fNIRS between 2010-2020

4.6. Co-citation Analysis

A popular analysis approach in Bibliometrics that complements the co-occurrence based term map analysis is to map highly cited articles and authors based on their co-citation profiles. In this case two articles or authors that are frequently cited together by other articles of a field are treated as similar. Figures 51-60 shows the co-citation maps generated with the VOSviewer software for the authors and the articles in five 10-year-long overlapping time periods. The changes in the centrality and the density of the connections show how the field has evolved within this timeframe. In the early days of the field's inception, pioneering studies that laid the basic groundwork are the most prominent nodes in the co-citation maps, featuring authors such as Chance, Jobsis, Wyatt, Cope and Delpy. As we get closer to the current time we tend to see new actors and articles, such as Boas, Ayaz, Ferrari, Huppert, Cui who made methodological contributions, authored influential reviews of the field, and expanded the use of fNIRS to new fields such as hyperscanning and neuroergonomics.

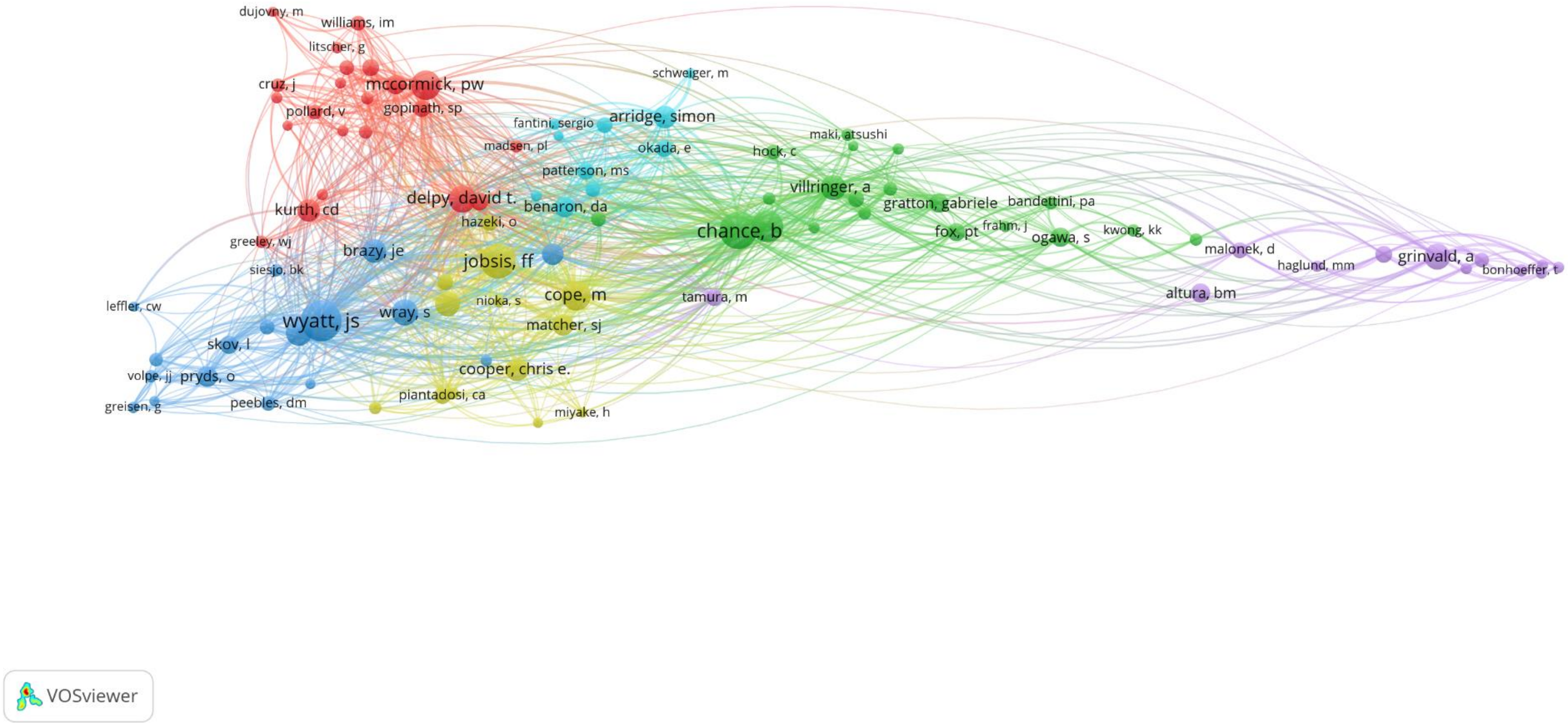

Figure 51: VOSviewer visualization of author co-citation map in the field of fNIRS between 1990-2000

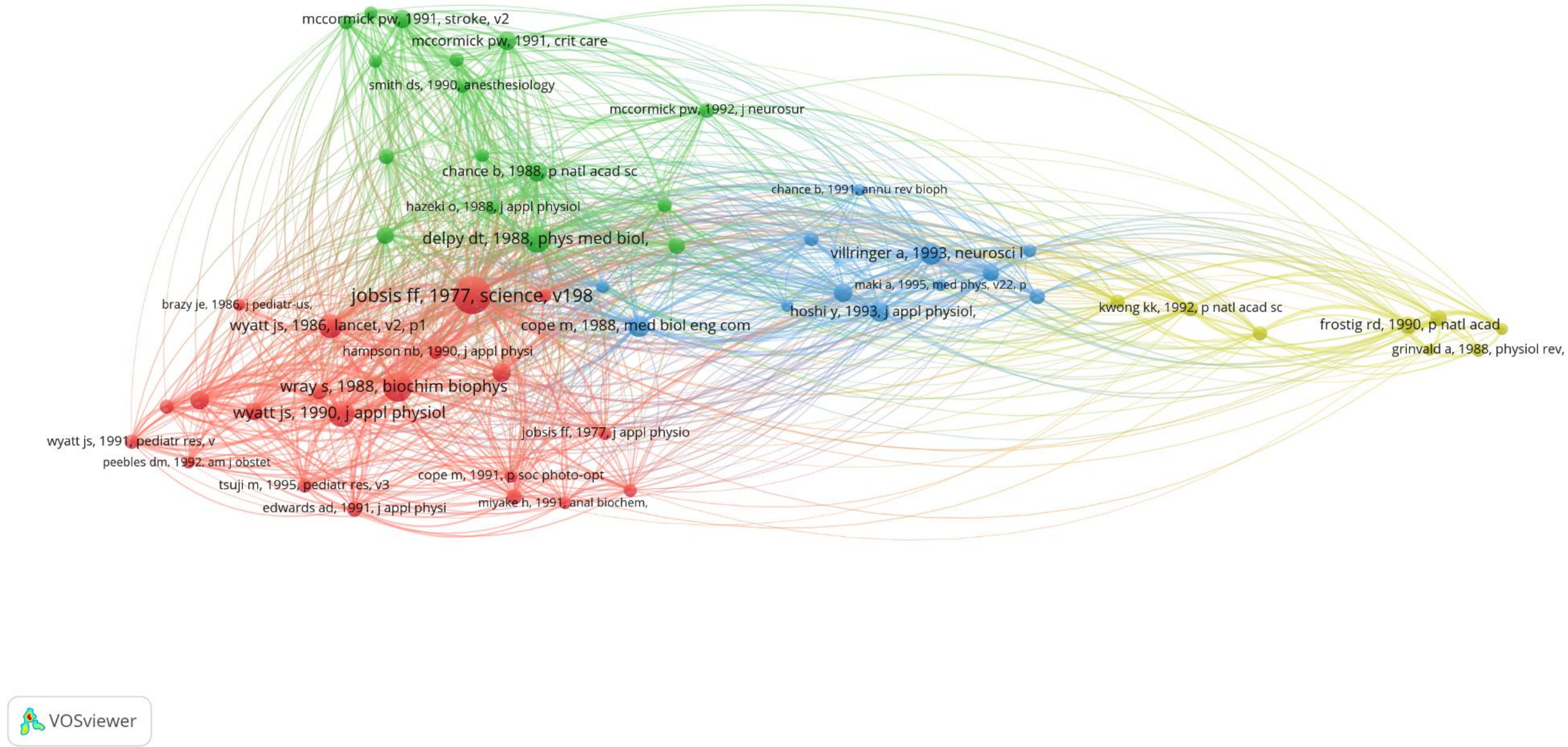

Figure 52: VOSviewer visualization of article co-citation map in the field of fNIRS between 1990-2000

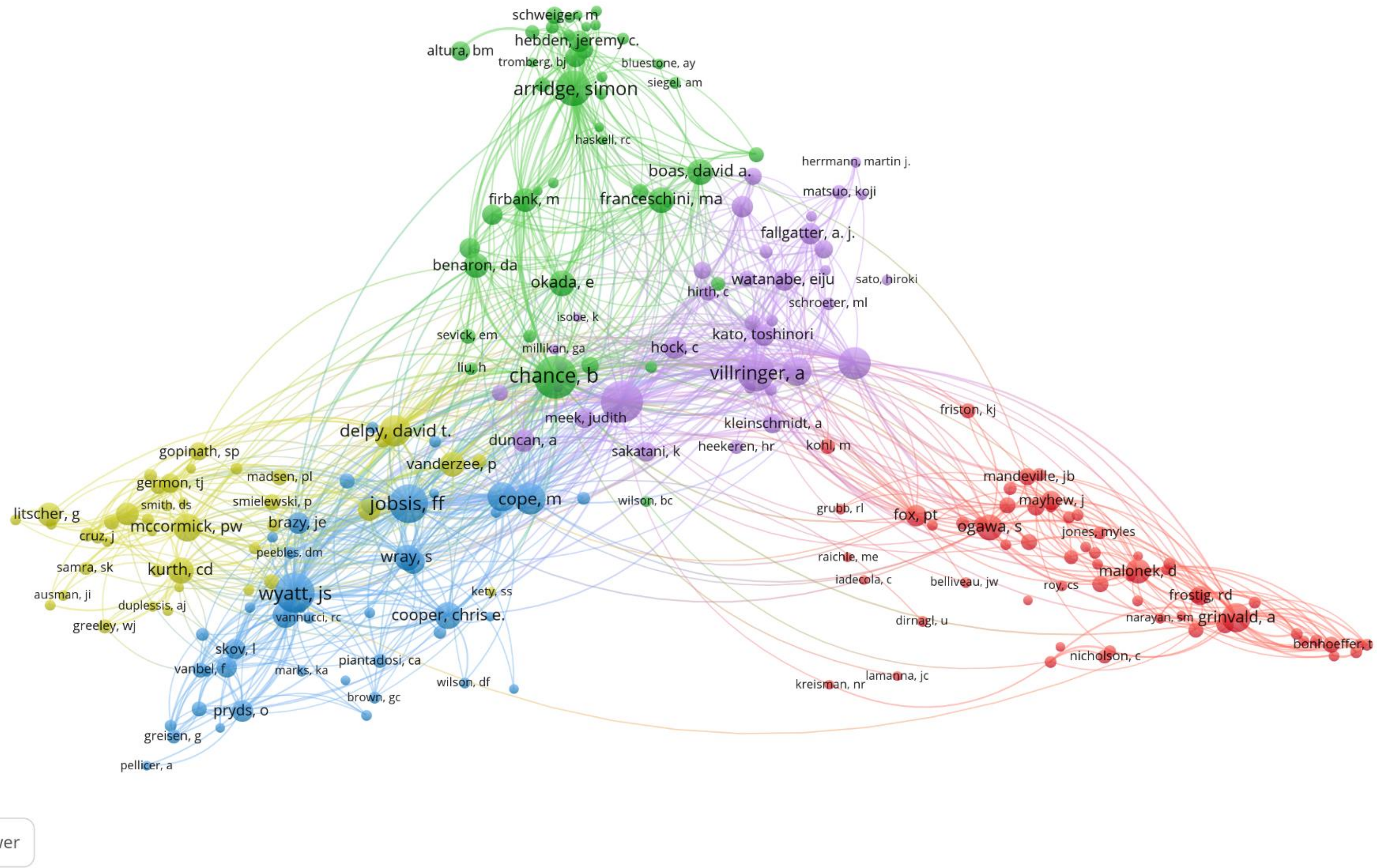

Figure 53: VOSviewer visualization of author co-citation map in the field of fNIRS between 1995-2005

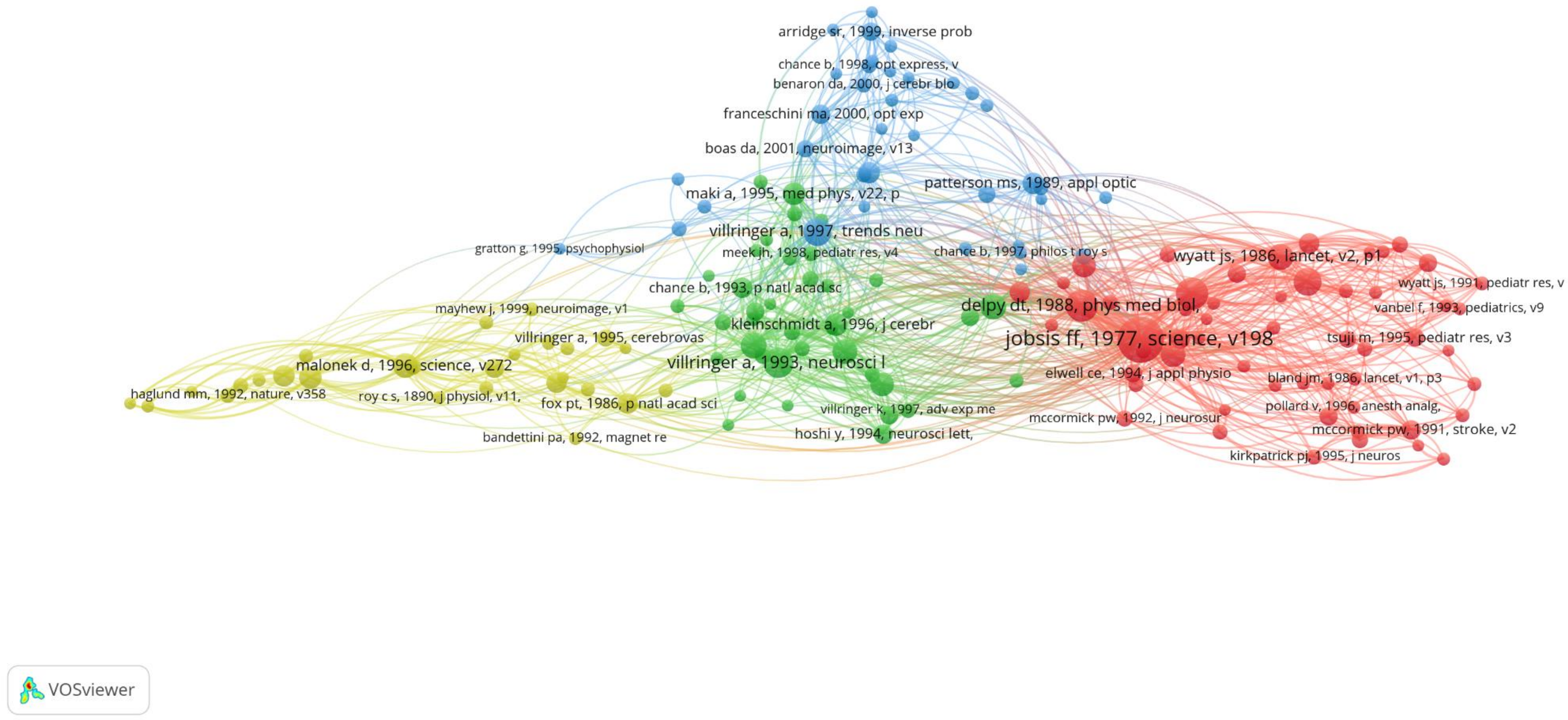

Figure 54: VOSviewer visualization of article co-citation map in the field of fNIRS between 1995-2005

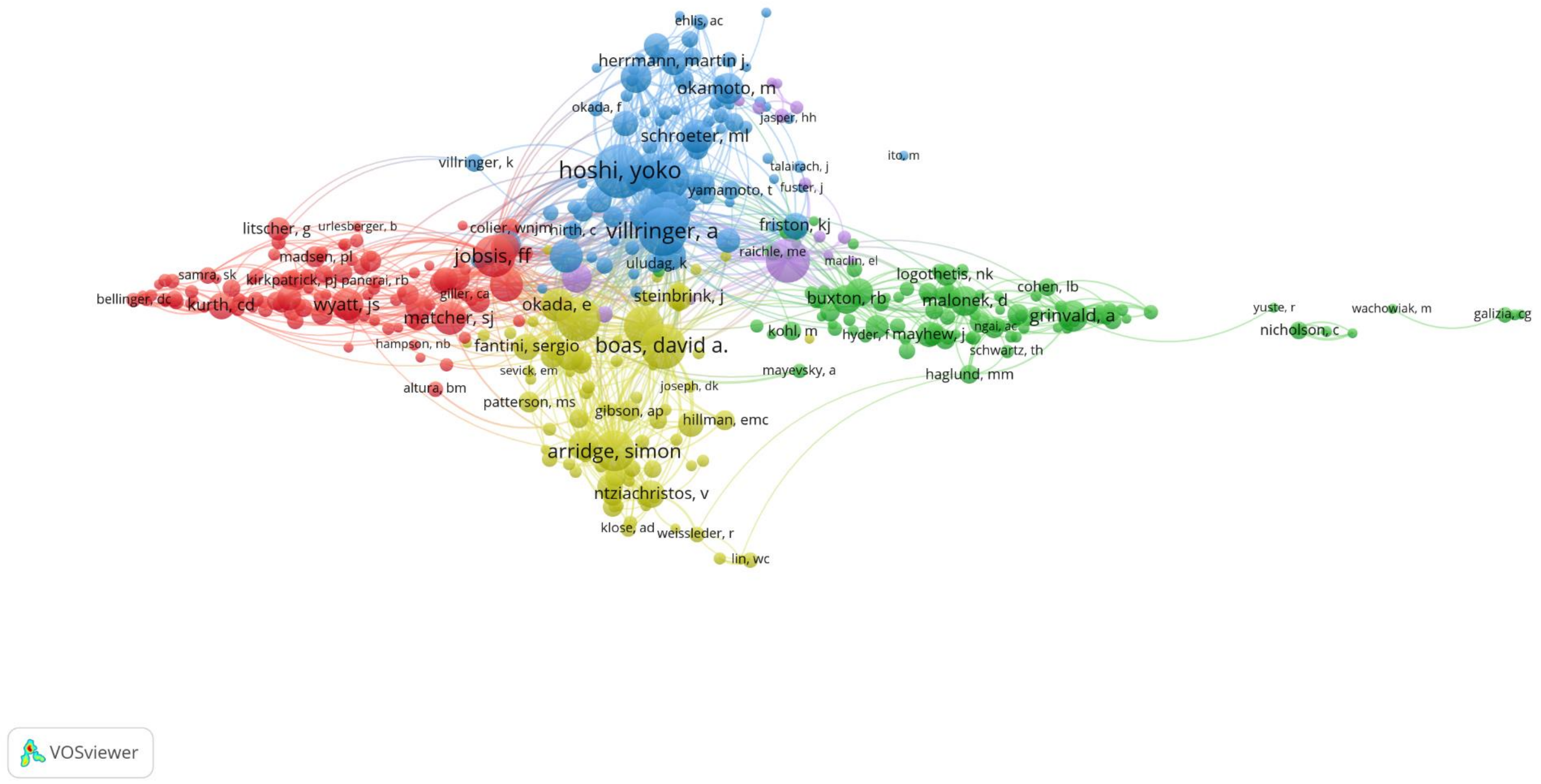

Figure 55: VOSviewer visualization of author co-citation map in the field of fNIRS between 2000-2010

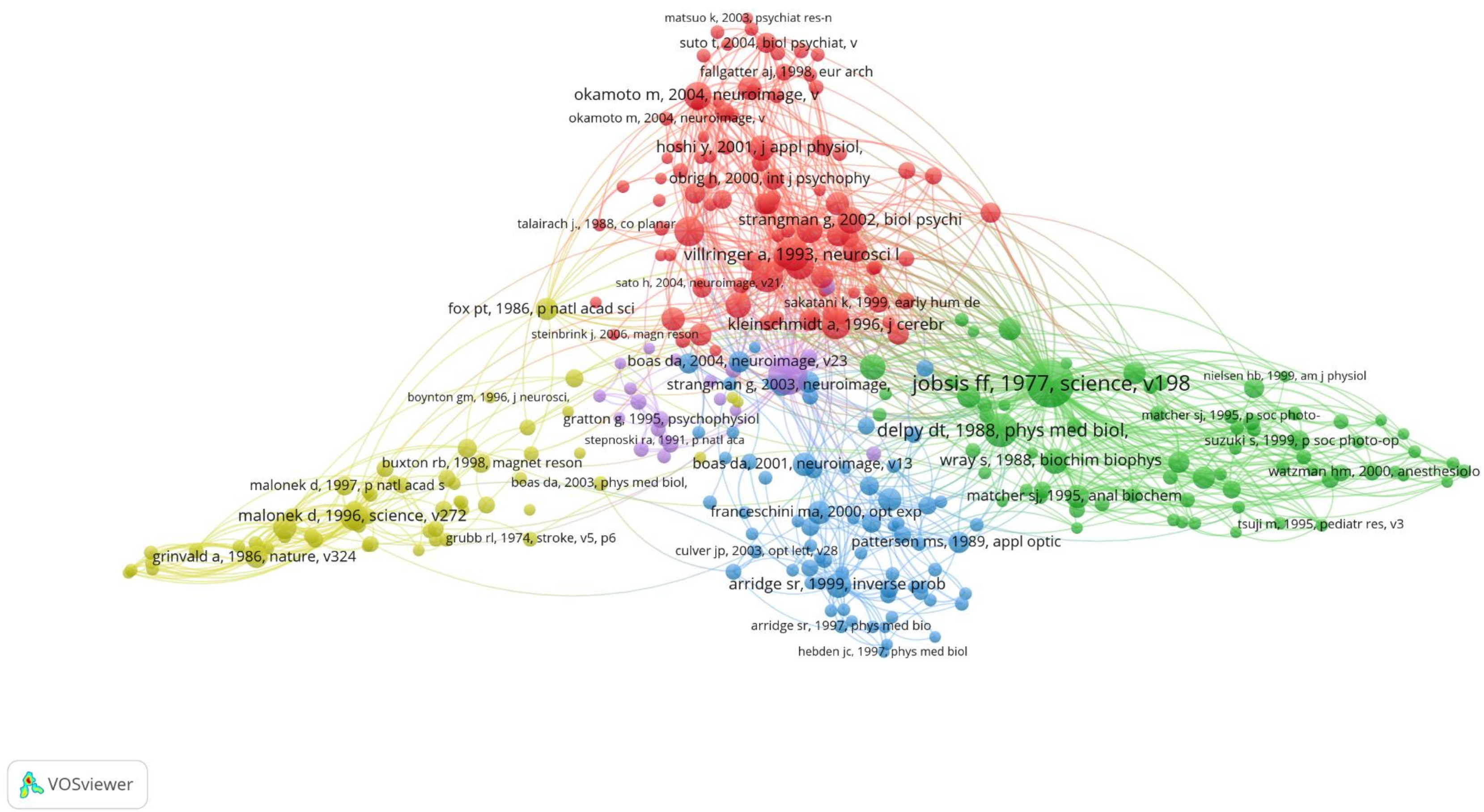

Figure 56: VOSviewer visualization of article co-citation map in the field of fNIRS between 2000-2010

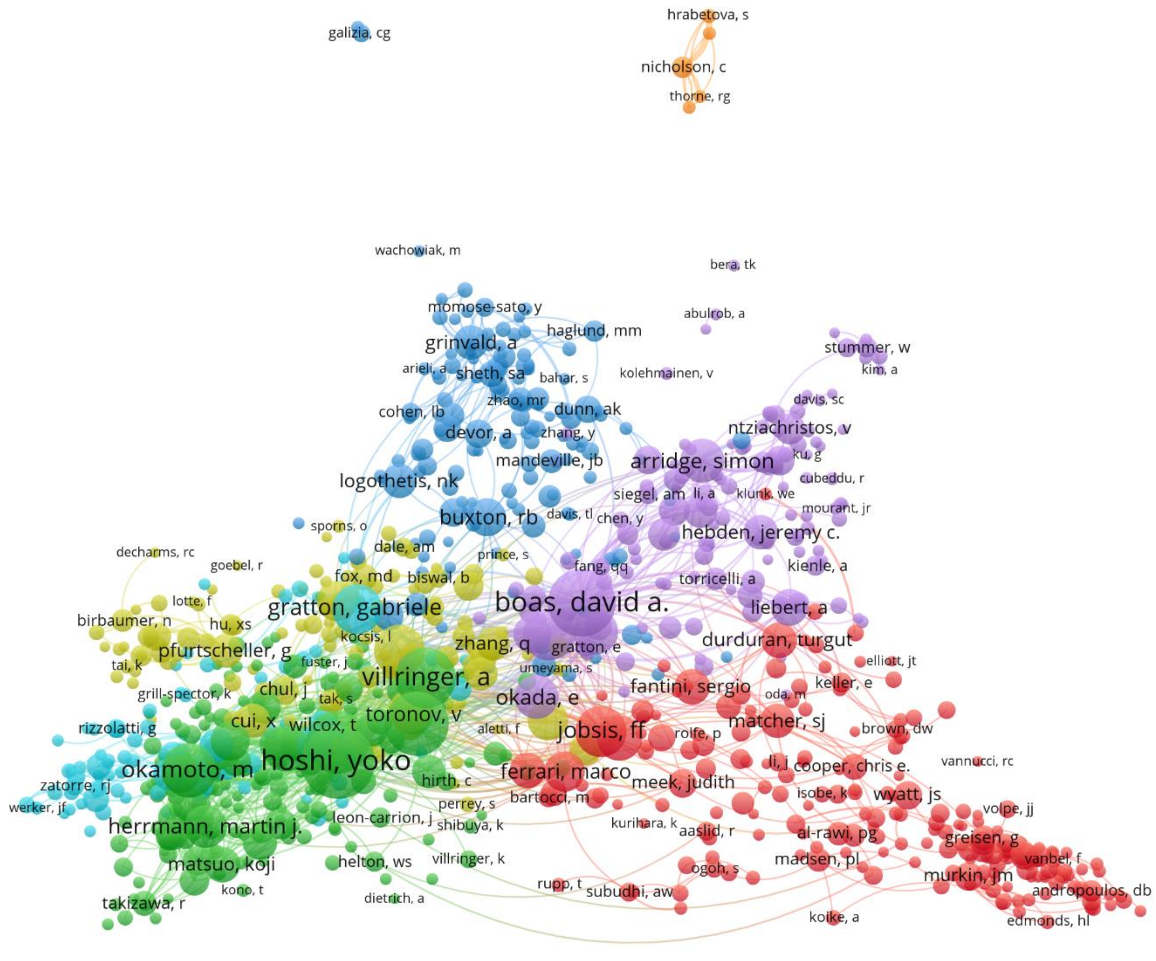

Figure 57: VOSviewer visualization of author co-citation map in the field of fNIRS between 2005-2015.

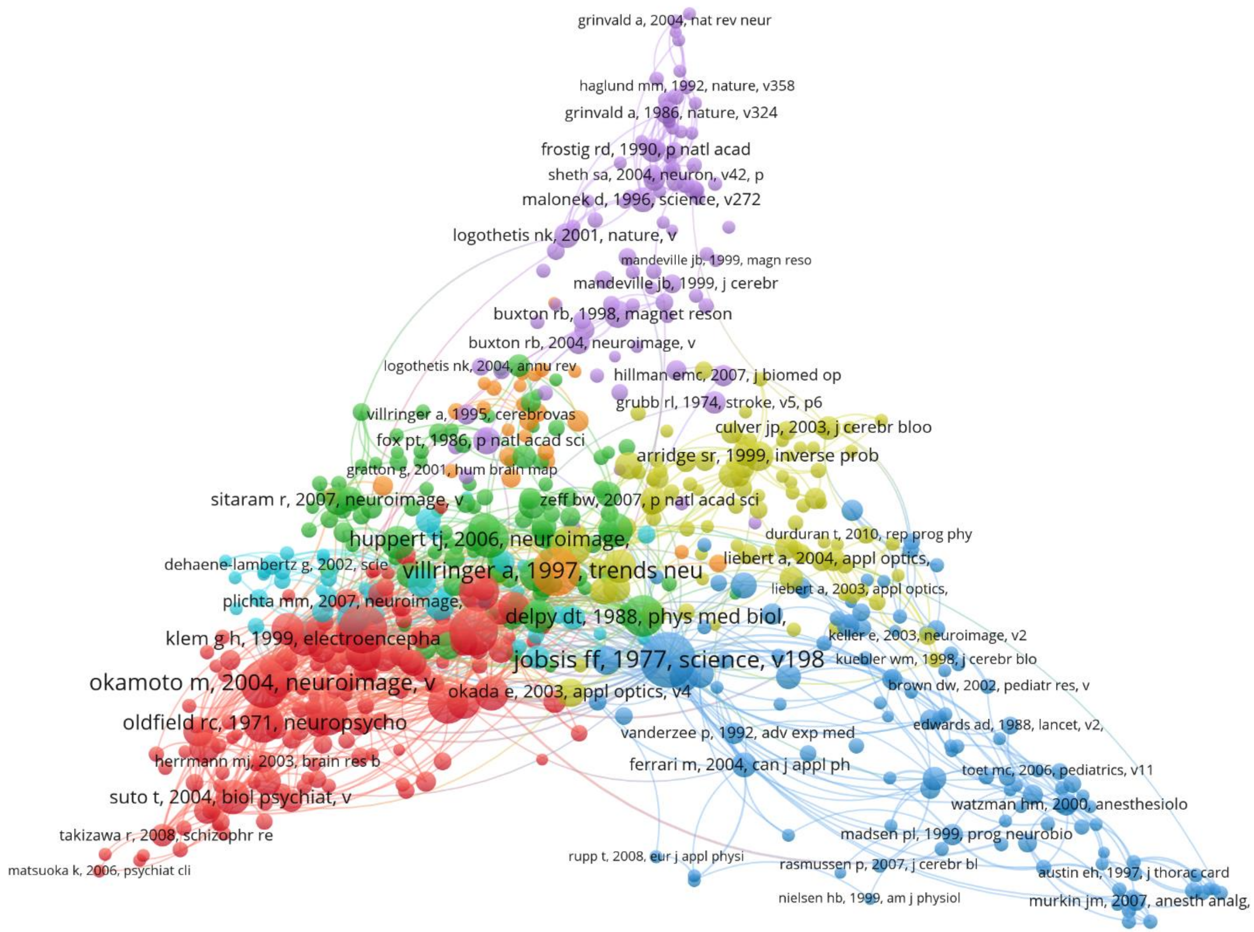

Figure 58: VOSviewer visualization of article co-citation map in the field of fNIRS between 2005-2015.

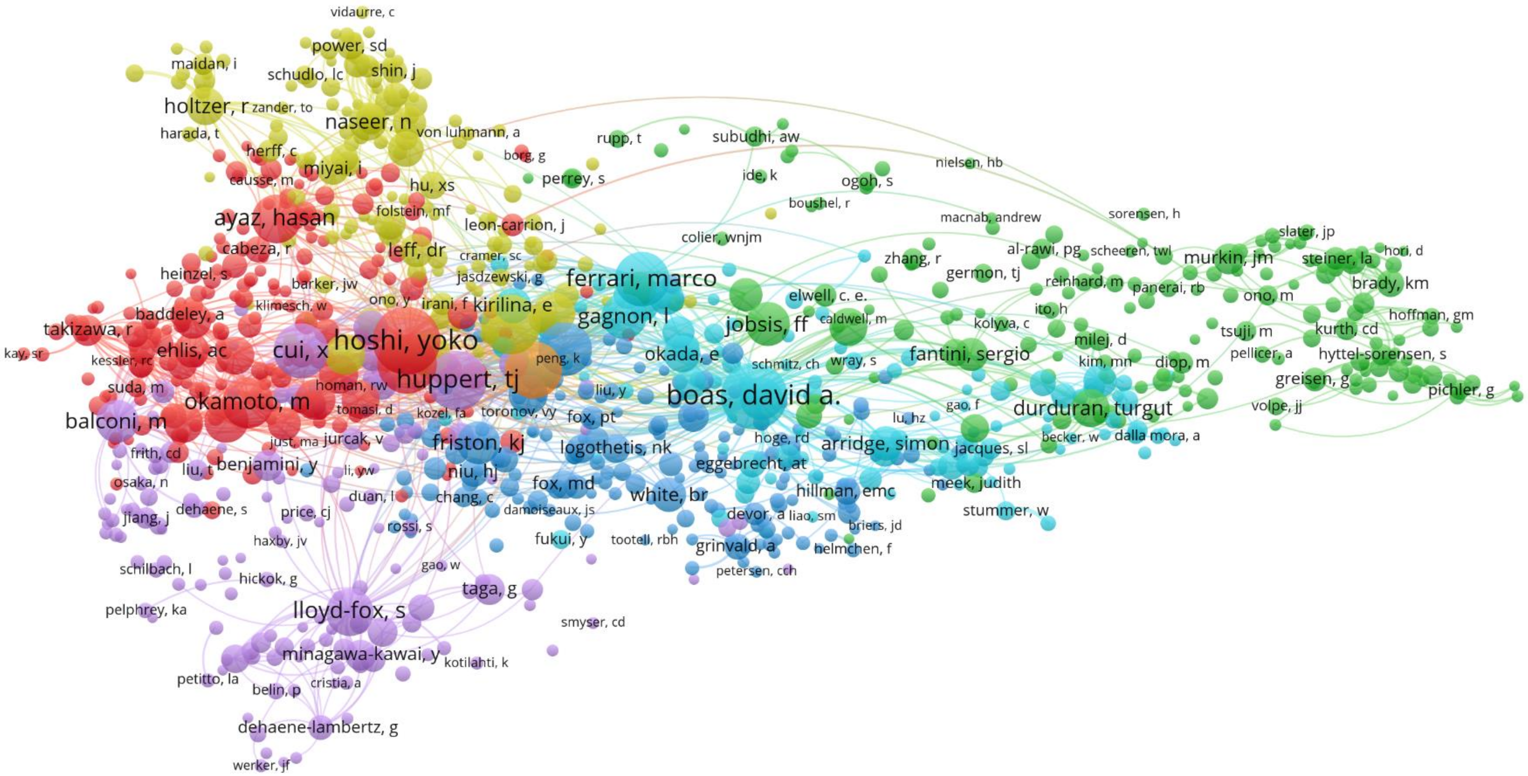

Figure 59: VOSviewer visualization of author co-citation map in the field of fNIRS between 2010-2020.

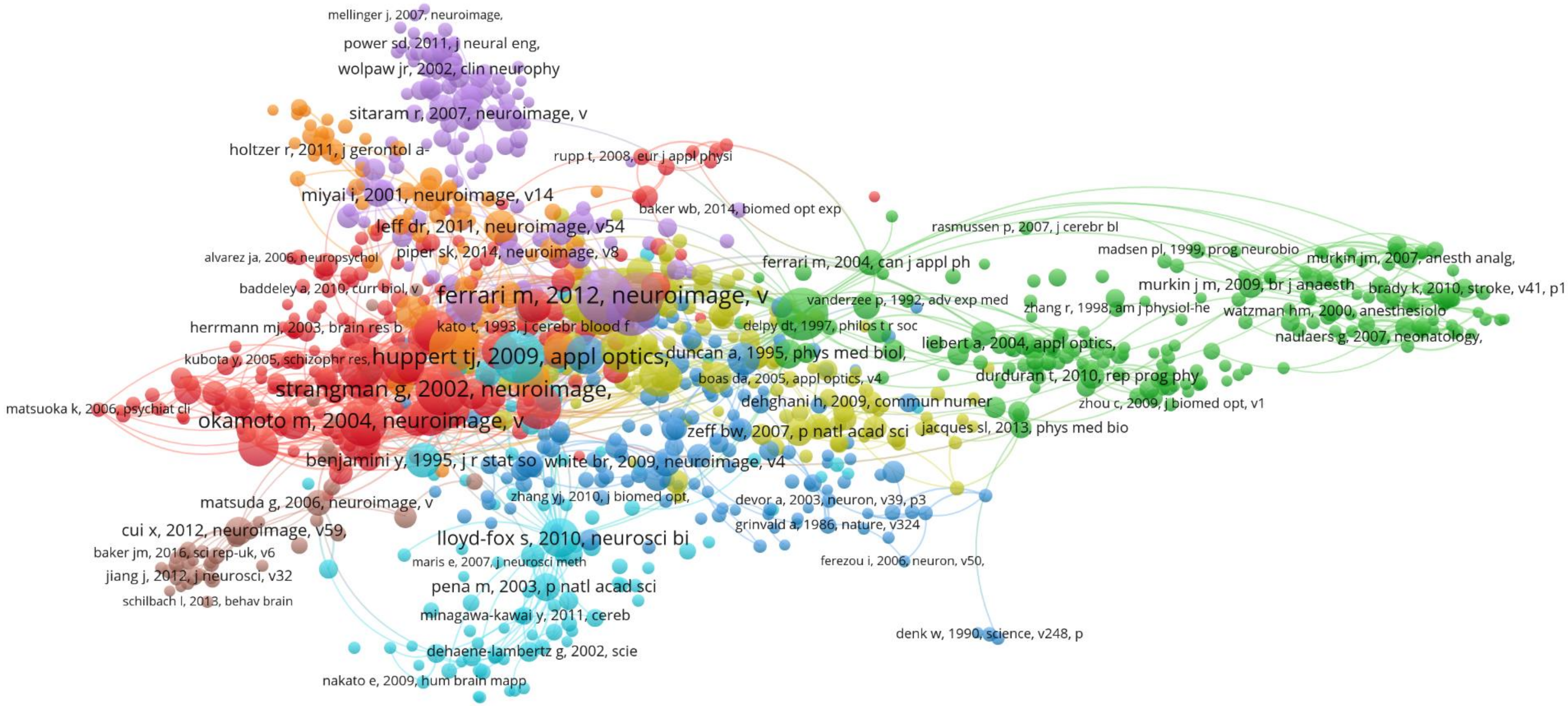

Figure 60: VOSviewer visualization of article co-citation map in the field of fNIRS between 2010-2020.

4.7. Burst Analysis

The keyword co-occurrence maps computed in VOSviewer is effective in terms of making observations about general emerging pattens and emergent relationships among keywords that form the topics or themes in a field like fNIRS. However, the temporal aspects of these changes are difficult to see when all the dataset is visualized in a single map. To partly mitigate this problem, we used multiple overlapping time windows, which allowed us to identify some temporal changes in the fNIRS literature. However, this approach still lacks precision in terms of pinpointing the specific timeframe in which a particular keyword, article or author gained or lost prominence.

Burst statistics are an alternative bibliometric analysis approach that aim to address the abovementioned disadvantages of co-citation maps by visualizing specific time frames in which a keyword, an author, an article or a country exhibited bursts in the frequency of publications or citations. CiteSpace (Chen, 2006) is one of the well-known software tools for visualizing and analyzing burst trends in scientific literature. To perform a CiteSpace analysis, users first input bibliographic data (such as article titles, author names, and publication dates), then the software visualizes the relationships between publications, authors, and concepts. These visualizations can help researchers identify emerging trends, influential authors, and significant research directions. CiteSpace uses various algorithms to identify key concepts and relationships between them, such as co-citation analysis, bibliographic coupling, and co-word analysis. The software can also generate maps of scientific literature over time, showing how different fields and subfields have evolved (Chen, 2016).

Citation Burst analysis identifies sudden spikes or surges in the number of citations received by a particular paper, author, or topic. When a paper or an author experiences a citation burst, their work attracts significant attention from other researchers. Thus, Citation Burst analysis can also identify the most influential papers or authors in a particular field within a specific timeframe. Analyzing the citation patterns of articles or authors over time makes it possible to identify those with a sustained and significant impact on the field and those with a more transient or short-term impact (Chen, 2016).

Figure 61 shows the list of top 50 keywords in our dataset that exhibited a significant citation burst, which is indicated by the length of the red line in the time interval column. The top 10 in the list include fundamental terminology that sustained their relevance in a long duration of time in fNIRS studies. For instance, (1) Cytochrome oxidase (Strength=26.41) is an enzyme involved in cellular respiration that can be used as a marker of metabolic activity in the brain. (2) Hemoglobin oxygenation (Strength=20.14) refers to the amount of oxygen bound to hemoglobin in the blood, which can be measured using various imaging techniques, including fNIRS. (3) Cerebral blood volume (Strength=14.26) refers to the amount of blood in the brain. (4) Cerebral blood flow (Strength=28.77) is the rate of blood flow in the brain, which can be measured using various imaging techniques, including fNIRS. (5) Cerebral ischemia (Strength=22.46) is a lack of blood flow to the brain, which can cause damage to brain tissue and lead to neurological deficits. (6) Blood pressure (Strength=15.51) states the blood pressure against the walls of blood vessels, which influences cerebral blood flow and oxygenation. (7) Cerebral blood oxygenation (Strength=14.69) refers to the amount of oxygen in the blood in the brain, which can be measured using various imaging techniques, including fNIRS. (8) Cerebral oxygenation (Strength=15.42) refers to the amount of oxygen available to brain tissue, which can be influenced by factors such as blood flow, hemoglobin oxygenation, and metabolic activity. (9) Light scattering (Strength=15.08 refers to the interaction of light with tissue, which can provide information about tissue structure and composition. Light scattering is used in various imaging techniques, including fNIRS. (10) Brain oxygenation (Strength=24.46) refers to the amount of oxygen available to brain tissue, which can be influenced by factors such as blood flow, hemoglobin oxygenation, and metabolic activity. All these keywords remained their prominence until 2010s due to their importance in fNIRS methodology as indicated by their burst graphs.

Starting with 2015, given that fNIRS has been established as a veridical neuroimaging modality, we begin to see bursts in application areas such as brain-computer interfaces, effective connectivity, working memory, mirror neuron system, autism, and virtual reality. These keywords have shown a strong upward trend in citation rates, indicating that they have been the focus of significant research and development in fNIRS over the last decade. Overall, the burst analysis supports our observations based on the co-citation maps, where the initial focus for a long duration time was over fundamental methodological aspects, which is followed by a burst in applications of fNIRS.

Keywords	**Year**	**Strength**	**Begin**	**End**	**1982 - 2020**
cytochrome oxidase	1993	26	**1993**	2000	
hemoglobin oxygenation	1993	20	**1993**	1997	
cerebral blood volume	1993	14	**1993**	2011	
cerebral blood flow	1994	28	**1994**	2001	
cerebral ischemia	1996	22	**1996**	2012	
blood pressure	1996	15	**1996**	2012	
cerebral blood oxygenation	1996	14	**1996**	2011	
cerebral oxygenation	1997	15	**1997**	2014	
light scattering	1999	15	**1999**	2011	
brain oxygenation	2002	1	**2002**	2008	
intrinsic optical signal	2003	19	**2003**	2005	
frequency domain	2004	19	**2004**	2006	
independent component analysis	2004	17	**2004**	2013	
bold signal	2006	25	**2006**	2012	
diffuse optical imaging	2006	24	**2006**	2009	
optical imaging	2007	61	**2007**	2013	

Figure 61: Top 50 Keywords with the Strongest Citation Bursts (Source: CiteSpace).

near-infrared spectroscopy (nirs)	2001	3	**2007**	2012	
frontal lobe	2008	29	**2008**	2012	
functional imaging		20	**2008**	2013	
near-infrared spectroscopy	1993	21	**2008**	2010	
motor execution	2008	18	**2008**	2012	
biomedical optics	2009	16	**2009**	2014	
resting state	2010	3	**2010**	2011	
functional connectivity	2010	35	**2010**	2011	
biomedical optical imaging	2010	19	**2010**	2011	
cerebral palsy	2010	1	**2010**	2015	
brain imaging	2001	15	**2011**	2017	
motor imagery	2007	14	**2011**	2012	
optical topography	2006	43	**2012**	2015	
near infrared spectroscopy	1992	20	**2012**	2015	
cortical hemodynamics	2012	20	**2012**	2014	
brain activity measurement	2012	15	**2012**	2014	
physiological noise	2013	17	**2013**	2016	
cortical oxygenation	2013	16	**2013**	2014	
functional near infrared spectroscopy	2010	24	**2014**	2015	
motor cortex	2014	19	**2014**	2016	
executive function	2009	18	**2014**	2016	
brain-computer interfaces	2013	17	**2014**	2015	
cortical activation	2010	18	**2015**	2016	
auditory cortex	2005	22	**2016**	2018	
visual cortex	2009	15	**2016**	2017	
brain-computer interface	2013	30	**2017**	2018	
support vector machine	2017	26	**2017**	2018	
mirror neuron system	2017	15	**2017**	2020	
working memory	2008	21	**2018**	2020	
graph theory	2018	21	**2018**	2020	

Figure 61: Top 50 Keywords with the Strongest Citation Bursts (Source: CiteSpace).

effective connectivity	2018	21	**2018**	2020	
artificial neural network	2018	19	**2018**	2020	
autism spectrum disorder	2014	15	**2018**	2020	
virtual reality	2014	15	**2018**	2020	

Figure 61: Top 50 Keywords with the Strongest Citation Bursts (Source: CiteSpace).

A similar analysis can be performed over the authors as well. In this case, the term "citation burst" refers to a sudden increase in the number of citations an author receives. This can happen when a paper or book becomes widely influential or addresses a topic that suddenly becomes very important in a field. A citation burst can indicate that an author has made a significant contribution to their field which attracted the interest of other researchers utilizing and/or discussing those findings.

Figure 62 below shows the citation burst of top 50 authors obtained from CiteSpace. A longer list is provided in the Appedix. The list starts with bursts associated with JOBSIS FF and CHANCE B, who are among the pioneers of fNIRS methodology. Britton Chance, who was a professor of biophysics, physical chemistry and radiologic physics at the University of Pennyslvania, pioneered some of the early methods and instruments as part of his general interest towards how living organisms capture, manage and produce cellular energy (Dutton, 2010). His graduate work under supervision of Glenn Millikan on enzyme mechanisms, his work over radar circuitry at MIT during WWII, and his enthusiasm in yachts where he developed radios and automatic steering systems illustrate Britton Chance’s multidisciplinary background. With his invention of a dual-wavelength spectrophotometer, Prof. Chance utilized optical methods to explore cellular redox cofactors in mithocondrial respiration chain including cytochrome c oxidase, energetic states of mitochondria (a key structure in energy production at the cellular level), and photosynthetic bacteria where he investigated electron transfer mechanisms in living cells. He later focused on the physics of light diffusion through scattering material such as biological tissue, where he demonstrated the monitoring of oxy- and deoxyhemoglobin levels in performing muscles, as well as locating tumors and cancerous tissue.

Franz Jobsis has also a multidisciplinary background in zoology and physiology. During his time as a postdoctoral researcher with Britton Chance, he got introduced to infrared based optical methods, before moving to the Physiology department at Duke University. Jobsis’ 1977 Science article is the first demonstration of monitoring oxy- and deoxy-hemoglobin concentration changes in the cerebral cortex, which opened up the use of NIRS as a brain imaging technology (Delpy et al., 2007).

The development of the method and the relationships between fMRI and cerebral oxygenation are also crucial at the beginning, with the share of next-generation researchers such as VILLRINGER A(1999), OBRIG (2004) H, STRANGMAN G(2004). LOGOTHETIS NK and OGAWA S are well known researchers in MRI/fMRI due to their work on the physiological basis of the blood oxygen level dependent signal (BOLD), whose increased citation burst in this era highlight the close relevance of this body of work in fNIRS methodology. The more recent citation bursts seem to be associated with applications of fNIRS in clinical medicine, psychology/psychiatry, human-computer interaction as well as methodological position papers.

Authors	Year	Strength	Begin	End	1982 - 2020
CHANCE B	1982	24.5	**1982**	2011	
JOBSIS FF	1982	15.19	**1982**	2005	
WYATT JS	1992	22.42	**1992**	2007	
WRAY S	1992	17.75	**1992**	2012	
EDWARDS AD	1992	11.87	**1992**	2002	
BRAZY JE	1992	11.5	**1992**	2007	
COPE M	1992	10.04	**1992**	2004	
FOX PT	1993	14.35	**1993**	2012	
ELWELL CE	1993	9.68	**1993**	2014	
ARRIDGE SR	1994	15.33	**1994**	2010	
BENARON DA	1995	12.48	**1995**	2008	
OGAWA S	1995	10.18	**1995**	2011	
COOPER CE	1996	12.14	**1996**	2010	
MEEK JH	1997	15.28	**1997**	2013	
HOSHI Y	1997	13.48	**1997**	2011	
KATO T	1997	12.23	**1997**	2008	
FIRBANK M	1997	9.5	**1997**	2013	
VILLRINGER A	1996	23.43	**1999**	2012	
GRATTON G	1997	11.3	**2000**	2012	
HINTZ SR	2000	11.06	**2000**	2012	
HIRTH C	2000	10.33	**2000**	2009	
HOCK C	2001	14.47	**2001**	2013	
SAKATANI K	2001	11.85	**2001**	2013	
KLEINSCHMIDT A	2001	11.74	**2001**	2009	
FRANCESCHINI MA	2000	21.39	**2002**	2013	
CANNESTRA AF	2002	9.74	**2002**	2009	
TORONOV V	2003	20.3	**2003**	2011	
WOLF M	2003	16.38	**2003**	2012	
WATANABE E	2003	13.71	**2003**	2015	
CULVER JP	2003	9.36	**2003**	2014	
OBRIG H	1996	26.94	**2004**	2012	
FALLGATTER AJ	2004	12.88	**2004**	2010	
STRANGMAN G	2004	11.34	**2004**	2010	
STEINBRINK J	2004	10.53	**2004**	2013	
OKADA E	1997	9.83	**2005**	2013	
HEBDEN JC	2005	9.75	**2005**	2010	
LOGOTHETIS NK	2005	9.57	**2005**	2015	
SCHROETER ML	2004	17.74	**2006**	2012	
OKAMOTO M	2006	15.76	**2006**	2012	
IZZETOGLU K	2006	10.08	**2006**	2015	
GIBSON AP	2006	9.02	**2006**	2014	
TAGA G	2005	9.18	**2008**	2012	

Figure 62: Top 50 Authors with the Strongest Citation Bursts (Source: CiteSpace).

ZEFF BW	2009	10.31	**2009**	2016	
IZZETOGLU M	2006	9.76	**2009**	2013	
TAKAHASHI T	2012	9.33	**2013**	2015	
TACHTSIDIS ILIAS	2017	11.94	**2017**	2020	
CHIARELLI AM	2018	13.1	**2018**	2020	
NASEER NOMAN	2016	11.12	**2018**	2020	
HONG KS	2015	11.03	**2018**	2020	
AASTED CM	2016	9.42	**2018**	2020	

Figure 62: Top 50 Authors with the Strongest Citation Bursts (Source: CiteSpace).

The top 25 countries with the strongest citation bursts refer to the countries whose researchers and academics have published research papers that have experienced sudden and significant increases in citations. The ranking is based on the number of times the country's research papers have been cited within a short period of time (Figure 63). The ranking of countries with the strongest citation bursts is dynamic and can change as new research is published and cited. The top 5 countries with the strongest citation bursts, according to the Web of Science citation index, were as follows: JAPAN, GERMANY, CHINA, SWITZERLAND, USA. Japan's bursts coincide with the introduction of fNIRS instruments by companies such as Hitachi, Shimadzu and Hamamatsu, and the initial applications performed with these devices. The burst information may not be effective in showing prolonged impact, as we can see in the profile us USA, which has initiated the field and has a sustained presence in leading fNIRS research.

Countries	**Year**	**Strength**	**Begin**	**End**	**1982 - 2020**
JAPAN	1997	217	2005	2011	
GERMANY	1997	159	2006	2008	
CHINA	2010	14	2019	2020	
SWITZERLAND	2009	141	2009	2012	
USA	1997	9	2009	2009	
CANADA	2009	6.5	2014	2015	
TAIWAN	2013	6.0	2013	2016	
SPAIN	2014	5.1	2019	2020	
PAKISTAN	2016	203	2016	2018	
TURKEY	2008	115	2019	2020	
BRAZIL	2012	99	2018	2020	
FRANCE	2011	107	2016	2016	
ENGLAND	1998	89	1998	1998	
ISRAEL	2012	89	2012	2014	
BANGLADESH	2019	8	2019	2020	
DENMARK	2018	147	2018	2018	
AUSTRIA	2013	126	2017	2018	
MEXICO	2016	105	2016	2016	
SOUTH KOREA	2010	10	2018	2018	
NEW ZEALAND	2013	88	2017	2018	
IRAN	2014	69	2017	2020	
RUSSIA	2017	61	2017	2020	
SINGAPORE	2012	53	2012	2013	

BELGIUM	2013	52	2018	2020	
SCOTLAND	2012	9	2018	2020	

Figure 63: Top 25 Countries with the Strongest Citation Bursts (Source: CiteSpace).

Figure 64 presents the results of the burst analysis over journals in the fNIRS dataset. These journals have high citation counts and a strong citation burst, indicating their significant impact on fNIRS. These journals cover brain imaging, cognitive neuroscience, clinical applications, and data analysis. They are highly respected in fNIRS and frequently cited in research papers, making them valuable sources for current research and advancements in the field. The citation bursts of the journal also illustrate the progression of the impact generated by fNIRS across disciplines. The initial bursts are associated with Nature, a multidisciplinary high impact journal, as well as Journal of Applied Physiology, Biochimica et Biophysica Acta, American Journal of Biophysics, Biophysics J, where the focus has been on establishing optical methods for the monitoring of tissue oxygenation and energy metabolism. This is followed by early clinical adoption of fNIRS in surgery, neurosurgery, pediatrics and anesthesiology as indicated by the bursts in the related journals including the high impact multidisciplinary journal Lancet. More recently citation bursts can be observed in applied fields such as Early Development, Human-Computer Interaction, Cognitive Neuroscience, and Neurorobotics, which illustrates the growing influence of fNIRS as a neuroimaging modality. The recent burst in the journal Neurophotonics seemingly does not fit to this pattern, but we should note that this a recently established journal in 2014 that quickly gained prominence due to the quick adoption by researchers active in fNIRS and other biomedical applications of NIRS.

Cited Journals	**Year**	**Strength**	**Begin**	**End**	**1982 - 2020**
J APPL PHYSIOL	1982	35.98	**1982**	2010	
BIOCHIM BIOPHYS ACTA	1982	25.21	**1982**	2012	
J NEUROSURG	1982	16.69	**1982**	2011	
AM J PHYSIOL	1982	14.62	**1982**	2008	
BIOPHYS J	1982	7.14	**1982**	2009	
NATURE	1984	8.91	**1984**	2012	
ADV EXP MED BIOL	1982	19.63	**1992**	2013	
LANCET	1992	18.27	**1992**	2007	
ARCH DIS CHILD-FETAL	1992	7.93	**1992**	2007	
PEDIATR RES	1993	31.96	**1993**	2009	
ANAL BIOCHEM	1993	15.31	**1993**	2009	
MED BIOL ENG COMPUT	1993	10.8	**1993**	2011	

Figure 64: Top 50 Cited Journals with the Strongest Citation Bursts

PEDIATRICS	1993	10	**1993**	2007	
BIOCHEM SOC T	1993	7.43	**1993**	2000	
ANESTHESIOLOGY	1993	6.9	**1993**	2008	
J CEREBR BLOOD F MET	1991	43.14	**1995**	2011	
PHYS MED BIOL	1993	22.6	**1995**	2010	
STROKE	1983	11.28	**1995**	2012	
CRIT CARE MED	1995	8.97	**1995**	2009	
CEREBROVAS BRAIN MET	1995	7.55	**1995**	2014	
MED PHYS	1997	23.73	**1997**	2013	
P ROY SOC B-BIOL SCI	1997	7.12	**1997**	2015	
AM J PHYSIOL-HEART C	1997	7.01	**1997**	2008	
P SOC PHOTO-OPT INS	1998	18.58	**1998**	2009	
PSYCHOPHYSIOLOG Y	1997	16.37	**2000**	2009	
PHILOS T ROY SOC B	2000	10.63	**2000**	2015	
PHOTOCHEM PHOTOBIOL	2000	8.59	**2000**	2009	
TRENDS NEUROSCI	1991	25.31	**2001**	2011	
NEUROREPORT	2001	15.48	**2001**	2013	
EARLY HUM DEV	2001	6.88	**2001**	2014	
OPT EXPRESS	2002	23.78	**2002**	2012	
OPT LETT	2002	19.48	**2002**	2013	
MAGNET RESON MED	1996	13.96	**2002**	2011	
INVERSE PROBL	2003	11.47	**2003**	2010	
J PERINAT MED	2003	10.81	**2003**	2012	
J OPT SOC AM A	1997	7.87	**2003**	2012	
BIOL PSYCHIAT	1998	10.51	**2004**	2010	
EUR ARCH PSY CLIN N	1997	9.68	**2004**	2012	
COGNITIVE BRAIN RES	1997	8.04	**2004**	2013	

Figure 64: Top 50 Cited Journals with the Strongest Citation Bursts

PEDIATR NEUROL	2004	7.23	**2004**	2014	
INT J HUM-COMPUT INT	2006	7.16	**2006**	2013	
J COMPUT ASSIST TOMO	2006	6.96	**2006**	2014	
IEEE ENG MED BIOL	2008	10.63	**2008**	2013	
MAGN RESON IMAGING	2006	7.53	**2008**	2014	
P ANN INT IEEE EMBS	2009	10.8	**2009**	2015	
BRAIN RES	1983	7.26	**2010**	2012	
SCI REP-UK	2015	44.86	**2018**	2020	
NEUROPHOTONICS	2015	35.34	**2018**	2020	
FRONT NEUROROBOTICS	2017	10.01	**2018**	2020	
FRONT BEHAV NEUROSCI	2015	8.97	**2018**	2020	

Figure 64: Top 50 Cited Journals with the Strongest Citation Bursts

4.8. Thematic Evolution Map and Trend Analysis

In the field of bibliometrics there are several other toolboxes and algorithms to help researchers explore a bibliographic dataset from additional perspectives. Biblioshiny is an R package that provides a modern web-based graphical user interface for bibliometric analyses. With Biblioshiny, users can quickly analyze and visualize bibliometric data, such as publication and citation counts, co-authorship networks, and keyword frequency (Azhari et al.,2023). In addition to these classical bibliometric mapping approaches, Biblioshiny also allows users to create thematic evolution maps, which can help researchers to gain insights into changes in research focus over time and identify areas where more research is needed. These maps can help researchers visualize changes in the frequency and co-occurrence of keywords over time, revealing emerging trends and shifts in research focus.

To generate a thematic evolution map using R-Biblioshiny, users can follow these general steps:

1. Load the bibliographic data into R-Biblioshiny, using one of the available input formats (e.g., BibTeX, EndNote, Zotero, etc.).

2. Preprocess the data by removing duplicates, cleaning up the author keywords, and selecting a subset of papers if necessary.

3. Extract the author keywords from the papers and generate a frequency table of the most common keywords for each period of interest (e.g., year, decade).

4. Use the frequency tables to generate co-occurrence matrices for each period that show the relationships between pairs of keywords.

5. Compare the co-occurrence matrices for each period to identify changes in the frequency and strength of keyword relationships over time.

6. Use a network visualization tool like the "visNetwork" package in R to create an interactive network graph showing the keyword relationships for each period.

7. Customize the visualization by adding labels, colors, and other features highlighting the main themes and topics covered in the papers over time.

The resulting evolution thematic map can explore relationship changes between keywords and identify emerging trends and shifts in research focus over time. Users can interact with the visualization by selecting specific periods, zooming in/out, highlighting specific keywords or keyword clusters, and exploring the links between them. Figure 65 below shows the thematic evolution map obtained over the fNIRS dataset for the time periods 1982-2012, 2013-2015, 2016-2017, and 2018-2020.

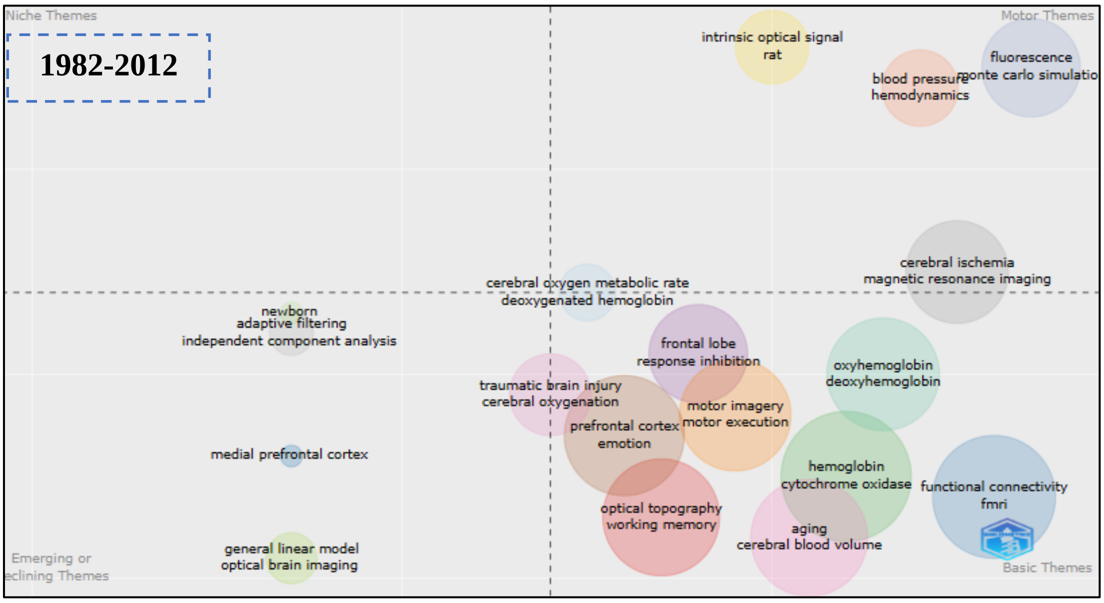

Figure 65: R- Biblioshiny thematic evolution map visualization of keywords in the field of fNIRS between the time periods 2013-2014, 2015-2016, 2017-2018, and 2019-2020.

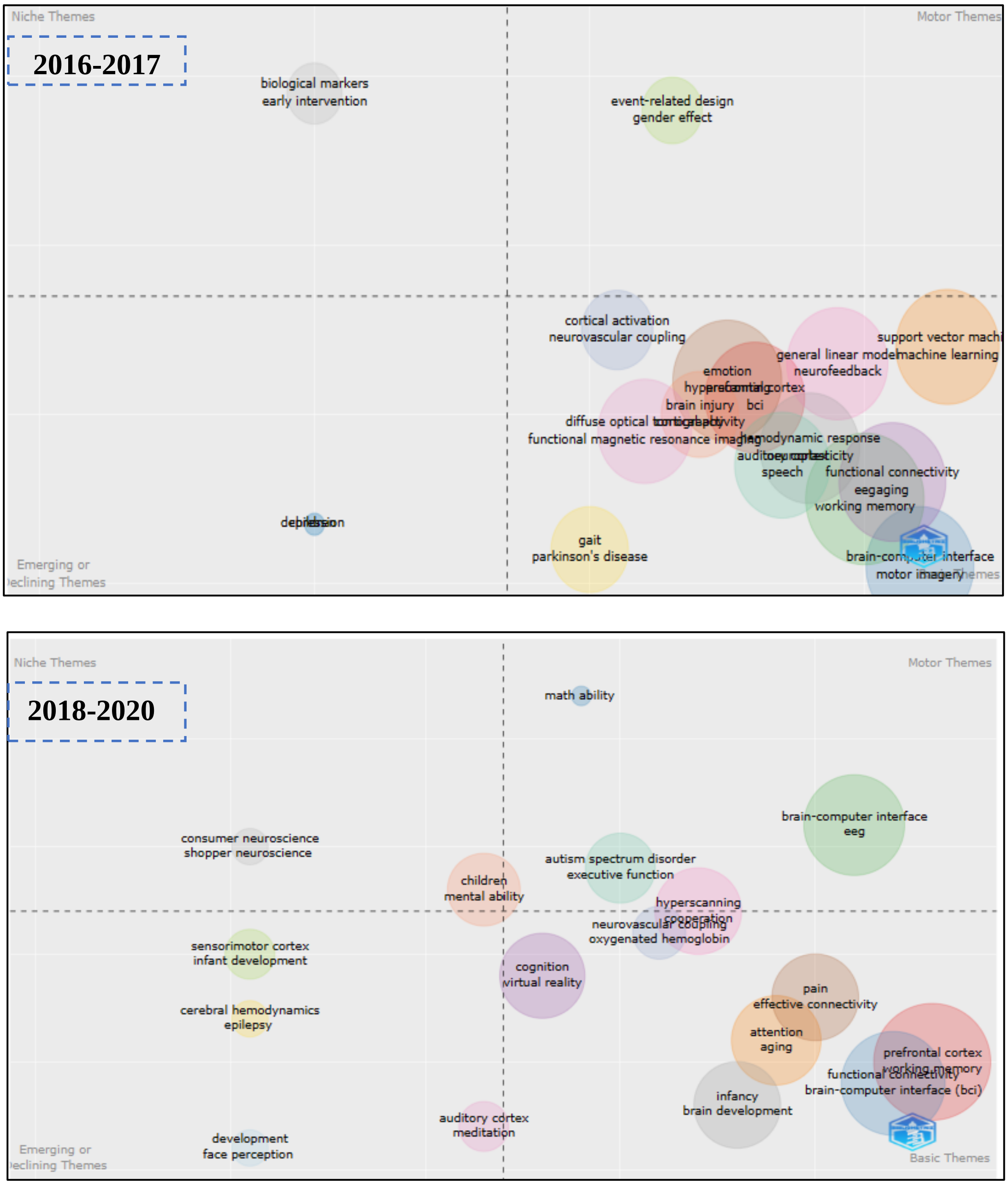

Figure 65: R- Biblioshiny thematic evolution map visualization of keywords in the field of fNIRS between the time periods 2013-2014, 2015-2016, 2017-2018, and 2019-2020.

In the thematic evolutíon map, the horizontal axis denotes the centrality of the obtained clusters, while the vertical axis indicates their density. The concepts of centrality and density are based on Callon et al.'s (1991) work, which provide network measurements for each cluster identified within each time period. Centrality measures the degree of network interaction with other networks, which is expressed as the external cohesion of the network. The motor themes in the upper right express the words that are frequently used and the interconnections between the words are strong; i.e. words that are used very often with each other. Motor themes show the most important themes for the development of the field. The niche themes in the upper left is very advanced but isolated themes. As can be understood from the name, the topics related to the keywords that appear here have been studied a lot, and accordingly, the bond within them is powerful. However, they do not yet have a strong relationship with other topics. The themes at the bottom left represent emerging concepts or declining topics. The topics at the bottom right are fundamental and transformative issues, which indicate topics that are important to the development of the field but have not been studied enough (Figure 65).

Figure 65 are shown the thematic evolution map (Cobo et al. 2011) for the keywords used in the analyzed documents. A thematic map is a condensed plot that allows readers to group related topics into four (4) quadrants. The themes can be analyzed according to the quadrant they are situated in:

- The first quadrant, namely the **motor theme** includes well-developed themes that are key to the structure of the research field and are characterized by high centrality and high density, including İntrinsic optical signal, hemodynamics, fluorescence, blood pressure, cerebral ischemia, monte carlo simulatio (1982-2012); traumatic brain injury, Alzheimer's disease, hemodynamic response, magnetic resonance imaging, optical topography. (2013-2015); event-related design, gender effect (2016-2017); and math ability, brain-computer interface, EEG, autism spectrum disorder, executive function, hyper scanning etc. (2018-2020).

- The second quadrant houses **basic themes** that are well-developed and very specialized themes but marginal in the overall field, including the frontal lobe, oxyhemoglobin, motor imagery, optical topography, aging etc. (1982-2012); gait, bci, cognition, fluorescence, linear discriminant analysis (2013-2015); cortical activation, support vector machine, functional connectivity, working memory etc. (2016-2017); cognition, virtual reality, pain, cognition, infancy, neurovascular coupling etc. (2018-2020).

- The third quadrant, **emerging and declining themes**, comprises both emerging and declining themes characterized by low density and centrality, which contains newborn, medial prefrontal cortex, general linear model optical brain imaging etc. (1982-2012); infancy, kinesthetic illusion, computer games etc. (2013-2015); depression (2016-2017); and auditory cortex, mediation, cerebral hemodynamics, sensorimotor cortex (2018-2020).

- Lastly, the fourth quadrant, **niche themes**, are themes with high centrality and low density, which contains no keywords in the early years of fNIRS research (1982-2012); and then includes superior temporal sulcus, verbal fluency task and brain activity measurement etc. (2013-2015); biological markers and early intervention (2016-2017); children, mental ability, consumer neuroscience and shopper neuroscience (2018-2020).

Biblioshiny also allows researchers to plot the abovementioned themes as a timeline to highlight the temporal changes in the field. In the thematic map (Figure 66), the author's keywords are shown under their year period, together with connections across the periods. For instance, when we follow the precursors of a recent theme like hyperscanning, we can see that its related to functional connectivity, which makes sense since hyperscanning refers to studies focusing on inter-brain synchronization patterns that are typically quantified with connectivity measurements.

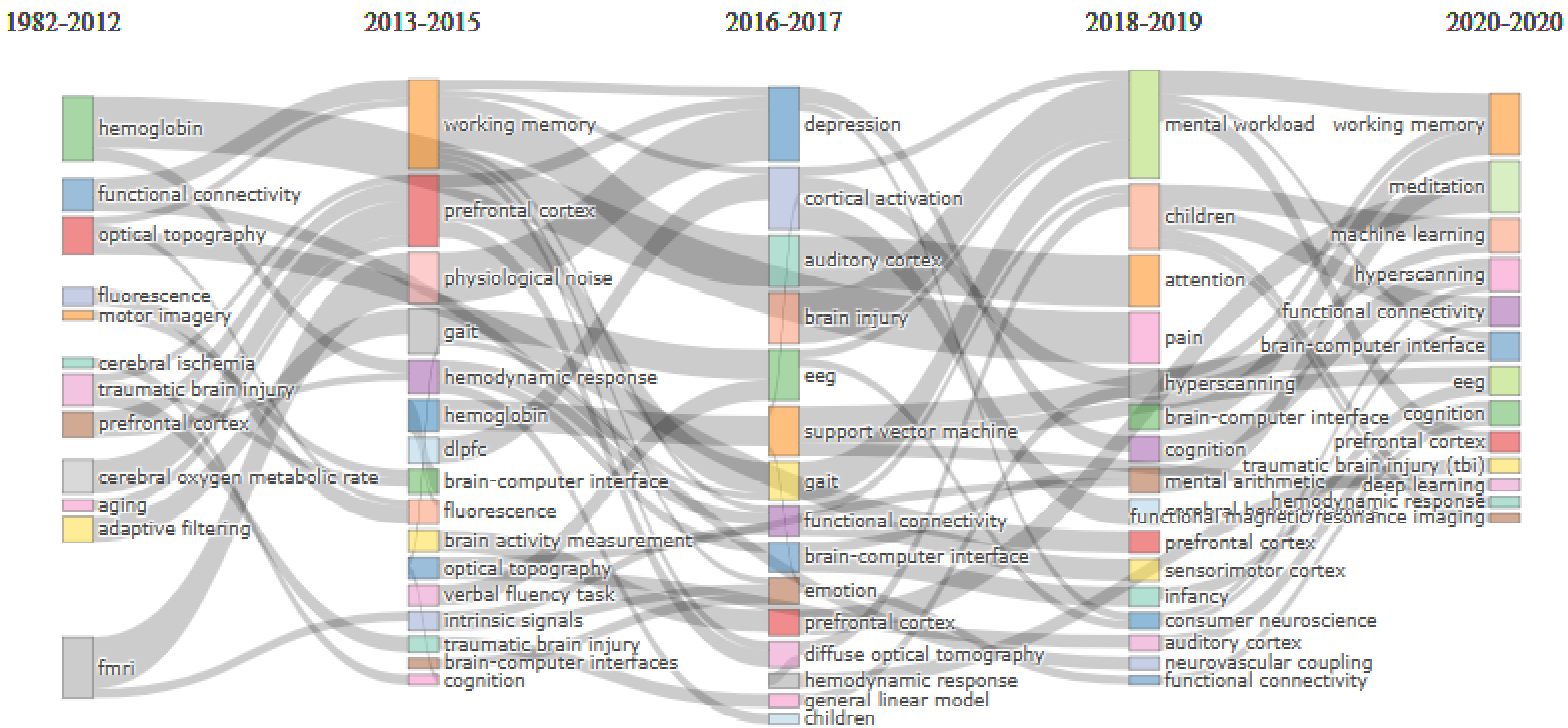

Figure 66: R- Biblioshiny Author's Keywords Thematic map visualization of keywords in the field of fNIRS between 2018-2020

Biblioshiny also provides a historiography plot of articles, which is a timeline view of citation links among papers sorted in chronological order. Such representations are often employed to trace the progression of ideas among seminal articles in a field. These plots replicate the historiographic structure in the field while referring to the highly influential articles in the historiography plot. Figure 67 shows the historiography plot for the top 20 highly cited fNIRS articles in our dataset. Such historiographic plots can be useful in tracing the intellectual origins of ideas within a field.

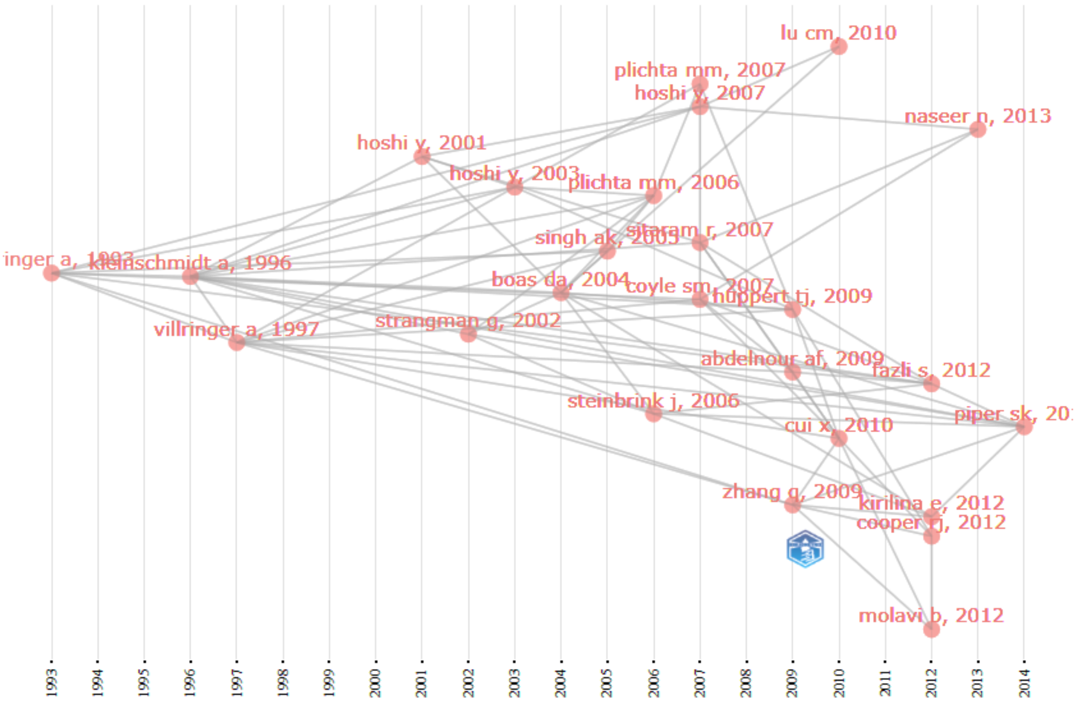

Figure 67: Historical direct citation network (Source:Biblioshiny, N=20).

Table 12 shows an example trace originating from the seminal works of Villringer et al that helped establish fNIRS as a brain imaging modality. Hoshi elaborates on Villringer et al with an animal model study that aim to improve our interpretation of the fNIRS signals. Strangman et al's subsequent work provides further validity for fNIRS by providing a systematic comparison among fNIRS recordings and the fMRI BOLD signal. This is followed by Boas et al.'s methodological contributions for increasing imaging sensitivity in diffuse optical correlation spectroscopy, which is consequential for fNIRS signals as well. Next in line we see a methodology paper that discusses how fNIRS probes can be spatially mapped to brain regions, followed by an fNIRS BCI application based on mental imagery by Sitaram. The article illustrating the features of an fNIRS signal analysis toolobox called Homer3 is followed by a popular signal cleaning approach by Cui based on the negative relationship between oxy- and deoxy-hemoglobin measures. Finally, Kirilina discusses further types of artifacts due to physiological factors, and ways to mitigate them to clean the fNIRS signals.

Table 12: Historical direct citation network

Authors	**Article Title**	**Year**	**Local Citation Score**	**Global Citation Score**
VILLRINGER A, 1993, NEUROSCI LETT	"Near-Infrared Spectroscopy (NIRS) - A New Tool to Study Hemodynamic-Changes During Activation of Brain-Function in Human Adults"	1993	260	787
VILLRINGER A, 1997, TRENDS NEUROSCI	"Non-İnvasive Optical Spectroscopy and Imaging of Human Brain Function"	1997	384	1153
HOSHI Y, 2001, J APPL PHYSIOL	"Interpretation of Near-Infrared Spectroscopy Signals: A Study with a Newly Developed Perfused Rat Brain Model"	2001	200	598
STRANGMAN G, 2002, NEUROIMAGE	"A Quantitative Comparison of Simultaneous BOLD fMRI And NIRS Recordings During Functional Brain Activation"	2002	378	884
BOAS DA, 2004, NEUROIMAGE	"Diffuse Optical Imaging of Brain Activation: Approaches to Optimizing İmage Sensitivity, Resolution, And Accuracy"	2004	284	538
SINGH AK, 2005, NEUROIMAGE	"Spatial Registration of Multichannel Multi-Subject FNIRS Data to Space Without MRI"	2005	302	437
SITARAM R, 2007, NEUROIMAGE	"Temporal Classification of Multichannel Near-İnfrared Spectroscopy Signals of Motor İmagery for Developing A Brain-Computer İnterface"	2007	198	391
HUPPERT TJ, 2009, APPL OPTICS	"Homer: A Review of Time-Series Analysis Methods for Near-İnfrared Spectroscopy of The Brain"	2009	520	795
CUI X, 2010, NEUROIMAGE	"Functional Near İnfrared Spectroscopy (NIRS) Signal improvement Based on Negative Correlation Between Oxygenated and Deoxygenated Hemoglobin Dynamics"	2010	266	423
KIRILINA E, 2012, NEUROIMAGE	"The Physiological Origin of Task-Evoked Systemic Artefacts in Functional Near Infrared Spectroscopy"	2012	272	351

4.9. Bibliometric Coupling Analysis Results

In bibliometrics studies another method for determining relatedness between items such as documents, authors, institutions, and countries is based on the number of references they share. In contrast to co-citation analysis, in this case the focus is not on the reference lists of the articles in the analyzed collection. In this case, the mapping is applied to the items in the collection, which can be informative for obtaining a current outlook of the relationships in the literature based on how items cite prior work.

In VOSviewer the nodes of the bibliometric coupling network can be color coded to reflect various different attributes, such as the average date of the publications in the corresponding item group. For instance, if we are plotting authors based on their bibliometric coupling relationsip, the color code of the node can be assigned as the average date of the papers by that author. This is another way of incorporating a time dimension into the analysis. In Figures 68-72, the color-coding ranges from dark blue to bright yellow where darker colors indicate earlier studies and the brighter color indicates recent work. Another visualization possibility for the coupling networks is to make the nodes proportional to a relevant statistic such as the number of published articles, link strength, or the citations accrued.

When we compare the maps obtained for the documents with co-citation and bibliometric coupling similarity metrics, seminal studies by Jobsis and Chance are not visible on the bibliometric coupling map. This is because the bibliometric coupling maps visualize the documents in the dataset, whereas the co-citation approach focuses on the documents in the reference lists that may reach older studies based on the co-citation patterns. In Figures 68-72 one can observe those authors, institutions and countries that have been active in fNIRS research for a longer duration of time with nodes marked with darker colors. Similar to the burst analysis, this method allows us to observe which articles, authors, journals, institutions or countries have become more prominent in time.

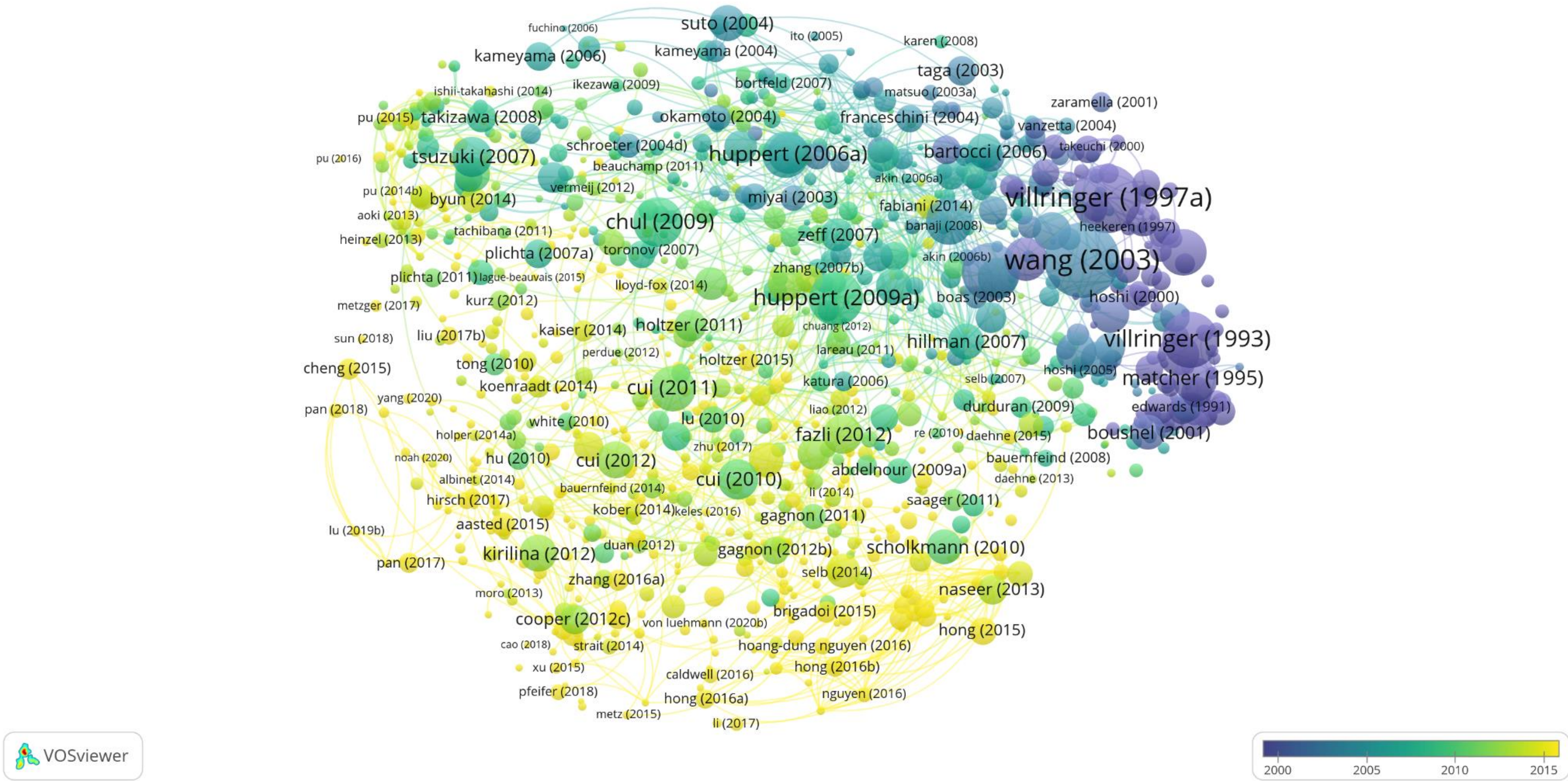

Figure 68: VOSviewer visualization of bibliometric coupling network of fNIRS articles between 1980-2020.

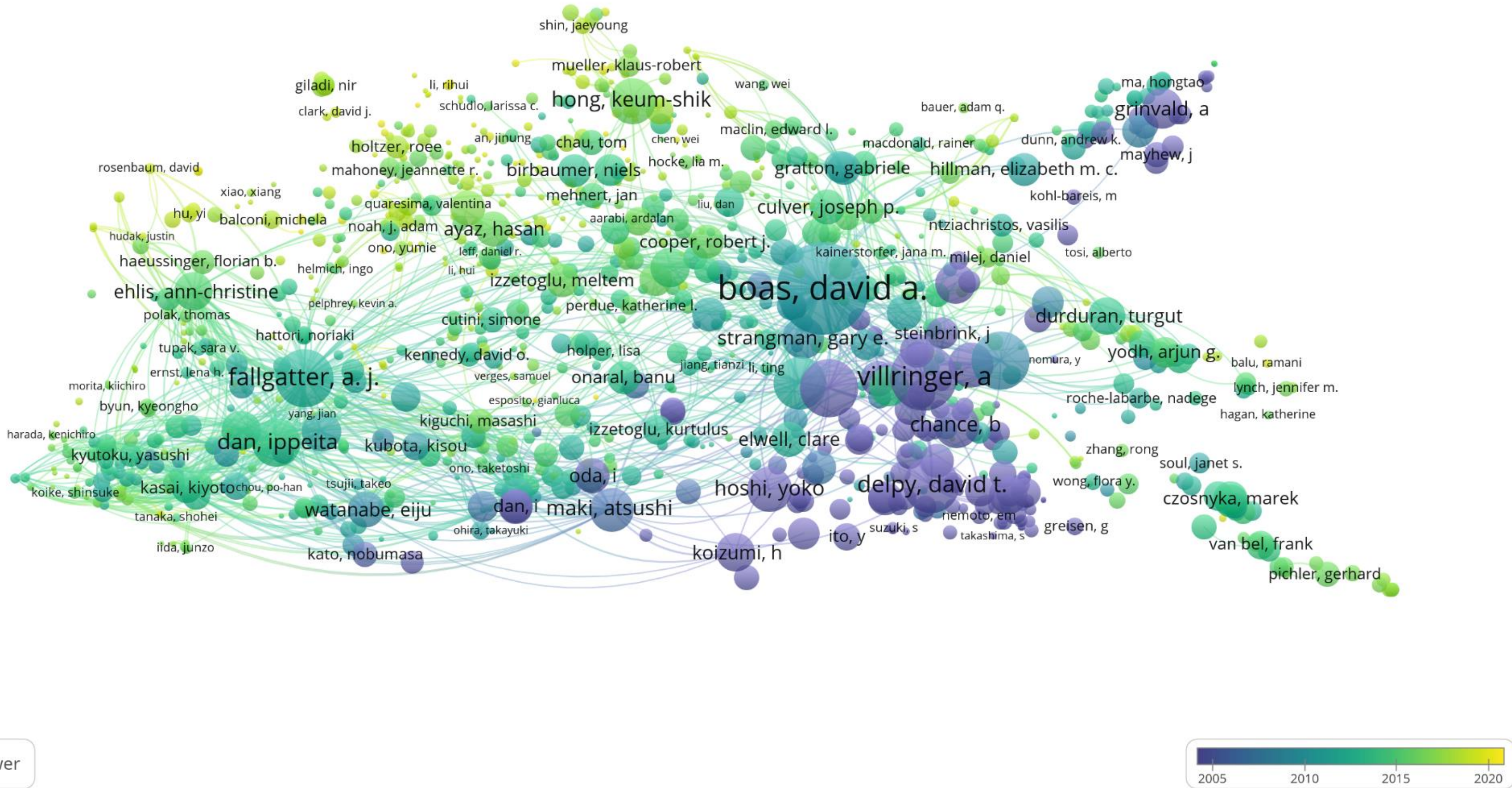

Figure 69: VOSviewer visualization of bibliometric coupling network of authors of fNIRS articles between 1980-2020.

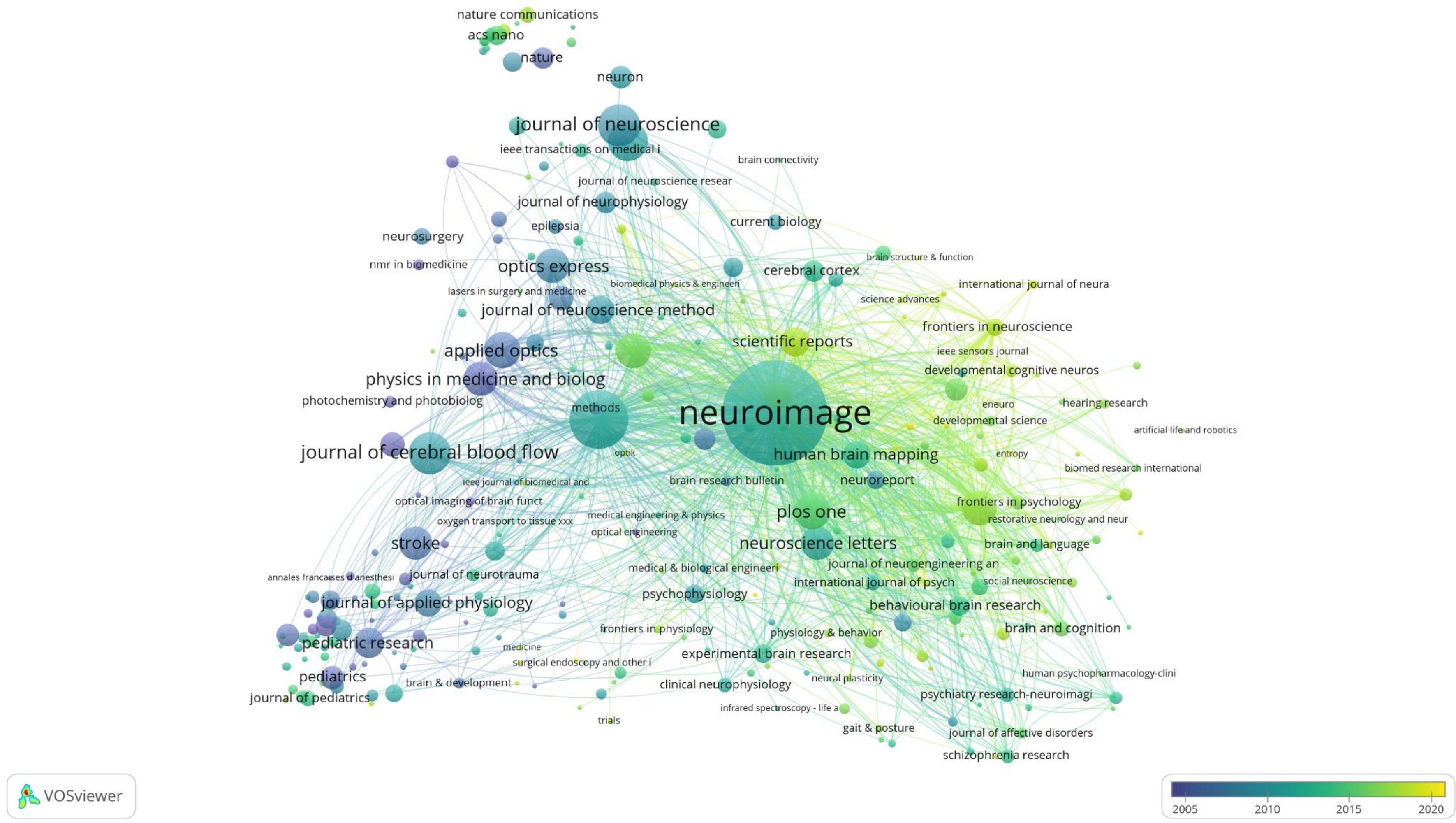

Figure 70: VOSviewer visualization of bibliometric coupling network of the journals where the fNIRS articles appeared between 1980-2020.

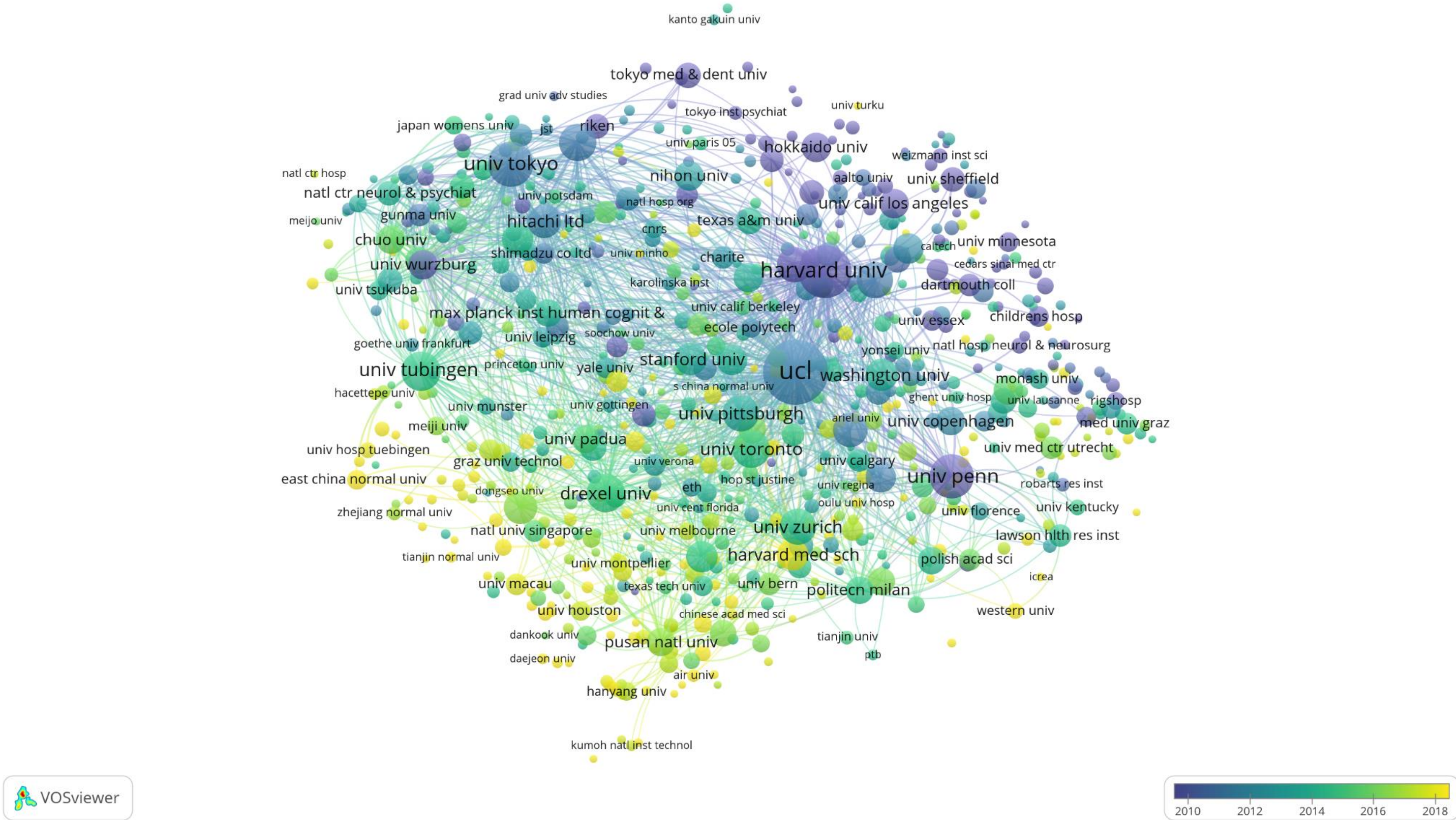

Figure 71: VOSviewer visualization of bibliometric coupling network of the institutions affiliated with the fNIRS articles appeared between 1980-2020.

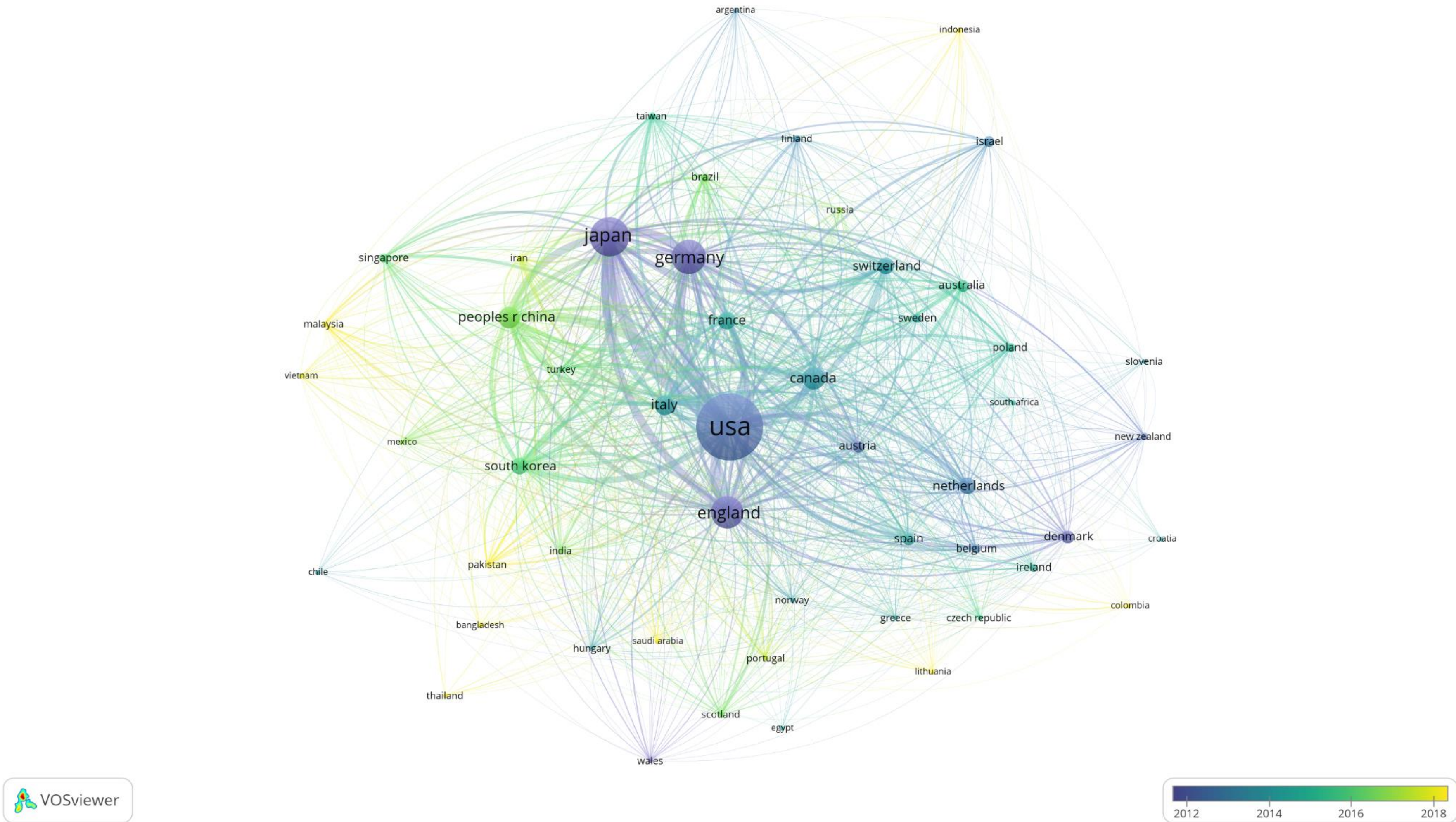

Figure 72: VOSviewer visualization of bibliometric coupling network of the countries affiliated with the fNIRS articles appeared between 1980-2020.

CHAPTER V

DISCUSSION AND CONCLUSIONS

This thesis study aims to explore the fNIRS literature by utilizing bibliometric analysis techniques. In particular, we aimed to investigate the interdisciplinary nature of the fNIRS literature with the help of various bibliometric analysis methods and indicators. Since a document set retrieved from a citation database constitutes our main data set, we initially focused on the departmental affiliation as a proxy for disciplinary characterization. We considered co-authorship across different departments as a practical indicator of multidisciplinary work. Since existing toolboxes do not currently provide a way to perform analysis on departmental affiliation data, we utilized a hybrid text mining technique to populate a similarity matrix of department names, which was then subjected to further clustering and visualization to aid the analysis of disciplinarity in the fNIRS literature. We also annotated fNIRS articles as disciplinary or interdisciplinary based on the diversity of the affiliations in the address sections of the articles. The diversity of the departments and countries also allowed us to expand this analysis to explore collaboration trends in the fNIRS literature.

Our analysis of the fNIRS literature suggests that at the beginning this field had been led primarily by studies conducted at specific departments such as Biophysics, Physiology, Bioengineering, Medical Physics (especially considering the affiliations of some of the pioneering researchers such as Chance, Jobsis, Delpy, Cope, Wyatt, Ferrari). This does not mean that the emergence of the fNIRS neuroimaging modality can be easily attributed to a single discipline, especially when one considers the mixed background of Britton Chance encompassing diverse fields such as engineering, electronics, biophysics, who has initiated and transformed the field with his innovations in theory and instrumentation. However, initial studies tended to take place within the confines of single disciplines since the focus has been to establish fNIRS as a viable measurement technique in biomedical contexts.

Such groundwork studies were then transformed into studies incorporating authors from multiple departments, firstly within medical sciences such as Pediatrics, Surgery, Geriatrics, and then in more applied fields such as Human Factors, Social Psychology, and Economics as evidenced in the diversity of the affiliations of the co-authors in fNIRS publications. In other words, with the expansion of the application areas of fNIRS, the studies have increasingly become more multidisciplinary. Nowadays such efforts are geared towards understanding the nature of brain responses in various contexts as diverse as monitoring tissue metabolism dynamics, movement coordination, decision making, social interaction, human-machine interfaces, etc., as evidenced in the term map analyses conducted in this study. Another key indicator of interdisciplinarity is the emergence of specialty journals that aim to cater to the need for pursuing cross disciplinary investigations of phenomena towards common goals. In our analysis of citation bursts, we detected the emergence of such a journal called Neurophotonics, with its increasing prevalence in clinical practice which has quickly become a central venue for fNIRS researchers to share their findings as evidenced in its burst performance. Therefore, one can argue that as a neuroimaging modality fNIRS is increasingly becoming a shared focus of such interdisciplinary research efforts in understanding the nature and limits of cognition.

The growth in the outreach of fNIRS across multiple domains and its increasingly multidisciplinary author composition have also positively contributed to the impact generated by fNIRS studies. Especially in the last 10 years interdisciplinary studies tended to generate more citations, whereas during the inception of fNIRS as a new field within Neuroimaging, studies of disciplinary nature tended to have a larger share of citations. Relatedly, in the last 10 years studies that are a product of institutional collaboration also tended to generate more citations, whereas during the inception of fNIRS as a new field within Neuroimaging, studies with no-institutional collaboration tended to have a larger share of citations.

We should note that this is still an unfolding growth pattern which is accompanied by a growth in the number of publications as well. When we considered normalized impact measures such as CPP and CNCI, there is not yet a significant separation between the two groups of publications. However, one should also consider that citation trends require a larger year span to make such comparisons, so in the next 5 years the trend we detected in total citations may also be reflected in the normalized impact measurements. Another supportive indication of this observation is the difference between the two groups in terms of their JIF quartile distributions. Our findings suggest that fNIRS articles that are products of interdisciplinary international collaboration have a significantly higher share in Q1 and Q2 categories, which has become more evident especially in the last few years.

Apart from comparisons with respect to impact measurements, we also explored the structure of the relationships among the disciplines involved with fNIRS research. Departments such as Radiology, Bioengineering, Biomedical Engineering, Medicine, Health, Neuroscience and Neurobiology constitute the core set of disciplines for fNIRS research. Other disciplines form peripheral but integrated clusters around this core set. For instance, there is a cluster including Developmental Psychology, Neuropsychiatry, Linguistics, and another including Pediatrics and Neonatal Care that interact with the core central fields. The cluster formed by Anesthesia and Rehabilitation seem to relate to the core cluster via the mediation of Neurosurgery, Surgery and Clinical Neuroscience fields. Co-authorship maps are also informative in terms of tracking which institutions and countries are actively involved with fNIRS research. The maps highlight the sustained impact of institutions based in the USA, England, Japan and Germany over this field, as well as the recent emergence of China.

The mapping of keywords in 10-year-long overlapping time periods allowed us to explore the prominent topics and their interrelationships over these time frames. In the first 10-year period we mainly observed keywords corresponding to basic science studies that aim to establish the veridicality of the fNIRS method for monitoring brain activity related phenomenon. Some early applications in newborns and language processing can also be seen in this period. In the next decade we begin to observe keywords indicative of more application-oriented studies along with basic groundwork studies, which focus primarily on monitoring prefrontal cortex activity in executive, attention and emotion tasks over both healthy and pathological populations. This period coincides with the emergence of portable fNIRS devices that can effectively monitor the parts of the prefrontal cortex underneath the hairless forehead (Quaresima & Ferrari, 2012). Given the advances in portable fNIRS neuroimaging sensors and signal processing capabilities we observe increasing prominence of topics such as brain-computer interfaces and hyperscanning studies that focus on the interrelationships among brain oxygenation dynamics of two or more participants.

Conducting keyword co-occurrence analysis over 10-year periods in a sliding window allowed us to observe the evolution of the field's interests in time. However, to be more precise about the time frame in which specific keywords gain or lose prominence, we utilized the citation burst analysis. Although burst statistics are effective in observing temporal changes, its not easy to see how bursting keywords relate to the other keywords. Thematic evolution maps can partly address this need by presenting the keywords on a quadrant where relative positions and the quadrant locations can be indicative of the increasing prominence of a topic or the emergence of a niche domain. Historiography plots that visualize the direct citation links among selected publications and authors can also be informative to trace the development of specific ideas and methods within a field such as fNIRS. Finally, bibliometric coupling based maps allow researchers to cluster items based on the similarity between their reference lists, which may be effective in identifying concentration areas that cite similar literature as they explore possibly related themes.

Existing bibliometric tools offer powerful ways to visualize and explore research fields such as fNIRS. Given a unit of analysis such as documents, authors, sources (e.g. journals), institutions, and countries, bibliometric methods typically establish a mathematical measure of relatedness among those units and utilizes algorithms such as clustering and multidimensional scaling to visualize those relationships. In the scope of this thesis we explored relatedness metrics based on co-authorship (e.g. the number of publications co-authored by the entities), co-occurrence (e.g. the number of documents that the entities occur together), citation (e.g. the number of times entities cite each other), bibliographic coupling (e.g. the number of shared references among entities), and co-citation (e.g. the number of times entities are cited together) measures, each of which provides a different but complementary perspective on a targeted field such as fNIRS. Maps based on co-authorship can be useful in identifying clusters of researchers engaged in collaborative work, whereas citation networks can be useful for observing pockets of studies building on each other. Co-occurrence based maps can be useful in identifying topics that are gaining and loosing prominence. Co-citation can be considered as a special case of co-occurrence in the reference lists of the publications in the targeted domain. Since co-citation maps are based on the reference lists rather than the publications themselves, the maps may include items that are not in the list of documents, since reference lists tend to move further back in time. Therefore, if the goal is to identify seminal studies in a field, co-citation maps can be more effective due to their extended historical coverage. On the contrary, maps built over bibliographic coupling focuses on mapping and clustering the documents in the target list, so depending on the sample of documents used, some of the older studies may not appear in the maps. However, if the goal is to explore relationships among emerging themes and recent trends, then the co-citation metrics may overemphasize older, highly cited/co-cited studies.

Bibliometric toolboxes have steadily improved in the recent years in terms of usability and the range of supported algorithms for clustering and mapping items. However, getting the most out of bibliometric analysis still requires some fine tuning and care in terms of the document list and the thresholds selected for analysis. If a dataset including loosely related or too few documents are selected, the maps may generate isolated pockets of items that do not offer much insights about core themes or authors in a field of study. Issues may also arise when a large dataset including a broad range of publications is selected. In this case most toolboxes suggest pruning the dataset to a certain size (e.g. limit the analysis to 1000 nodes, or impose minimum number of documents or citations for selecting items), so that the clustering and scaling algorithms can be run efficiently in a reasonable amount of time. Constraints such as limiting the analysis over documents that accrued a certain minimum number of citations may overemphasize a specific group of entities and may make it difficult to get a more complete sense of a research area. On the other hand, trying to be overly inclusive may lead to maps that are cluttered and difficult to interpret. Finally, most toolboxes rely on certain parameters to be used during clustering (e.g. attraction/repulsion parameters in VOSviewer) which will lead to different map layouts and clustering decisions. Therefore, the choice of the document set, establishing appropriate thresholds, and being informed about the input parameters of clustering and layout algorithms are of key importance.

Another important concern in building bibliometric maps that are informative for a field is the data cleaning aspects. Bibliometric databases such as WoS and Scopus have been steadily improving their database contents for misspellings and unconventional abbreviations, as well as providing more structured information where multiple entities such as authors and institutions are mapped to unique identifiers. In contrast to document-centered approach of the past the data resources are much more suitable for bibliometric analysis. However, data cleaning is still a relevant limitation since the text mining algorithms tend to pick up words or phrases that are uninformative, or search terms used to collect the document set (e.g. fNIRS) may appear as the most prominent keyword masking the others if left unchecked. Most toolboxes like VOSviewer allow the user to inspect and check/uncheck the words and phrases, or provide thesaurus lists to match words or author names to a specific label, before they will be subjected to bibliometric analysis.

For future work, bibliometric methods can be improved to better accommodate the needs of researchers in the field of fNIRS in particular and in Neuroimaging and Neurosciences in general. Firstly, these fields are gradually producing a taxonomy of words, such as distinctions made among anatomical structures, cognitive functions, disorders, measures of activation/connectivity, and experimental paradigms exploring the relations between structures and functions. Such distinctions may need different types of graph structures such as bimodal graphs where relationships among items from different sets can be visualized and explored. In current bibliometric mapping approaches graph structures incorporating documents, themes and authors are rare due to methodological difficulties. However, such graphs are explored in network science, and can be useful especially to aid knowledge discovery in the field of Neuroimaging. Another challenge with bibliometric approaches is the difficulty in tracking the temporal growth of knowledge through the connection patterns growing and changing in time. We aimed to emulate this partly by building multiple maps with different overlapping time spans, but due to the challenges involved with multidimensional scaling based algorithms in computing layouts, finding a mapping and gradually reorganizing its structure to accommodate a new time window is a challenging problem. CiteSpace toolbox aims to provide a visualization to display growth patterns, but its rather limited in its scope for capturing transitions that bring a reorganization of the existing paradigms, such as introduction of a new neuroimaging modality like fNIRS, or growing emphasis of connectivity analysis as opposed to approaches that focused on the functional roles of specific brain regions.

Overall, the findings of this thesis study suggest that fNIRS is an increasingly interdisciplinary field of study within Neuroimaging, whose impact is growing as fNIRS is increasingly utilized in previously unexplored settings thanks to its portability and advances in instrumentation and signal processing. Our findings also demonstrate that bibliometric techniques can be used to effectively explore the trends and seminal studies in a field. We also observed that choices made during data and parameter selection are consequential on the visualizations and clusters obtained, and their interpretations. Resorting to purely statistical measures to arrive at an in-depth view of a field is not tenable without any content knowledge. However, strategic utilization of existing bibliometric toolboxes with adequate understanding of their assumptions and limitations can be a powerful method to get a general sense of a field, which would be very difficult to achieve by tracing the reference list of a few influential papers in a field.

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APPENDICES

APPENDIX A

OCCURRENCE OF KEYWORDS IN THE FIELD OF FNIRS BY YEAR

Year	#Occurrences	#Avg. citations	#Links	#Total link strength
1996				
xe-133 clearance	6	17,00	19	36
1998				
c-oxidase	5	59,60	19	27
1999				
cerebral blood-flow	14	183,14	45	63
sensory stimulation	6	381,50	29	34
2000				
spectrophotometry	11	49,64	45	63
2004				
oxidative-metabolism	12	197,17	54	72
deoxyhemoglobin concentration	8	70,25	44	51
cytochrome-oxidase	7	20,00	27	28
piglet brain	5	26,20	19	21
2005				
cerebral blood-volume	18	81,89	65	107
intrinsic signals	6	198,00	28	31
2006				
flow	21	35,10	73	121
carbon-dioxide	10	16,90	39	51
consumption	5	37,60	28	29
2007				
newborn-infants	24	89,42	80	144
preterm	9	25,44	37	49
rat-brain	6	36,33	17	20
sleep	5	104,60	24	28
2008				
absorption	21	41,48	80	137
hemoglobin oxygenation	19	124,63	76	123
rat	18	53,06	55	80
quantification	15	28,00	56	78
2009				
visual-stimulation	15	94,87	57	92

scattering	14	90,50	50	82
media	13	49,23	43	61
saturation	10	28,10	29	36
pet	9	39,89	40	43
oximetry	8	20,75	24	29
reflectance	8	31,38	31	39
blood oxygenation changes	5	236,20	31	34
hypoxia-ischemia	5	20,20	23	30
2010				
neuronal-activity	22	63,82	82	133
cerebral oxygenation	20	29,80	71	106
cerebral blood	20	106,60	88	127
volume	19	56,00	79	121
preterm infants	15	33,13	56	87
oxygenation changes	13	158,54	64	93
hemodynamic-changes	11	71,64	48	71
frontal activation	11	57,09	43	73
reconstruction	8	39,88	25	31
tissue oxygenation	8	70,00	33	38
flight	7	35,29	32	40
images	6	25,83	28	35
noninvasive assessment	6	30,50	32	35
transcranial doppler	5	59,60	19	20
2011				
oxygenation	148	43,41	258	881
hemodynamics	59	49,03	147	339
light	31	44,77	88	164
hemoglobin	31	28,35	101	186
topography	30	59,63	93	172
visual-cortex	30	62,80	100	177
metabolism	28	50,36	95	159
optical topography	20	76,00	78	113
adult head model	14	102,14	58	100
injury	13	31,08	53	66
transcranial functional brain	12	72,58	45	77
blood-volume	12	38,08	53	72
pathlength	11	32,36	47	66
tissues	9	30,78	35	44
reduction	9	21,67	47	52
neural activity	9	189,67	36	49
blood	8	31,13	35	41
delivery	6	10,33	12	13
localization	6	35,83	32	35

breast	5	38,80	28	34
expression	5	14,80	16	17
noninvasive measurement	5	16,60	27	29
negative bold	5	21,40	24	29
pleasant	5	39,60	20	27
2012				
stimulation	77	63,13	180	468
tissue	73	49,67	154	402
humans	39	24,44	123	230
time	37	60,43	116	185
light-propagation	28	70,18	90	186
tomography	28	26,96	86	151
resolution	26	54,46	102	163
photon migration	24	66,96	85	146
functional mri	23	50,35	81	127
adult head	23	81,78	84	146
bold	21	47,24	77	131
somatosensory cortex	16	43,81	60	97
areas	16	34,81	76	115
optical-properties	16	37,94	62	94
spatial-resolution	14	53,43	57	92
mni space	14	42,50	54	93
lateralization	13	27,62	59	77
selective attention	13	55,15	49	66
scattering media	9	18,89	40	51
transport	8	44,88	27	33
pressure	8	33,88	40	44
turbid media	8	93,63	36	43
limitations	8	19,13	31	36
reproducibility	7	76,29	42	52
ischemia	7	20,71	26	35
cerebral hemoglobin oxygenation	7	100,43	37	51
bold fmri	6	40,67	38	43
cerebral-cortex	6	22,67	34	37
awake infants	6	56,00	29	41
depressed-patients	6	27,83	29	37
cerebral blood oxygenation	6	112,50	26	32
wavelength dependence	5	207,00	27	29
segmentation	5	48,80	25	27
2013				
human brain	82	37,80	200	481
cerebral-blood-flow	77	49,61	184	429
cerebral hemodynamics	69	48,04	169	428

blood-flow	67	38,96	173	376
infants	46	41,17	137	259
mri	36	51,58	141	229
signal	31	54,10	103	177
spectroscopy	28	61,71	84	113
bold signal	23	43,91	87	139
event-related fmri	20	44,25	79	115
positron-emission-tomography	18	24,83	72	101
low-frequency oscillations	17	66,29	72	117
in-vivo	15	17,87	53	65
representations	14	25,79	66	91
frequency	13	19,69	60	87
blood oxygenation	13	91,00	61	85
adult	12	27,58	48	65
evoked-potentials	11	39,64	39	58
oxygen-saturation	10	33,30	42	52
magnetic-resonance	8	35,88	33	35
optical tomography	8	49,75	41	49
perfusion	7	16,86	28	29
focal changes	7	23,14	36	50
human head	7	47,00	27	35
balloon model	6	107,50	28	44
specificity	5	13,80	19	26
sentence comprehension	5	7,00	25	28
reliability	5	22,20	28	33
arousal	5	28,40	21	26
design	5	32,00	23	24
postural control	5	56,80	22	31
2014				
cortex	214	33,28	302	1204
brain activation	110	35,05	237	660
system	97	41,35	196	525
hemodynamic-response	63	66,02	173	397
diffuse optical tomography	40	60,80	119	249
stroke	39	23,56	110	202
false discovery rate	27	32,11	105	171
optical pathlength	26	63,73	91	140
cortical activation	24	41,13	91	141
head	24	45,00	76	128
frontal-cortex	20	65,75	72	123
fluctuations	19	46,16	71	125
representation	18	16,39	71	104
adults	17	32,76	66	92

acquisition	16	29,44	57	86
anterior cingulate cortex	14	44,57	58	92
technology	12	38,50	39	50
systems	12	35,17	64	81
verbal-fluency task	12	24,67	47	66
infant brain	11	24,09	52	75
speech-perception	11	40,82	29	42
imitation	11	16,09	40	54
registration	10	29,40	45	58
architecture	10	29,20	43	57
epilepsy	9	18,00	41	48
primary motor cortex	9	50,78	47	56
algorithms	8	59,88	42	56
sustained attention	8	20,63	36	49
episodic memory	8	25,25	33	43
default-mode	8	53,13	33	47
structural connectivity	7	69,86	37	48
anatomy	7	24,00	30	36
parameters	7	7,86	37	47
hypoxic-ischemic encephalopathy	7	27,43	20	25
adhd	6	19,67	24	33
comprehension	6	22,83	33	41
fmri data	6	33,17	31	37
dominance	6	32,67	29	37
cerebral oxygen-saturation	6	39,67	22	27
extraction	6	9,00	31	34
neurons	6	20,33	20	23
identification	6	49,00	30	36
hemoglobin concentration	6	21,17	23	25
wrist extensor	5	9,80	20	22
motion artifact cancellation	5	43,40	23	29
anesthesia	5	8,40	16	18
quantitative-evaluation	5	37,80	27	30
2015				
near-infrared spectroscopy	419	42,58	389	2224
activation	379	33,58	386	2267
fmri	245	31,82	327	1425
nirs	126	32,74	239	767
task	95	27,02	204	547
responses	91	28,53	184	519
signals	80	43,84	145	470
model	58	25,60	159	305
brain activity	47	28,53	142	277

motor cortex	42	33,24	139	253
hemodynamic-responses	42	33,31	122	270
recognition	37	22,00	111	218
interference	37	69,76	122	250
alzheimers-disease	33	38,73	105	186
spatial registration	33	40,82	110	198
sensitivity	29	28,21	105	176
modulation	29	23,45	93	167
mechanisms	28	19,29	101	162
oscillations	26	32,00	80	155
recovery	26	15,62	82	127
dynamics	25	25,40	84	141
movements	20	40,40	78	117
stimuli	18	28,00	55	96
reorganization	18	26,78	64	106
removal	18	35,00	66	105
state	17	37,47	66	107
brain-computer interface	17	66,94	56	107
accuracy	15	51,60	64	95
brain-function	15	30,47	63	87
orbitofrontal cortex	14	16,57	56	84
premotor cortex	14	34,64	56	80
stress	14	6,43	58	76
attention-deficit/hyperactivity disorder	13	32,15	45	79
propagation	13	28,15	52	68
dorsolateral prefrontal cortex	12	38,42	46	63
execution	12	60,75	55	77
disease	12	44,00	58	67
inhibition	11	10,36	51	62
regions	11	45,55	57	71
independent component analysis	11	40,91	56	72
reward	11	27,73	33	53
functional brain	11	63,27	57	78
area	10	13,20	37	52
therapy	10	14,70	35	51
dependence	8	14,38	35	41
gender-differences	8	25,25	29	37
impact	7	28,43	18	22
autoregulation	7	21,43	28	35
stroop task	7	16,71	39	44
cognitive tasks	7	18,57	26	40
autism	7	32,00	34	47
nirs signal	7	80,29	39	50

prefrontal cortex activity	6	28,50	33	40
face	6	33,00	33	39
risk	6	44,67	28	32
mind	6	10,33	22	26
statistical-analysis	6	19,00	22	28
monte-carlo	6	93,17	21	21
long-term	5	36,20	16	23
finger movements	5	24,20	23	29
tdcs	5	19,00	20	29
enhancement	5	27,20	16	19
nirs data	5	24,60	22	31
glioblastoma	5	9,80	8	8
discrimination	5	40,60	20	24
involvement	5	13,20	28	32
working-memory task	5	22,40	26	32
primary somatosensory cortex	5	18,80	24	31
artifact	5	65,60	29	33
potentials	5	43,20	27	30
2016				
brain	191	27,87	292	1043
prefrontal cortex	187	27,30	291	1070
performance	141	35,40	237	835
fnirs	110	28,29	219	635
working-memory	100	27,37	218	585
children	66	17,64	159	346
motor imagery	63	46,57	127	368
attention	49	34,69	133	263
motor	48	32,58	144	281
networks	40	21,03	127	264
communication	38	55,74	90	215
memory	34	21,24	97	172
perception	32	28,47	94	179
gait	32	29,72	91	195
schizophrenia	30	17,53	89	168
language	29	24,66	101	175
verbal fluency task	26	38,23	81	149
plasticity	23	21,52	63	105
behavior	22	24,18	78	120
decision-making	22	19,55	67	109
organization	21	28,62	89	133
imagery	20	42,85	60	118
age	19	20,21	70	104
diagnosis	18	20,67	56	73

rehabilitation	18	18,89	75	114
depression	17	10,53	65	101
parietal cortex	17	16,18	58	86
validation	15	25,47	55	65
specialization	15	23,07	58	82
movement	15	19,93	52	82
sex-differences	14	21,21	57	76
information	14	26,64	62	83
tasks	13	28,62	57	86
time-series	13	35,69	52	87
parkinsons-disease	13	23,77	62	83
cognition	12	34,58	47	63
pain	12	16,92	47	70
dysfunction	12	11,17	55	70
bipolar disorder	12	32,67	47	76
variability	11	35,82	50	70
deficit hyperactivity disorder	11	19,27	48	77
hand	10	18,80	45	59
cerebral-blood	10	24,00	43	51
hemispheric-asymmetry	10	18,40	46	61
disorder	10	11,50	48	59
single-trial classification	9	38,78	31	50
hand movements	9	18,56	37	59
experience	9	12,00	36	50
voice	9	26,44	34	42
simulation	9	28,11	46	62
retrieval	9	19,44	36	50
dementia	9	33,00	41	62
movement artifacts	9	52,44	40	58
age-related-changes	9	12,78	36	51
methodology	8	8,38	39	50
stroop interference	8	26,50	31	41
rtms	8	11,88	32	40
infrared spectroscopy signals	8	15,88	29	37
facial expression	8	35,13	25	42
arterial-blood pressure	8	33,13	32	50
deficits	8	16,25	35	46
heart-rate	7	35,86	26	27
Neuroimaging	7	24,00	30	45
small-world	7	29,86	32	39
self-regulation	6	71,50	25	27
test-retest reliability	6	38,17	32	46
workload	6	49,00	26	33

parietal	6	20,67	36	41
cognitive Neuroimaging	6	19,67	25	31
top-down	6	21,33	32	38
social cognition	6	54,00	24	34
deficit/hyperactivity disorder	6	17,00	23	32
faces	6	7,50	25	30
mirror neuron system	6	38,83	24	41
short-term-memory	6	25,50	33	40
spectral-analysis	5	19,80	26	30
models	5	32,80	22	26
global signal	5	22,40	26	30
pain perception	5	9,60	24	29
quality-of-life	5	15,40	22	23
instrumentation	5	15,60	23	29
vigilance	5	22,40	25	28
prediction	5	19,20	22	24
functional-organization	5	17,00	20	24
frontal-lobe	5	20,60	29	32
behavioral-inhibition	5	23,60	19	30
neurorehabilitation	5	22,40	30	33
2017				
classification	102	37,26	175	584
connectivity	61	24,62	157	361
eeg	57	29,60	139	311
functional connectivity	33	26,55	117	210
artifacts	29	28,69	91	169
metaanalysis	23	19,39	88	138
cognitive control	23	15,26	94	144
executive function	23	36,52	76	133
coherence	22	24,91	76	118
auditory-cortex	21	36,71	77	139
older-adults	20	23,00	68	121
bci	20	35,95	49	115
network	19	15,16	71	103
individual-differences	19	17,63	67	100
neural basis	19	22,16	71	102
patterns	19	20,16	84	119
mental workload	19	20,05	58	104
motion	18	22,17	67	105
synchronization	18	24,94	77	116
emotion	17	13,00	53	82
response-inhibition	16	13,13	53	96
mild cognitive impairment	15	34,33	50	84

abnormalities	15	25,60	57	94
association	14	9,43	45	65
transcranial magnetic stimulation	14	16,57	52	69
prefrontal activation	13	12,31	55	82
algorithm	13	14,77	45	62
fnirs data	12	10,67	52	72
improvement	12	22,08	44	66
direct-current stimulation	12	25,50	46	69
heart-rate-variability	11	21,73	42	50
disorders	11	16,18	51	67
cortical activity	11	20,00	48	52
asymmetry	11	35,00	49	66
excitability	10	14,50	41	56
verbal fluency	10	12,80	53	68
default mode	10	14,10	44	63
anxiety	10	17,70	43	61
brain-computer-interface	10	31,40	29	53
cognitive impairment	9	25,56	37	46
noise	9	24,22	32	41
traumatic brain-injury	9	12,56	34	38
self	9	13,33	38	51
cognitive function	9	58,56	38	52
empathy	9	9,00	37	45
integration	8	7,25	32	45
balance	8	14,88	28	39
validity	8	18,13	30	38
event-related potentials	8	11,75	32	43
brain responses	8	13,50	27	32
adaptation	6	17,33	27	31
emotion regulation	6	34,83	23	29
temporal cortex	6	21,50	28	32
exposure	6	13,83	20	22
amygdala	6	10,00	25	30
cortex activity	6	18,83	28	33
state functional connectivity	6	14,00	22	31
elderly subjects	5	22,40	19	31
deception	5	28,20	27	35
expressions	5	12,00	17	24
capacity	5	13,60	28	34
vegetative state	5	29,40	23	29
young	5	30,60	22	23
cortical control	5	23,80	25	33
conflict	5	28,40	26	29

scalp	5	56,80	27	31
2018				
speech	20	23,50	69	118
walking	18	22,28	56	106
adhd children	12	10,08	43	74
exercise	12	12,33	51	68
impairment	11	7,36	38	51
cooperation	11	30,27	34	46
adolescents	10	10,60	49	60
executive functions	9	23,44	47	67
inhibitory control	9	25,56	52	65
physical-activity	8	30,75	32	47
people	7	15,14	26	33
fatigue	7	14,57	31	38
young-children	7	12,57	32	40
facial expressions	6	11,00	19	27
individuals	6	19,33	31	37
social-perception	6	18,83	25	34
degraded speech	6	12,67	27	32
brain networks	6	15,17	37	44
health	6	14,17	32	40
global interference	6	62,17	22	28
inferior frontal gyrus	6	18,33	31	34
neural efficiency	5	6,40	20	29
symptoms	5	16,20	27	31
components	5	18,00	21	28
neural mechanisms	5	13,60	22	24
whole-head	5	20,40	27	32
neurobiology	5	6,20	27	31
resting-state networks	5	31,80	25	31
parcellation	5	53,80	30	38
brain-development	5	11,40	17	21
brocas area	5	8,60	23	27
intelligence	5	24,00	24	34
efficiency	5	13,40	20	21
mirror	5	17,40	26	29
psychosocial stress	5	46,40	25	34
questions	5	30,80	18	27
2019				
brain-computer interfaces	10	32,30	31	53
selection	7	18,29	31	46
severity	6	42,83	31	40

APPENDIX B

TREND TOPIC ANALYSIS (BIBLIOSHINY)

Keywords	frequency	Year (start)	Year (Mediam	Year (finish)
near-infrared spectroscopy	838	2014	2017	2019
activation	758	2013	2016	2019
fmri	490	2014	2017	2019
cortex	428	2012	2016	2018
oxygenation	296	2007	2013	2017
classification	204	2015	2018	2020
working-memory	200	2015	2018	2019
human brain	164	2011	2014	2017
cerebral-blood-flow	154	2011	2014	2017
stimulation	154	2009	2015	2018
hemodynamics	118	2007	2013	2018
infants	92	2012	2015	2018
light	62	2009	2012	2015
topography	60	2008	2011	2014
visual-cortex	60	2008	2012	2016
newborn-infants	48	2003	2007	2014
behavior	44	2014	2019	2020
flow	42	1999	2006	2015
absorption	42	2000	2010	2014
speech	40	2016	2019	2020
hemoglobin oxygenation	38	2002	2009	2013
cerebral blood-volume	36	1998	2006	2011
rat	36	2003	2010	2015
cerebral blood-flow	28	1994	1998	2005
mni space	28	2009	2011	2016
media	26	2006	2009	2012
oxidative-metabolism	24	2000	2004	2008
exercise	24	2019	2020	2020
spectrophotometry	22	1995	1997	2005
brain-computer interfaces	20	2019	2020	2020

APPENDIX C

TOP KEYWORDS EACH GROUP NETWORK

Imaging Method/Analysis Methodology/Physical Phenomenon (light, optics etc.)		Physiological Phenomena		Cognitive Processes/Abnormalities		Application Area		Brain Regions		Population	
Keywords	**occurrences**	**Keywords**	**occurrences**	**Keywords**	**occurrences**	**Keywords**	**occurrences**	**Keywords**	**occurrences**	**Keywords**	**occurrences**
fmri	514	oxygenation	319	working memory	324	bci	223	prefrontal cortex	652	infant	227
eeg	253	hemodynamic response	263	attention	170	exercise	105	cortex	480	children	211
stimulation	158	cerebral oxygenation	183	alzheimer's disease	140	gait	103	human brain	264	motor imagery	127
diffuse optical tomography	151	functional connectivity	183	traumatic brain injury	132	surgery	93	motor cortex	105	humans	112
mri	148	stroke	174	schizophrenia	131	cardiopulmonary bypass	90	visual cortex	100	older adults	101
tomography	119	cerebral hemodynamics	159	verbal fluency task	126	aging	89	frontal cortex	77	rat	95
metaanalysis	98	network	150	perception	115	cardiac surgery	88	auditory cortex	59	preterm infants	92
oximetry	86	saturation	131	executive function	114	movement	71	dorsolateral prefrontal cortex	59	adult	86
sensitivity	86	autoregulation	125	cognition	105	recovery	67	default mode	50	newborn	67
fluorescence	84	connectivity	115	brain injury	105	therapy	65	somatosensory cortex	50	cells	62
positron-emission-tomography	78	metabolism	110	language	104	walking	64	anterior cingulate cortex	43	individual-differences	57

resolution	77	tissue oxygenation	107	motor	95	injury	62	lateralization	40	neonate	52
functional mri	73	perfusion	106	time	93	stress	61	parietal cortex	37	newborn-infants	52
optical topography	72	hemoglobin	101	recognition	86	rehabilitation	60	cerebral-cortex	35	adult head	46
scattering	72	oxygen-saturation	87	memory	83	reconstruction	57	frontal lobe	33	mice	41
light-propagation	70	intracranial pressure	77	emotion	83	pain	54	premotor cortex	33	rat-brain	38
microscopy	68	ischemia	77	depression	82	diagnosis	52	barrel cortex	32	preterm	37
interference	67	neurovascular coupling	77	behavior	73	anesthesia	52	orbitofrontal cortex	30	premature-infants	34
validation	66	flow	76	speech	68	cooperation	45	prefrontal activation	29	infancy	32
optical-properties	64	communication	73	dysfunction	63	sex-differences	41	asymmetry	27	birth-weight infants	27
modulation	63	oscillations	65	parkinsons disease	60	development	38	primary motor cortex	26	mouse	24
spatial registration	63	plasticity	65	cognitive control	59	sleep	36	amygdala	25	mouse-brain	24
bold	57	hypoxia	64	dementia	51	glioma	36	inferior frontal gyrus	25	adolescents	23
coherence	57	cerebral autoregulation	63	executive functions	50	balance	36	temporal cortex	24	childhood	23
diffuse correlation spectroscopy	57	neural activity	63	resting state	49	cancer	34	hemispheric-asymmetry	20	mouse model	23
bold signal	55	low-frequency oscillations	57	mild cognitive impairment	49	motion	32	human visual-cortex	20	neonatal encephalop athy	19
transcranial magnetic stimulation	54	cortical activation	56	decision-making	49	glioblastoma	32	resting-state functional connectivity	20	awake infants	17

independent component analysis	53	heart rate variability	53	response inhibition	46	virtual reality	31	state functional connectivity	20	gender	17
photon migration	52	reactivity	52	bipolar disorder	46	physical-activity	30	dlpfc	19	transgenic mice	17
topography	51	cerebrovascular autoregulation	50	mental workload	44	subarachnoid hemorrhage	29	prefrontal cortex activity	19	young	16
hyperscanning	50	inhibition	50	epilepsy	41	neurofeedback	29	resting-state	19	young-children	16
optical pathlength	50	cerebral blood volume	48	risk	40	breast	27	primary somatosensory cortex	18	infant brain	15
false discovery rate	48	absorption	47	speech perception	39	age-related-changes	27	functional architecture	17	women	15
transcranial doppler	48	cerebral oxygen saturation	47	impairment	35	resection	25	mirror neuron system	17	newborn piglets	14
optical tomography	46	heart rate	43	imagery	35	therapeutic hypothermia	24	primary visual-cortex	17	neonatal	13
cerebral oximetry	43	delivery	40	visual-stimulation	34	motor control	24	sensorimotor cortex	17	swine model	13
turbid media	42	blood-volume	39	fatigue	34	feedback	24	ventrolateral prefrontal cortex	17	adult brain	12
indocyanine green	41	hypothermia	39	anxiety	33	brain-development	24	frontal activation	16	gender-differences	12
resuscitation	41	hypoxic-ischemic encephalopathy	38	verbal fluency	32	neuroprotection	23	medial prefrontal cortex	16	handedness	12
artifacts	39	muscle	38	stroop task	32	neuroergonomics	23	reduced frontopolar activation	16	sheep	12
event-related fmri	39	blood-pressure	35	dual task	32	drug-delivery	23	white-matter	16	monkey	11
optical spectroscopy	39	oxyhemoglobin	35	cognitive impairment	31	imitation	22	resting-state networks	15	elderly	10

simulation	39	hypercapnia	34	attention-deficit/hyperactivity disorder	31	locomotion	20	supplementary motor area	15	healthy	10
functional magnetic resonance imaging	35	perfusion-pressure	34	abnormalities	31	carotid-endarterectomy	20	basal ganglia	14	prematurity	10
monte carlo simulation	35	arterial	33	emotion regulation	30	breast-cancer	20	cortex activity	14	child	9
nanoparticles	35	intraventricular hemorrhage	33	deficits	30	neurodevelopmental outcomes	19	default mode network	14	elderly subjects	9
synchronization	35	cardiac arrest	31	cognitive performance	29	maximal exercise	19	parietal	14	elderly-patients	9
reflectance	34	excitability	31	sustained attention	28	incremental exercise	19	lateral prefrontal cortex	13	patient	9
in-vitro	33	oxygenated hemoglobin	29	social cognition	28	cardiopulmonary-resuscitation	19	human cerebral-cortex	12	sex	9
cerebral perfusion	32	oxygenation changes	29	major depressive disorder	28	neurorehabilitation	18	human motor cortex	12	age-related differences	8
adult head model	31	transcranial functional brain	29	deficit hyperactivity disorder	28	music	18	right-hemisphere	12		
bold fmri	30	cerebral perfusion pressure	27	reward	27	health	18	superior temporal sulcus	12		
frequency-domain	30	hemoglobin concentration	27	empathy	27	glioblastoma-multiforme	18	corpus-callosum	11		
noninvasive measurement	30	propagation	27	major depression	24	angiogenesis	18	dominance	11		
spatial-resolution	29	hemoglobin oxygenation	26	inhibitory control	24	reproducibility	17	hippocampus	11		
discrimination	28	oxygen-metabolism	26	autism spectrum disorder	24	quality-of-life	17	resting-state fmri	11		
localization	28	blood pressure	25	adhd	24	mortality	17	temporo-parietal junction	11		
mni space	28	microcirculation	25	workload	23	inflammation	17	inferior frontal-cortex	10		

tdcs	28	desaturation	24	social interaction	23	tumors	16	occipital cortex	10		
time-series	27	hemodynamic-changes	24	arousal	23	severe head-injury	16	structural connectivity	10		
diffuse reflectance	26	5-aminolevulinic acid	23	voice	21	personality	16	anterior prefrontal cortex	9		
diffuse optical imaging	25	consumption	23	seizures	21	general-anesthesia	16	autonomic nervous-system	9		
direct-current stimulation	25	blood oxygenation	22	risk-factors	21	congenital heart disease	16	connectome	9		
event-related potentials	25	cardiac-output	22	n-back	21	brain development	16	prefrontal hemodynamic response	9		
scattering media	25	hypotension	22	spreading depression	20	aerobic exercise	16	rat somatosensory cortex	9		
biomarker	24	blood flow	21	mood	20	skin	15	corticospinal excitability	8		
effective connectivity	24	blood-brain-barrier	21	language acquisition	20	postural control	15	prefrontal function	8		
evoked-potentials	24	cytochrome-c-oxidase	21	facial expressions	20	neurocritical care	15	dorsolateral prefrontal activation	7		
magnetic-resonance	24	hemorrhage	21	emotions	20	head-injury	14	left frontal-lobe	7		
neural synchronization	24	oxidative-metabolism	21	damage	20	flight	14				
in vivo imaging	23	receptor	21	autism	20	brain tumor	14				
machine learning	23	acute ischemic-stroke	20	vigilance	19	posture	13				
pet	23	cerebral blood oxygenation	20	retrieval	19	perinatal asphyxia	13				
reliability	23	cerebral ischemia	20	episodic memory	18	pathophysiology	13				
ultrasound	23	circulation	20	cognitive load	18	maturation	13				

molecular imaging	22	hypothermic circulatory arrest	20	temporal-lobe epilepsy	17	malignant glioma	13				
optogenetics	22	oxidative stress	20	face	17	long-term	13				
support vector machine	21	propofol	20	anatomy	17	hand movements	13				
transcranial doppler ultrasound	21	self-regulation	20	addiction	17	growth	13				
concurrent fmri	20	apoptosis	19	stroop interference	16	gene-expression	13				
contrast	20	arterial-blood pressure	19	mental arithmetic	16	cardiac-arrest	13				
intrinsic optical imaging	20	blood-flow velocity	19	intelligence	16	angiography	13				
meg	20	cerebral-ischemia	19	working-memory task	15	patent ductus-arteriosus	12				
neuromonitoring	20	cerebrovascular circulation	19	social-perception	15	motor recovery	12				
registration	20	hyperoxia	19	adaptation	15	dynamic exercise	12				
voltage-sensitive dye	20	muscle oxygenation	19	selective attention	14	biological motion	12				
general linear model	19	neural efficiency	19	obsessive-compulsive disorder	14	bilingualism	12				
granger causality	19	physiological noise	19	motor execution	14	aneurysmal subarachnoid hemorrhage	12				
noise	18	nitric-oxide	18	migraine	14	physical-exercise	11				
probes	18	oxygen-consumption	18	faces	14	photodynamic therapy	11				
segmentation	18	skeletal-muscle	18	cortical spreading depression	14	necrotizing enterocolitis	11				
brain perfusion	17	astrocytes	17	cognitive decline	14	mobility	11				
brain stimulation	17	brain plasticity	17	motor learning	13	fitness	11				

congenital heart-disease	17	calcium	17	vision	12	feasibility	11				
diffuse-reflectance	17	balloon model	16	talking	12	asphyxia	11				
image-reconstruction	17	birth asphyxia	16	response function	12	apnea	11				
light-scattering	17	dopamine	16	learning	12	aerobic fitness	11				
brain connectivity	16	hyperventilation	16	face perception	12	sepsis	10				
diffuse optical spectroscopy	16	metabolic-rate	16	consciousness	12	safety	10				
image reconstruction	16	spontaneous fluctuations	16	comprehension	12	heart-surgery	10				
pathlength	16	circulatory arrest	15	cognitive tasks	12	focal cerebral-ischemia	10				
real-time fmri	16	cytochrome-oxidase	15	adhd children	12	treadmill	9				
wavelet coherence	16	hypertension	15	space	11	training	9				
atlas	15	ischemic-stroke	15	short-term-memory	11	stroke rehabilitation	9				
graph theory	15	regional cerebral oxygen saturation	15	sentence comprehension	11	shoulder surgery	9				
intensity	15	brain-damage	14	interpersonal brain synchronization	11	hypocapnia	9				
intrinsic signals	15	heart	14	fear	11	gait speed	9				
optical coherence tomography	15	hypoxia-ischemia	14	emotion recognition	11	complex walking	9				
small-world	15	proteins	14	delirium	11	term infants	8				
test-retest reliability	15	brain hemodynamics	12	decline	11	swallowing	8				
tms	15	glutamate	12	deception	11	seizure	8				
amplitude-integrated electroencephalography	14	haemodynamics	12	concussion	11	respiration	8				

computed-tomography	14	nutrition	12	cognitive dysfunction	11	neurosurgery	8				
electrical-stimulation	14	reperfusion	12	awareness	11	dysphagia	8				
electrophysiology	14	altitude	11	theory of mind	10						
encephalopathy	14	blood-flow autoregulation	11	temperament	10						
magnetoencephalography	14	cerebrospinal-fluid	11	reaction-time	10						
motion artifact	14	co2	11	load	10						
movement artifacts	14	desynchronization	11	impulsivity	10						
negative bold	14	intrinsic signal	11	facial expression	10						
pulse oximetry	14	thickness	11	expressions	10						
biomedical optics	13	vasomotion	11	distraction	10						
isoflurane	13	anemia	10	behavioral-inhibition	10						
methylphenidate	13	artery	10	words	9						
monte-carlo	13	cerebral metabolic rate of oxygen	10	two-person neuroscience	9						
optical brain imaging	13	cerebral metabolism	10	panic disorder	9						
phantom	13	cortical oxygenation	10	neurodevelopment	9						
sevoflurane	13	deoxyhemoglobin	10	multiple sclerosis	9						
skin blood-flow	13	haemodynamic response	10	executive control	9						
spatiotemporal dynamics	13	initial dip	10	developmental-changes	9						
speed	13	norepinephrine	10	conflict	9						

support vector machines	13	venous oxygen-saturation	10	attentional control	9						
transcranial direct current stimulation	13	cardiac output	9	syntax	8						
voltage-sensitive dyes	13	cbf	9	stroop	8						
bispectral index	12	cerebral hemoglobin oxygenation	9	mood disorders	8						
diffuse optics	12	cerebral oxygenation changes	9	mirror	8						
linear discriminant analysis	12	cmro2	9	mini-mental-state	8						
multimodal neuroimaging	12	deoxygenated hemoglobin	9	interpersonal neural synchronization	8						
noninvasive assessment	12	discharges	9	face recognition	8						
optical properties	12	mitochondria	9	face processing	8						
p300	12	oxygen delivery	9	dual-tasking	8						
simultaneous eeg	12	oxygen metabolism	9	divided attention	8						
single-trial classification	12	spontaneous circulation	9	developmental dyslexia	8						
time-course	12	ventilation	9	developing brain	8						
two-photon microscopy	12	cerebral oxygen-metabolism	8	matching stroop task	7						
depth	11	compensation	8	affective style	7						
doppler	11	dynamic cerebral autoregulation	8								
high-resolution	11										
magnetic stimulation	11										

motion artifacts	11										
nirs-fmri	11										
parcellation	11										
positron emission tomography	11										
somatosensory stimulation	11										
transcranial doppler sonography	11										
wave spectroscopy	11										
electrocorticography	10										
electromyography	10										
fast optical signal	10										
laser speckle imaging	10										
maps	10										
mutual information	10										
neuromodulation	10										
phase	10										
rtms	10										
skin blood flow	10										
surface-based analysis	10										
time-resolved reflectance	10										
component analysis	9										
entropy	9										
erp	9										
inverse problem	9										
spectral-analysis	9										

time-resolved spectroscopy	9										
tissue oxygenation index	9										
voltage-sensitive dye imaging	9										
wavelet transform	9										
whole-head	9										
approximate entropy	8										
artifact removal	8										
bold response	8										
coherence analysis	8										
dye bolus	8										
laser-doppler	8										
light scattering	8										
multimodal	8										
thresholds	8										
laser speckle	7										
wavelet phase coherence	7										

APPENDIX D

TOP 150 AUTHORS WITH THE STRONGEST CITATION BURSTS

Authors	Year	Strength	Begin	End	1982 - 2020
WYATT JS	1992	217.064	**1992**	2007	
JOBSIS FF	1992	159.768	**1992**	2005	
WRAY S	1992	14.97	**1992**	2012	
FOX PT	1993	141.709	**1993**	2012	
COPE M	1993	9.904	**1993**	2004	
BRAZY JE	1993	6.531	**1993**	2007	
TAMURA M	1993	6.088	**1993**	1999	
DELPY DT	1993	5.112	**1993**	2003	
CHANCE B	1995	203.505	**1995**	2009	
OGAWA S	1995	115.077	**1995**	2011	
VANDERZEE P	1995	99.033	**1995**	2006	
VILLRINGER A	1996	107.259	**1996**	2006	
MATCHER SJ	1996	89.854	**1996**	2008	
SKOV L	1996	89.484	**1996**	2007	
EDWARDS AD	1996	8.106	**1996**	2000	
MEEK JH	1997	147.407	**1997**	2013	
KATO T	1997	126.823	**1997**	2008	
COOPER CE	1997	105.824	**1997**	2010	
BENARON DA	1997	10.384	**1997**	2008	
ELWELL CE	1997	88.635	**1997**	2014	
OKADA F	1997	69.994	**1997**	2007	
GRATTON G	1997	61.432	**1997**	2005	

DUNCAN A	1997	53.949	**1997**	2004	
MAKI A	1997	52.381	**1997**	2006	
FIRBANK M	1998	9.823	**1998**	2013	
ARRIDGE SR	1999	149.176	**1999**	2009	
HIRTH C	2000	99.659	**2000**	2009	
HINTZ SR	2000	92.774	**2000**	2012	
FRANCESCHINI MA	2000	89.669	**2000**	2009	
FANTINI S	2000	83.797	**2000**	2014	
HEEKEREN HR	2000	77.354	**2000**	2010	
HOCK C	2001	127.543	**2001**	2013	
SAKATANI K	2001	126.304	**2001**	2013	
KLEINSCHMIDT A	2001	12.344	**2001**	2009	
HOGE RD	2002	65.523	**2002**	2008	
MALONEK D	2002	52.257	**2002**	2010	
TORONOV V	2003	145.869	**2003**	2011	
WATANABE E	2003	118.514	**2003**	2015	
CULVER JP	2003	83.679	**2003**	2014	
POGUE BW	2003	76.171	**2003**	2013	
SIEGEL AM	2003	74.975	**2003**	2009	
BLUESTONE AY	2003	73.234	**2003**	2009	
WOLF M	2003	63.254	**2003**	2012	
YAMASHITA Y	2003	5.828	**2003**	2011	
FALLGATTER AJ	2004	122.318	**2004**	2015	
MATSUO K	2004	87.741	**2004**	2012	
KOIZUMI H	2004	8.149	**2004**	2013	
YAMAMOTO T	2004	7.384	**2004**	2014	
STEINBRINK J	2004	57.032	**2004**	2009	

OBRIG H	1996	56.264	**2004**	2008	
TAGA G	2005	103.907	**2005**	2012	
CANNESTRA AF	2005	94.661	**2005**	2009	
HEBDEN JC	2005	91.711	**2005**	2010	
OKADA E	1997	85.457	**2005**	2014	
FUKUI Y	2005	7.123	**2005**	2012	
LOGOTHETIS NK	2005	63.978	**2005**	2015	
PENA M	2005	53.837	**2005**	2012	
GIBSON AP	2006	102.179	**2006**	2013	
MEHAGNOUL-SCHIPPER DJ	2006	82.162	**2006**	2011	
SCHROETER ML	2004	81.333	**2006**	2009	
LIEBERT A	2006	73.526	**2006**	2013	
KENNAN RP	2006	59.666	**2006**	2012	
ULUDAG K	2006	59.086	**2006**	2009	
SEIYAMA A	2006	56.463	**2006**	2011	
HOROVITZ SG	2006	55.072	**2006**	2012	
SUTO T	2007	103.029	**2007**	2013	
TORONOV VY	2007	72.094	**2007**	2012	
WILCOX T	2007	52.362	**2007**	2014	
ZEFF BW	2008	9.995	**2008**	2016	
IZZETOGLU K	2006	92.799	**2008**	2015	
BUNCE SC	2008	69.684	**2008**	2013	
WORSLEY KJ	2008	55.724	**2008**	2014	
GLOVER GH	2009	52.348	**2009**	2013	
ROLFE P	2009	52.348	**2009**	2013	
JOSEPH DK	2009	51.198	**2009**	2014	
ABDELNOUR AF	2010	103.116	**2010**	2013	

JASPER HH	2010	89.922	**2010**	2012	
ZHAO HJ	2003	81.667	**2010**	2012	
COYLE SM	2010	81.112	**2010**	2017	
MUEHLEMANN T	2010	68.668	**2010**	2014	
FOX MD	2010	63.592	**2010**	2013	
MORREN G	2010	56.224	**2010**	2013	
MATTHEWS F	2010	56.224	**2010**	2013	
RIZZOLATTI G	2010	53.032	**2010**	2015	
MINAGAWA-KAWAI Y	2011	52.546	**2011**	2015	
SUZUKI M	2009	69.802	**2012**	2016	
SHATTUCK DW	2009	6.721	**2012**	2014	
JANG KE	2010	59.341	**2012**	2015	
TAKAHASHI T	2012	10.728	**2013**	2015	
KIRILINA E	2013	95.854	**2013**	2017	
SAAGER RB	2009	89.217	**2013**	2016	
YAMADA T	2012	83.726	**2013**	2018	
CUTINI S	2011	71.008	**2013**	2016	
POWER SD	2011	58.488	**2013**	2016	
TIAN FH	2009	107.003	**2014**	2017	
HAEUSSINGER FB	2014	88.191	**2014**	2020	
GERVAIN J	2014	81.817	**2014**	2018	
HEINZEL S	2014	75.526	**2014**	2017	
LIN PY	2014	65.378	**2014**	2016	
VIRTANEN J	2010	6.472	**2014**	2015	
FANG QQ	2014	60.664	**2014**	2018	
LOTTE F	2014	58.971	**2014**	2015	
COOPER RJ	2012	5.818	**2014**	2016	

ROCHE-LABARBE N	2014	56.621	**2014**	2017	
GAGNON L	2012	55.067	**2014**	2016	
DURDURAN T	2009	53.907	**2014**	2016	
HERFF C	2015	86.209	**2015**	2020	
COYLE S	2007	75.075	**2015**	2017	
OOSTENVELD R	2015	71.381	**2015**	2016	
PIPER SK	2015	68.812	**2015**	2020	
NAITO M	2011	64.268	**2015**	2017	
SASAI S	2015	62.959	**2015**	2020	
SCHUDLO LC	2015	58.624	**2015**	2018	
KOESSLER L	2015	55.142	**2015**	2017	
BRIGADOI S	2014	165.585	**2016**	2020	
KHAN MJ	2015	96.493	**2016**	2020	
DEROSIERE G	2016	85.643	**2016**	2017	
BISWAL B	2010	77.687	**2016**	2020	
DAVIDSON RJ	2016	75.182	**2016**	2017	
BALCONI M	2016	72.879	**2016**	2017	
[ANONYMOUS]	2012	71.589	**2016**	2020	
NASEER N	2014	65.671	**2016**	2018	
TAK S	2013	65.663	**2016**	2020	
SHIMADA S	2006	65.066	**2016**	2017	
STRANGMAN GE	2015	63.315	**2016**	2020	
HOLPER L	2010	60.621	**2016**	2018	
MIHARA M	2013	5.Ara	**2016**	2020	
SCHOLKMANN F	2012	249.292	**2017**	2020	
HONG KS	2015	169.539	**2017**	2020	
NASEER NOMAN	2016	160.198	**2017**	2020	

TACHTSIDIS ILIAS	2017	15.987	**2017**	2020	
BENJAMINI Y	2006	131.256	**2017**	2020	
BARKER JW	2017	107.283	**2017**	2020	
FISHBURN FA	2017	104.658	**2017**	2020	
NIU HJ	2011	101.375	**2017**	2020	
ZHANG X	2017	99.409	**2017**	2020	
TSUZUKI D	2008	82.935	**2017**	2018	
MCKENDRICK R	2015	78.663	**2017**	2020	
PARASURAMAN R	2017	6.392	**2017**	2020	
DURANTIN G	2017	55.921	**2017**	2020	
SHIN J	2018	172.307	**2018**	2020	
CHIARELLI AM	2018	154.662	**2018**	2020	
YUCEL MA	2015	128.777	**2018**	2020	
AASTED CM	2016	120.059	**2018**	2020	
ZAFAR A	2018	115.893	**2018**	2020	
JIANG J	2018	94.775	**2018**	2020	
BLANKERTZ B	2018	70.164	**2018**	2020	
MOLAVI B	2013	66.826	**2018**	2020	
YOSHINO K	2015	65.979	**2018**	2020	
KAMRAN MA	2015	56.524	**2018**	2020	

APPENDIX E

TOP 150 CITED JOURNALS WITH THE STRONGEST CITAITON BURSTS

Cited Journals	Year	Strength	Begin	End	1982 - 2020
J APPL PHYSIOL	1982	359.751	**1982**	2010	
BIOCHIM BIOPHYS ACTA	1982	252.087	**1982**	2012	
J NEUROSURG	1982	166.863	**1982**	2011	
AM J PHYSIOL	1982	146.233	**1982**	2008	
BIOPHYS J	1982	Tem.14	**1982**	2009	
J BIOL CHEM	1982	61.649	**1982**	2012	
ACTA PHYSIOL SCAND	1982	42.374	**1982**	2014	
FEBS LETT	1982	40.633	**1982**	1998	
ADV NEUROL	1982	39.721	**1982**	2003	
NATURE	1984	89.062	**1984**	2012	
J NEUROCHEM	1984	Nis.92	**1984**	2008	
ADV EXP MED BIOL	1982	196.291	**1992**	2013	

LANCET	1992	182.695	**1992**	2007	
ARCH DIS CHILD-FETAL	1992	79.278	**1992**	2007	
BIOCHEMISTRY-US	1992	47.193	**1992**	2000	
AM J OBSTET GYNECOL	1992	45.637	**1992**	2005	
ARCH BIOCHEM BIOPHYS	1992	39.585	**1992**	2004	
PEDIATR RES	1993	319.626	**1993**	2009	
ANAL BIOCHEM	1993	153.061	**1993**	2009	
MED BIOL ENG COMPUT	1993	107.956	**1993**	2011	
PEDIATRICS	1993	99.987	**1993**	2007	
BIOCHEM SOC T	1993	74.266	**1993**	2000	
ANESTHESIOLOGY	1993	68.954	**1993**	2008	
CLIN PERINATOL	1994	66.344	**1994**	2014	
J CEREBR BLOOD F MET	1991	431.383	**1995**	2011	
PHYS MED BIOL	1993	226.028	**1995**	2010	
STROKE	1983	11.283	**1995**	2012	
CRIT CARE MED	1995	89.742	**1995**	2009	

CEREBROVAS BRAIN MET	1995	75.505	**1995**	2014	
ANESTH ANALG	1996	41.005	**1996**	2009	
MED PHYS	1997	23.725	**1997**	2013	
P ROY SOC B-BIOL SCI	1997	71.171	**1997**	2015	
AM J PHYSIOL-HEART C	1997	70.093	**1997**	2008	
ANAESTHESIA	1997	47.834	**1997**	2008	
P SOC PHOTO-OPT INS	1998	185.795	**1998**	2009	
BRIT J ANAESTH	1998	52.719	**1998**	2008	
ANN NEUROL	1993	50.588	**1999**	2007	
EXP NEUROL	1999	47.291	**1999**	2011	
ACT NEUR S	1999	39.334	**1999**	2006	
PSYCHOPHYSIOLOGY	1997	163.692	**2000**	2009	
PHILOS T ROY SOC B	2000	106.327	**2000**	2015	
PHOTOCHEM PHOTOBIOL	2000	8.591	**2000**	2009	
P NATL ACAD SCI USA	1982	63.816	**2000**	2011	
TRENDS NEUROSCI	1991	253.097	**2001**	2011	

NEUROREPORT	2001	154.803	**2001**	2013	
EARLY HUM DEV	2001	68.839	**2001**	2014	
OPT EXPRESS	2002	237.774	**2002**	2012	
OPT LETT	2002	194.755	**2002**	2013	
MAGNET RESON MED	1996	139.632	**2002**	2011	
NMR BIOMED	2002	55.344	**2002**	2009	
INVERSE PROBL	2003	114.702	**2003**	2010	
J PERINAT MED	2003	108.125	**2003**	2012	
J OPT SOC AM A	1997	7.868	**2003**	2012	
ANNU REV BIOMED ENG	2003	68.102	**2003**	2013	
REV SCI INSTRUM	2003	56.058	**2003**	2007	
BIOL PSYCHIAT	1998	105.133	**2004**	2010	
EUR ARCH PSY CLIN N	1997	96.796	**2004**	2012	
COGNITIVE BRAIN RES	1997	80.367	**2004**	2013	
PEDIATR NEUROL	2004	72.261	**2004**	2014	
SCHIZOPHRENIA BULL	2004	62.305	**2004**	2008	

PSYCHOL MED	2004	37.388	**2004**	2009	
J NEUROPHYSIOL	1984	67.451	**2005**	2011	
INT J HUM-COMPUT INT	2006	71.551	**2006**	2013	
J COMPUT ASSIST TOMO	2006	69.624	**2006**	2014	
ANNU REV PHYSIOL	2006	45.971	**2006**	2013	
NEUROPSYCHOBIOLOGY	2006	39.773	**2006**	2013	
MAGN RESON MED	2006	39.085	**2006**	2009	
NEUROL RES	2006	36.943	**2006**	2008	
J DEV BEHAV PEDIATR	2007	39.513	**2007**	2014	
IEEE ENG MED BIOL	2008	106.285	**2008**	2013	
MAGN RESON IMAGING	2006	75.337	**2008**	2014	
J NEUROPSYCH CLIN N	2004	5.965	**2008**	2014	
PSYCHIAT RES-NEUROIM	2004	55.164	**2008**	2012	
EUR J NEUROSCI	1995	4.715	**2008**	2011	
NEURON	2004	4.553	**2008**	2009	
MED IMAGE ANAL	2008	44.162	**2008**	2014	

NEUROSCI RES	2008	41.081	**2008**	2012	
P ANN INT IEEE EMBS	2009	107.969	**2009**	2015	
CLIN NEUROPSYCHOL	2009	63.372	**2009**	2013	
J CHILD NEUROL	2009	60.435	**2009**	2014	
EPILEPSIA	2004	50.417	**2009**	2015	
P SPIE	2009	45.851	**2009**	2010	
J MAGN RESON IMAGING	2009	44.362	**2009**	2014	
BRAIN RES	1983	72.646	**2010**	2012	
SCIENCE	1983	63.232	**2010**	2011	
ELECTROENCEPHALOGR C	2010	5.214	**2010**	2011	
C P IEEE ENG MED BIO	2010	39.102	**2010**	2011	
BIOMED TECH	2011	5.561	**2011**	2016	
DEV NEUROBIOL	2011	45.283	**2011**	2014	
J COMP NEUROL	1984	43.166	**2011**	2014	
FRONT NEUROENERGETICS	2011	39.733	**2011**	2016	
DEV NEUROPSYCHOL	2011	38.519	**2011**	2012	

PHILOS T R SOC A	2010	57.245	**2012**	2014	
NEUROCRIT CARE	2012	53.495	**2012**	2016	
LECT NOTES ARTIF INT	2012	50.328	**2012**	2015	
SEIZURE-EUR J EPILEP	2012	48.569	**2012**	2013	
EPILEPTIC DISORD	2012	45.635	**2012**	2015	
ACTA PAEDIATR	1996	44.992	**2012**	2014	
ELECTROENCEPHALOGRAP	2012	42.027	**2012**	2016	
J NEURAL TRANSM	2009	40.931	**2012**	2016	
J EXP PSYCHOL GEN	2013	48.827	**2013**	2015	
PHYS THER	2013	46.828	**2013**	2017	
BIOMED ENG ONLINE	2010	45.796	**2013**	2016	
J NUCL MED	2010	45.465	**2013**	2016	
ANN BIOMED ENG	1982	41.318	**2013**	2017	
BRAIN RES REV	2008	40.074	**2013**	2014	
MED ENG PHYS	2013	39.586	**2013**	2018	
STATISTICAL PARAMETRIC MAPPING: THE ANALYSIS OF FUNCTIONAL BRAIN IMAGES	2013	3.954	**2013**	2014	

J NEAR INFRARED SPEC	2013	49.969	**2014**	2016	
B AM METEOROL SOC	2012	43.717	**2014**	2015	
NONLINEAR PROC GEOPH	2014	41.922	**2014**	2015	
COGN PROCESS	2014	39.464	**2014**	2017	
J CLIN NEUROPHYSIOL	2009	39.041	**2014**	2017	
J PERS SOC PSYCHOL	2015	57.601	**2015**	2020	
J PSYCHIATR NEUROSCI	2015	38.288	**2015**	2016	
HEARING RES	2015	51.326	**2016**	2018	
ACM T INTEL SYST TEC	2016	50.955	**2016**	2017	
PHYSIOL REV	1991	44.799	**2016**	2017	
PATTERN RECOGN	2016	44.203	**2016**	2017	
STAT PARAMETRIC MAPP	2013	43.363	**2016**	2018	
J CLIN MONIT COMPUT	2014	39.067	**2016**	2018	
J COGN PSYCHOL	2016	3.851	**2016**	2017	
NAT COMMUN	2017	52.048	**2017**	2020	
CORTEX	2010	50.853	**2017**	2020	

J STAT SOFTW	2017	44.844	**2017**	2018	
J ACOUST SOC AM	2017	43.613	**2017**	2018	
PSYCHOSOM MED	2017	39.536	**2017**	2018	
SCI REP-UK	2015	448.591	**2018**	2020	
NEUROPHOTONICS	2015	353.426	**2018**	2020	
FRONT NEUROROBOTICS	2017	100.106	**2018**	2020	
FRONT BEHAV NEUROSCI	2015	89.691	**2018**	2020	
BRAIN STRUCT FUNCT	2017	54.504	**2018**	2020	
BRAIN IMAGING BEHAV	2016	54.032	**2018**	2020	
DEV PSYCHOPATHOL	2018	53.065	**2018**	2020	
INT J NEURAL SYST	2016	51.486	**2018**	2020	
BIOMED RES INT	2016	50.103	**2018**	2020	
DIAGNOSTIC STAT MANU	2018	48.278	**2018**	2020	
PSYCHONEUROENDOCRINO	2018	48.278	**2018**	2020	
BRAIN BEHAV	2016	4.803	**2018**	2020	
WIRES COGN SCI	2018	43.193	**2018**	2020	

NEUROREHAB NEURAL RE	2011	42.999	**2018**	2020	
PLOS BIOL	2009	41.456	**2018**	2020	
MOL PSYCHIATR	2015	4.087	**2018**	2020	
JAMA-J AM MED ASSOC	2014	40.142	**2018**	2020	
R LANG ENV STAT COMP	2018	38.108	**2018**	2020	
RES DEV DISABIL	2018	38.108	**2018**	2020	

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