NETWORK ANALYSIS OF RELATIONSHIP IN HOBBIES INTEREST AMONG 50 COUNTRIES AND THE CHANGES FROM COVID-19

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MASTER OF SCIENCE
IN DIGITAL INNOVATION AND FINANCIAL TECHNOLOGY

GRADUATE SCHOOL
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A THESIS SUBMITTED TO CHIANG MAI UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN DIGITAL INNOVATION AND FINANCIAL TECHNOLOGY

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หัวข้อปริญญานิพนธ์ การวิเคราะห์เครือข่ายความสัมพันธ์ในความสนใจงานอดิเรกใน50 ประเทศและการเปลี่ยนแปลงจากโควิด19

ผู้เขียน นางสาวญาดา ธรรมประเสริฐ

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บทคัดย่อ

แม้ว่าสถานการณ์ความไม่แน่นอนจาก COVID-19 ยังคงปรากฏอยู่ทั่วโลก ผลกระทบจากสถานการณ์ที่เกิดขึ้นไม่ได้จำกัดเฉพาะปัญหาสุขภาพร่างกายเท่านั้น การระบาดยังทำให้ผู้คนต้องปรับตัวในด้านต่าง ๆ หลายด้าน พฤติกรรมและการรับรู้ของผู้คนเปลี่ยนแปลงไปตลอดการแพร่ระบาด ถึงแม้ผู้คนที่ดำรงชีวิตภายใต้วัฒนธรรมที่แตกต่างกัน มีการรับรู้และตอบสนองต่อสิ่งต่าง ๆ แตกต่างกัน มีการค้นพบว่าการแพร่ระบาดของโควิด-19 ส่งผลกระทบต่อการรับรู้ของบุคคลและสังคม นอกจากนี้ การระบาดใหญ่ของโควิด-19 มีอิทธิพลอย่างมากต่อการวางแนววัฒนธรรม กิจกรรมยามว่างซึ่งเป็นหนึ่งในหลายวิธีในการแสดงออกถึงวัฒนธรรม เป็นจุดเน้นของการวิจัยนี้ งานวิจัยนี้มีวัตถุประสงค์เพื่อระบุรูปแบบความเชื่อมโยงของความสนใจในงานอดิเรกทั่วโลก และเรียนรู้รูปแบบความเชื่อมโยงดังกล่าวก่อนและหลังการเกิดขึ้นของ COVID-19 ด้วยการแสดงกราฟเครือข่าย ในทศวรรษที่ผ่านมา Google Trends ได้รับการพิสูจน์แล้วว่าเป็นเครื่องมือที่มีแนวโน้มในการศึกษาพฤติกรรมศาสตร์ ช่วยให้นักวิจัยดึงข้อมูลอนุกรมเวลาโดยสรุปจากขนาดตัวอย่างของผู้ใช้ Google ทั่วโลกได้ฟรี เครื่องมืออย่างหนึ่งจะรวบรวมคำค้นหาต่างๆ ที่อยู่ในหัวข้อเดียวกันในคำพ้องความหมายและภาษาต่างๆ เป็นหัวข้อที่มีประโยชน์อย่างยิ่ง งานวิจัยนี้ได้รวบรวมข้อมูลของงานอดิเรกที่ได้รับการคัดเลือก 10 รายการใน 50 ประเทศที่มี GDP สูงสุด (ปี 2020) ตั้งแต่วันที่ 1 มกราคม 2018 ถึง 31 มีนาคม 2021 ด้วยหัวข้อ Google Trends งานนี้ถือว่าช่วงก่อนวันที่ 11 มีนาคม 2020 เป็นช่วงก่อนการระบาด และช่วงนับจากวันนี้เป็นช่วงหลังการระบาดตามประกาศขององค์การอนามัยโลก จากนั้นบทความนี้จะคำนวณเมทริกซ์สหสัมพันธ์และแสดงภาพด้วยกราฟเครือข่าย การวิเคราะห์แสดงการปรับเปลี่ยนที่สำคัญในรูปแบบความสัมพันธ์ทั่วโลกที่ได้รับผลกระทบจากการแพร่ระบาดในหัวข้อการค้นหาส่วนใหญ่

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ABSTRACT

While the uncertainty from COVID-19 persists throughout the globe, the impact it triggered is not only limited to physical health issues. The pandemic forced people to adapt in many aspects. People's behaviours and perceptions has shifted throughout the pandemic. Though, inhabitants of distinct culture perceive and react to things differently. There are findings that the COVID-19 pandemic has an effect on individuals and society perception. Furthermore, the COVID-19 pandemic strongly influences cultural orientation. Leisure activity, which is one of many approaches to express cultures, is a focus of this research. The research is intended to spot global connection patterns in hobby interest and learn how the patterns has changed by the occurrence of pre and post COVID-19 with network graphs visualization. In the last decade, Google Trends has been proven to be a promising tool in behavioural science studies. It allows researchers to draw summarized time-series data from the sample size of global Google users for free. One of its tools accumulates different search queries that belong to the same topic in different synonyms and languages as a topic which is essentially useful. This research has collected scaled data of ten selected hobbies, in fifty top internet user (2020) countries from January 1st, 2018 thru April 30st, 2022 with Google Trends topics. This work marks the period before March 11th,2020 as pre-pandemic and the period from this date as post-pandemic according to the World Health Organization's announcement. This paper then calculate correlation matrices and visualize with

network graphs. The analysis shows significant adjustments in global relationship patterns affected by the pandemic in most search topics.

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CHAPTER 1

Introduction

1.1 Background and Rationale

The novel coronavirus disease which was later renamed as "COVID-19" emerged in China in late 2019. The disease quickly spread overseas, and its trend continued to grow. On 11 March 2020, the World Health Organization (WHO) publicly announced COVID-19 as a pandemic. At that time, there were 4,291 deaths from approximately 118,000 cases in 114 nations (WHO. 2020). The number was surprising but incomparable to the figure of a year later. On 11 March 2021, the world had lost more than 2.8 million lives from the disease which has infected more than 130 million people. Another year later in March 2022, there were more than 6 million deaths and 468 million confirmed cases. The pandemic has not only caused health issues to those infected but also posed challenges to public health administrators around the globe (Van Bavel et al. 2020). Several measures have been imposed ranging from lockdown, isolation, quarantine to local confinement to protect the world population. Apart from direct effects, the pandemic has forced people to adapt in many aspects (Cole et al. 2013). Recently, researchers from around the world have studied both direct and indirect effects from COVID-19. In behavioural science, key focus in this phenomenon has been on how people perceive the pandemic and then shift actions due to the shock and also what are the reasons behind those changes (Kramer et al. 2014)

One noticeable thing from most major life changing events ever recorded in world history is the fact that each country reacts and responds to those events differently, and this COVID-19 pandemic is not an exception. Governments around the world have developed their own non pharmaceutical intervention policies to tackle the problem. According to a study (Yan et al. 2020), responding schemes of all countries are observed and could be grouped down into four distinct strategies which are nudge represented by Sweden, mandate represented by China, decree represented by France, and boost represented by Japan as shown in Figure 1.1.

Sweden's COVID-19 response has been described as a "nudge strategy" which aims to change behaviour without limiting freedom of choice. It is considered to be among the least strict of the countries that has implemented measures to control the pandemic. This approach has been controversial as it did not impose a full lockdown as seen in most of Europe. The authorities in Sweden have stated that the effort to manage the pandemic is a long-term undertaking, and policies must be designed in a way that is sustainable for the population over time.

China's response strategy to the COVID-19 pandemic is described as a "mandate strategy" which involves both coercion by authorities and social agreement. Since the outbreak was recognized, policy interventions have been implemented to control the pandemic and stop the spread of the virus. These interventions include lockdown measures that were first implemented in Wuhan and were subsequently adopted in 30 other provinces. The authorities in China were quick to take severe measures early on and make sure it's being implemented throughout the country.

France's response to the COVID-19 pandemic is described as a "decree strategy," which is characterized by legal restrictions on certain behaviours, as opposed to a mandate strategy, which relies on both legal measures and social agreement. In the early stages of the outbreak, the French authorities implemented softer measures to try to slow the spread of the virus, and the population continued to go about their lives as usual. However, as the virus began to spread more rapidly, the response strategy shifted to one of suppression, with more strict measures being put in place. The legal aspect of this approach is more pronounced as France quickly enacted laws to enforce the restriction of certain activities.

Japan's approach to COVID-19 response is referred to as a "boost strategy" which aims to increase people's ability to make good choices by modifying their environment and providing them with information. This approach has been reflected in Japan's policy interventions in their fight against the COVID-19 virus. The Japanese government issued initial guidelines on February 25, 2020, which have been updated multiple times since then, particularly after a state of emergency was declared in six specific prefectures in April 7th. This approach focus more on providing citizens with all the necessary information, guidelines and support to make sure they can take the right decision for their own safety.

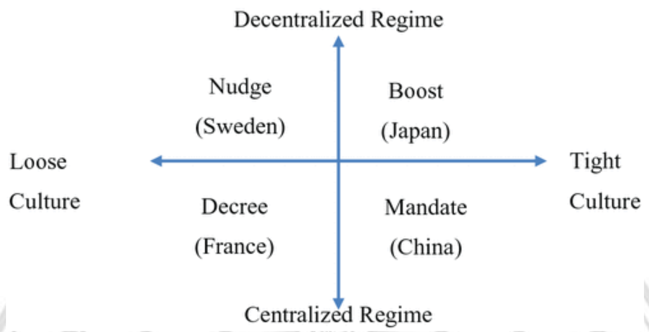


Figure 1.1: Four different strategies to tackle COVID-19

This example confirms that each country has their own response based on their contextual factors but not as totally different. While being different, it shows some degree of similarities by being able to be grouped easily. This intrinsically points out that there are influences or some linkages among countries. While regulations influences could be explained by governments ideologies and some logics, this research will instead study the voluntary cultural linkages changes between countries from the pandemic.

There are more findings that culture strongly influences both individuals and society's perception of events including this one (Biddlestone et al. 2006). Different perceptions often lead to different behaviours, together with peers gradually reinforcing the culture. In social sciences, family, work, and religious beliefs are generally considered to shape an individual's behaviour (Markus et al. 1991). Leisure is not commonly included (Triandis & H. 2018). Yet growing leisure investigations under modernism, recreation practice and cultural consumption are at least as essential. Normally, hobbies are activities people choose to do in their spare time relative to their core values (San Martin et al. 2018). Hobby preference might be influenced by peers in any community, but the bottom line is that no one would or could effectively force others to take interest in a hobby in the long term. This makes hobbies a good representative to study freewill cultural expression and how it is transmitted and connected across the globe.

Studying cultural expression of an individual requires some explicit evidence. Using hobby preference needs something that shows an individual's interest in some form. Before getting to that part, it is a good practice to define which hobbies should be included in this study, and what should not. There are countless hobbies to start with, but they could be categorised to make it more manageable. Since the hobbies are considered to be less serious activities, the standard and universal classification does not exist. However, most websites and sources show some of these overlapping groups which this study will use as a loose placeholder. Each hobby group or topic also possesses their own distinctive characteristics. There are 10 topics chosen which are Collecting, Arts, Game, Crafts, Sports, Performing Art, Music, Learning, Cooking, and Pets. The next several paragraphs will discuss the key characteristics of each topic included in the study.

1.2 Hobbies

1.2.1 Collecting for individuals reflects the desire to accumulate possessions with a long track record of cultural and historical studies, primarily in extreme conditions such as hoarding. However, just in the late 20th century, psychoanalytical approaches have emerged and gained popularity to help describe the inner drives of numerous human behaviours, including collecting. There are 4 simplified steps in the collecting process (Dillon 2019) which are

1. Knowledge development of the collectibles of interest
2. Target framing: by evaluating commitment of acquiring and associated cost
3. Acquisition: by going after and attain the item
4. Controlling: make use by either manipulating, cataloguing, displaying, selling, etc.

While the process seems to be very intuitive, it implicitly shows a satisfactory cycle if not addiction in the collecting hobby. From antiquities to tribal relics to pop culture arts to non-fungible tokens (NFTs), collecting all share this process and endorphin loop to some degree which is a unique characteristic in this hobby

1.2.2 Arts can be expressed in countless ways through countless mediums. It is easy to relate but hard to be concretely defined, even in academia (Davies 1991). Therefore, works of art seem to agree on one thing: that they all involve creativity or imagination at some degree. There are three classical branches of art which are sculpture, architecture, and painting. While performing arts, literature, music, interactive media, et cetera are in a broader extended definition. Purpose of art varies throughout history which researchers have grouped into two categories, namely non-motivated and motivated (Lévi-Strauss 2011).

Non-motivated functions of art are voluntarily created by an individual's expression without serving any specific purpose. On the other hand, motivated functions of arts are conscious, and intentional actions of the creator to transmit ideas, emotions, messages to the society. However, art in the hobby and interest context is usually for leisure.

1.2.3 Game is another form of arts by broad definition. However, playing games is obviously not the same kind of activity as working on an art project. Games are interactive while most activities are not. In the modern settings, games are almost automatically inferred to digital video games such as computer games, consoles, or mobile due to its dominance. Games could be played alone or with a small group of friends or with more than millions of other random players depending on the game of choice. While being interactive and flexible, games rarely yield products.

1.2.4 Crafts on the other hand, is heavily based on creating self-made products. It is usually uncomforting to distinguish crafts from classical arts, but this comparison chart as shown in Table 1.1 could be useful to give some ideas (Surbhi 2020).

Table 1.1 Art and Craft comparison chart

BASIS OF COMPARISON	**ART**	**CRAFT**
Meaning	An unstructured and boundless form of work that expresses emotions, feelings and vision is called art.	Craft refers to an activity, which involves creation of tangible objects with the use of hands and brain.
Based on	Creative merit	Learned skills and technique
Serves	Aesthetic purpose	Decorative or functional purpose
Emphasises	Ideas, feelings and visual qualities.	Right use of tools and materials.
Quantification	Difficult	Easy
Reproducible	No	Yes
Emergence	Heart and soul	Mind
Result of	Innate talent	Skill and experience

1.2.5 Sports is undoubtedly one of the first hobbies to come to mind. Research found participating in outdoor sport beneficial for health by significantly reducing stress if not traumatised by any stressful life incident (Caltabiano 2013). However, due to the pandemic with people spending much less time outdoors together, this thesis might give a glance on what is going on with the level of interest in sports and its interrelation between countries. Note that sports interest both accounts for active participation by self and passively enjoying others doing sports such as watching professional soccer or volleyball matches. Some aspects in sports may migrate to online platforms with ease while some might find it impossible.

1.2.6 Performing Art is another hobby which might be affected by restricted gathering. While sports are more on the active side which may or may not require company, performing arts on the other hand is more oriented to require both performing party and audience. Evidence shows that consumers of performing arts are heavily skewed towards high income peers (Throsby & W. 1979). Again, this hobby is suspected to be heavily affected by COVID-19, and this research might at least partially answer.

1.2.7 Music, one of the most important universal cultures in human history, prehistoric actually (Nettl 1956), had its purpose to serve religious and entertaining roles in ancient times. Later on, music expanded its purpose to express and modulate emotions. Relaxing music is found to be helpful in relieving stress on bad days. War songs induce aggressiveness and comradery which might be useful to overcome fear, prolong stamina, promote teamwork and ultimately improve the chance to survive in the battlefields. Mozart along with other classical music are suggested to boost prenatal development, at least to make baby kick. Ed Sheeran's romantic songs might have set the right mood in many people's wedding proposals. Most importantly, a long playlist of instrumental music could help researchers to concentrate through their tedious academic papers.

Music could be enjoyed by passively listening to at the baseline, while many seek for more engagement by playing and creating music by oneself through instruments. With the pandemic, physical gathering in events such as concerts should be more restricted while a large portion of people who enjoy online music streaming on a daily basis might not feel much affected. It is interesting enough to see where it leads in terms of interest levels and how countries react to each other before and after the widespread.

1.2.8 Learning might not sound like a hobby for some people, yet for many it is and gives a satisfying experience. The goal of learning in general is to acquire new skills, knowledge, and sometimes to prove the ability. It is a remarkably rewarding activity in the long term, and it is clearly projected to be more crucial as our social landscape will be much more competitive, and those without sufficient competency are likely to be left behind.

Conventional learning or formal education involves getting through universities, schools, or other institutions' systems, taking qualification exams, and earning some kind of certifications. With the gathering restriction, those mentioned processes needed to find a substitute. Online learning went from niche to mainstream in a few weeks. With such sudden change, opinions vary. Some thought the education quality would be severely compromised, and skills could not be built as expected, especially for young children which requires more parental involvement, stealing their time. While some perceived the change as a major opportunity to have more choices to learn anywhere in anytime at their own speed from world class experts with a fraction of original cost, feeling more productive.

1.2.9 Cooking is obviously making food edible but there is more delicacy in it. As playing music enjoyment is to create an ear-pleasing experience, cooking on the other hand is to create four other senses pleasing experience with taste, smell, look, and touch. With this in mind, eating fine food with good music should stimulate pleasure in all senses. Surprisingly, cooking for leisure purposes just became a thing in the mid-twentieth century. Before that, it was totally the work done to feed (DeVault 1991). Amplified with globalisation later in the same century, people can casually travel to other parts of the world they once thought impracticable before and expose themselves with foreign ingredients and cuisines. Since then, cooking has become more adventurous (Hartel 2007). Nowadays, international foods and fusion foods are around the corner. With COVID-19, there might be some significant change in culinary influences between countries.

1.2.10 Pets were known to be beneficial in coping with stress to the level that psychologists recommend helping rehabilitate patients with depression. Pets provide belongingness to alleviate loneliness especially in stressful episodic traumas such as divorce or bereavement (Sable 1995). Giving pets to kids also promotes some life values like responsibility, empathy, compassion, respect, patience, trust, and much more. Both pets and kids could mutually enjoy high energy play as well as being a cuddle buddy in nap time (Trautner 2017).

During social isolation where human-to-human interaction was limited, pets might be a greater option than ever as touch deprivation may impact on quality of life, and Coronavirus does not transmit between species in normal settings. Pets could replicate touch from humans and promote health. A study even suggests that human-pet relationship could be one of our greatest health-promoting resources at dire times (Young et al. 2020)

Studying human behaviour often involves conducting surveys, interviews, or observing subjects. However, doing so can be costly and prone to be biassed which makes these methods impractical on a global scale. Nevertheless, in the digital era, the internet has solved and eased countless issues including research (Makhortykh et al. 2020). When people are interested in something, people inquisitively search (Zitting et al. 2020). Google is the largest search provider in the world with more than 91% share in 2021 (Alex, 2021) which makes its free Google Trends service quite powerful in research. This allows behavioural science studies to have significantly more sample size than ever (Vosen 2011) and allows researchers to conveniently extend their experiment worldwide (Kristoufek 2013) Google Trends has also proven to be a promising data source improving explanation power in prediction problems (Choi et al. 2012).

1.3 Current situation of Hobbies

There are a wide variety of hobbies that people enjoy, and the current situation for each one is likely to be different. However, in general, the COVID-19 pandemic has had a major impact on many hobbies and the ways in which people are able to participate in them. Outdoor activities such as hiking, biking, and gardening have seen an increase in popularity, as people are able to socially distance while participating in these hobbies. Online marketplaces for buying and selling bicycles, for example, have seen an uptick in sales. Similarly, many people have taken up gardening or starting vegetable gardens as a way to grow their own food during the pandemic.

However, many hobbies that involve close contact with other people, such as team sports, dancing, and group fitness classes, have had to be put on hold or moved online. Indoor hobbies such as playing instruments, painting and drawing has seen a surge in popularity as well as online classes and tutorials have provided access to learn and practice these.

Many hobby-related businesses, such as craft stores, music shops, and dance studios, have had to close or move online. Some of them have developed new ways to engage with customers, such as offering online classes, curb side pickup, and home delivery.

In general, the current situation has been challenging for many people and their hobbies. However, many people have found new ways to participate in their hobbies, and the pandemic has led to an increase in creativity and innovation in how people engage with their hobbies.

1.4 Google Trend: As a tool for collecting hobby preference behaviour

Google Trends is a tool provided by Google that allows users to see how often specific terms are searched for on the internet over a given period of time. In academic research, Google Trends can be a useful tool for tracking the popularity of certain topics or for identifying trends in search behaviour.

One of the key benefits of using Google Trends in academic research is that it provides real-time data on search trends. This can be especially useful for studying emerging topics or for identifying sudden changes in search behaviour.

Google Trends data can be used in a variety of academic research contexts, including marketing, economics, sociology, and more. For example, researchers in marketing might use Google Trends data to understand consumer interest in certain products or brands, while economists might use the data to track changes in the popularity of certain economic indicators.

Overall, Google Trends is a valuable resource for researchers looking to track trends and understand patterns in search behaviour. It is important to note, however, that

Google Trends data should be interpreted with caution, as it only reflects search behaviour on Google and may not be representative of broader trends.

This work sees an opportunity to utilise Google Trends in studying cultural expression with 10 hobbies among 50 countries and their relationships in both before and after the official COVID-19 pandemic announcement, then visualises the preference linkage between countries to give exploratory insights of cultural relationship in network graphs comparing between pre and post pandemic to examine the effect of COVID-19. Based on our knowledge, this work is the first empirical research attempt to study the effect of COVID-19 on the preference of hobbies between countries. This work attempts to show empirical linkages but not to be confused with influential power. This research is not designed to prove any causal relationship and cannot claim that one country has an influence over another country even if true. This work is only interested in the patterns involving which countries are trending together and how it changes along with the pandemic.

1.5 Network Analysis

A correlation matrix is a popular tool used to identify relationships between different variables or factors. It is usually represented as a square grid, with each cell containing a numerical correlation coefficient that indicates the strength of the relationship between the corresponding pair of variables. While a correlation matrix can be useful for identifying the strength of a specific relationship, it can be difficult to understand the overall relationships among all the variables. One way to overcome this limitation is to use a network graph algorithm to visualize the data from the correlation matrix.

A network graph, also known as a graph or network diagram, is a visual representation of relationships between nodes or points. Each node in the graph represents a variable, and the edges or lines between the nodes represent the relationship between the corresponding pair of variables. By feeding the correlation matrix into an appropriate network graph algorithm, it will generate a visualization that makes it easier to understand the overall pattern of relationships among the variables. The graph visualizes the positive and negative relationship between different variables and how the relationship strength.

Network graph algorithms typically make use of algorithms that are specific for the purpose of clustering, positioning and visualizing the large data sets. To have a good visualization the data must be clustered together based on the strength of the relationship. The algorithm will also take into account the position of the nodes, in order to minimize the number of crossing lines and to make the graph easy to read.

This approach is a powerful way to transform a complex and hard-to-interpret data set into a simple and easy-to-understand visualization. By using a network graph algorithm to visualize the data from a correlation matrix, one can quickly identify the key relationships among the variables and gain a more comprehensive understanding of the data visualised in Figure 1.2 (Contreras 2019).

Sector	A	B	C	D	E
A	a_{AA}	a_{AB}	a_{AC}	a_{AD}	a_{AE}
B	a_{BA}	a_{BB}	a_{BC}	a_{BD}	a_{BE}
C	a_{CA}	a_{CB}	a_{CC}	a_{CD}	a_{CE}
D	a_{DA}	a_{DB}	a_{DC}	a_{DD}	a_{DE}
E	a_{EA}	a_{EB}	a_{EC}	a_{ED}	a_{EE}

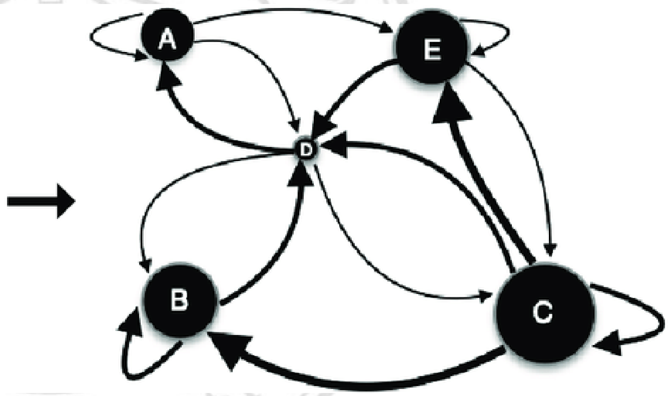


Figure 1.2 Correlation Matrix vs Network Graph (source: Contreras 2019)

1.6 Research Problem

1.6.1 Problem statement

The COVID-19 pandemic has had a significant impact on the way people live their lives, including how they spend their free time and what hobbies and interests they pursue. The COVID-19 pandemic has causing disruptions in the way they spend their free time, engage in leisure activities, and interact with others. With the implementation of social distancing measures and lockdowns, individuals have been compelled to alter their routines and find alternative ways to socialize and entertain themselves.

According to a recent study by the American Psychological Association, more than 70% of Americans reported increased stress levels due to the pandemic, with a significant percentage attributing this to changes in their leisure activities (APA, 2020). As a result, people have turned to new hobbies and interests that can be pursued from the comfort of their homes, such as cooking, gardening, and online gaming. However, not all individuals have equal access to resources that enable them to engage in these activities. For instance, low-income households may struggle to afford equipment and materials necessary for certain hobbies, while individuals living in rural areas may face challenges accessing high-speed internet needed for online activities. This has resulted in the exacerbation of existing inequalities, highlighting the need for policymakers to address these gaps.

Considering these challenges, it is crucial to prioritize the development of initiatives and policies that ensure equal access to resources and opportunities for all individuals to engage in meaningful leisure activities. Doing so can not only help mitigate the negative effects of the pandemic on mental health but can also promote a more equitable and inclusive society (APA, 2020).

This study aims to understand the relationships among countries in terms of hobbies and interests in the pre- and post-COVID-19 pandemic . This study uses network analysis to gain insight from the relationship among countries in terms of hobbies and interests in the pre- and post-COVID-19 pandemic . To achieve the aim of study, the existence of relationship is computed. Later, the significant relationships are selected, converted and visualized using network analysis. Here are a few emphasized purposes.

1. Understanding the Impact of COVID-19: This research aims to understand how the pandemic has influenced the preferences and habits of people across different countries and how these changes might be related to one another. This will help researchers, policymakers, and society at large to understand the broader societal impacts of the pandemic.

2. Identifying the underlying mechanisms: By analysing the relationship between countries in terms of hobbies and interests before and after the outbreak of the pandemic, the research could help identify potential underlying mechanisms that led to these changes and could help us to understand how similar disruptions to society might manifest in the future.

3. Linkage among countries: By using network analysis framework, the study aims to understand the linkage among countries, which can help to identify any potential shared experiences or trends across different countries. This can give insight into whether there are any cross-border patterns that could be addressed through international cooperation.

4. Network graph visualization: By using network graph visualization, the study aims to present the big picture of the transition happened in the hobby interests of countries, this can help to understand how the trends are changing and how the countries are linking with each other.

Altogether, the results of this research could have important implications for understanding the impact of the COVID-19 pandemic on society, and potentially inform policy and decision-making in a variety of fields in the future.

1.6.2 Research Questions

1. What are types of relationships among countries in terms of hobbies and interests in the pre and post-COVID-19 pandemic?

2. How are the relationships among countries in terms of hobbies and interests in the pre- and post-COVID-19 pandemic explained?

1.6.3 Research Objectives

1. To gain exploratory insights of the relationships among countries in terms of hobbies and interests in the pre- and post-COVID-19 pandemic.

2. To explain relationships the relationships among countries in terms of hobbies and interests in the pre- and post-COVID-19 pandemic.

3. To create networks of the relationships among countries in terms of hobbies and interests in the pre- and post-COVID-19 pandemic by using network analysis

4. To explain the networks of the relationships among countries in terms of hobbies and interests in the pre- and post-COVID-19 pandemic.

1.7 Terminology

Application Programming Interface (API) is a collection of computer code that facilitates data to flow between multiple software pieces. It also includes the protocol of the exchange which consists of two components. First, the technical specification governing the exchange channels between software in either a request for processing form or data delivery protocols form. Second, the software interface written to the specification that represents it.

Correlation coefficient is used to present the magnitude of a relationship between two variables. Correlation coefficients can be represented in several ways. The most popular one is Pearson's correlation which is designed for normal distributed data, used frequently in linear functions. Pearson's correlation function is used to find the coefficient which returns a value ranging between -1 and 1, where -1 represents a perfectly negative relationship, 0 shows exactly no relationship, 1 represents a perfectly positive relationship, and the value between shows anywhere between those above extreme cases.

Correlation matrix is presenting correlation coefficients across k variables in the form of k by k tables. Each cell in the table shows the correlation between two variables. Correlation matrices are used to explore data, as a diagnostic for some questions, and as an input for a more advanced analysis.

Edge in this work's context is the connections linking between the nodes or vertices in network graphs, mostly represented by lines. Edges can be either undirected representing bidirectional linkages by having no or two-way arrows like on the end of the lines or directed showing one-way relationships recognised by one-way arrows like on one end.

Google Trends is a free web service provided by Google offering the ability to query for keywords and search topics to see scaled popularity derived from search volume over a time period.

Hobby is a voluntary activity or interest that humans pursue for leisure and not for occupational purposes. Participation in hobbies encourages acquiring notable skills and knowledge in certain areas. In this research, its scope covers only 10 listed hobbies, findings, suggestions, and conclusions drawn from this research could only the said ten, not including its extensions.

Library in this context is not a room filled with books but as a collection of pieces of programming codes to aid programming and software development. It usually contains pre-written code, subroutines, classes, values, templates, configuration data, and documentation to help handle repetitive tasks that occur among programming communities.

Network Graph is a type of diagram mostly used to show connectivity between nodes or variables in the big picture. Connectivity could be either one or two-way depicted by corresponding edges. Network graph must at least consist of nodes and edges.

Node in this work refers to nodes in graph theory. A node is a unit of data on a graph, conditionally linked to other nodes by edges. Mostly represented by a circle which in this work will represent a country, where its size is proportional to its internet users.

Pandemic is an outbreak disease that spreads widely across multiple countries or continents, affecting a large proportion of the population. This research does not include other pandemics apart from COVID-19, and the starting date of this pandemic is 11 March 2020 according to the World Health Organization, making the period before the date called "pre-pandemic" and the period after called "post-pandemic".

Python in this research contest refers to a popular programming language, not to be confused with a snake species. Python was released in 1991 by its creator, Guido van Rossum. It is originally used to perform complex mathematics simulation, calculation and programming, then server-side web development, and later in general software development. Python's popularity comes from different factors. It works on many platforms from Windows, Mac, Linux, Raspberry Pi, et cetera. It has a simple syntax very close to English language which might be the key factor of its success. It runs on an interpreter system which is fast, great for prototyping. Lastly, it could be written in many ways according to the programmer's style, whether in a procedural or functional or object-oriented way. The latest version that is in use at the time of writing is Python3.

Threshold in this research context is a number representing a minimum quantity away from zero to draw an edge on the network graph. An absolute value of correlation coefficient below the threshold will not be drawn and counted as irrelevant relation. The purpose of having thresholds is to separate meaningful relationships from the opposite.

CHAPTER 2

Theoretical Background and Literature Review

2.1 Theoretical Background

2.1.1 Google Trends Principle

Google Trends as a powerful and versatile tool for analysing search behaviour and identifying emerging trends in online activity. Its accessibility and ease of use have made it as a valuable resource for researchers and practitioners across many fields, but careful attention must be paid to the limitations and potential sources of bias when interpreting search data (Cho et al., 2015). In consequence, knowing its principle could be proved helpful.

Google Trends collects data by analysing search queries made on Google Search. The tool measures the popularity of specific search terms and compares their search volumes over time. Afterwards it uses a scale from 0 to 100 to represent the popularity of a given search term, with 100 representing the peak popularity of the search term during the selected time frame then utilises its combination of algorithms and data analysis techniques to identify patterns and trends in search behaviour. The tool uses a variety of data sources, including web search logs and data from Google News, Google Images, and Google Shopping. Google Trends also uses natural language processing techniques to understand the meaning of search queries and to group related search terms together into a so-called “Topic” (Mavragani et al, 2020).

One of the main advantages of Google Trends is its ability to provide insights into what people are searching for online, and how their interests and preferences are changing over time. By analysing search data, researchers could identify emerging trends, monitor changes in consumer behaviour, and track the spread of news and information. Here are a few examples that Google Trends could be utilised (Abraham et al.,2021).

1) Identify popular search terms related to a particular topic or industry.

2) Monitor changes in consumer demand for specific products or services.

3) Analyse the popularity of political candidates, parties, or issues.

4) Track the spread of infectious diseases or public health concerns.

5) Monitor changes in consumer sentiment or brand awareness.

6) Search engine optimization (SEO) and digital marketing.

Overall, Google Trends is a powerful tool for analysing search behaviour and identifying emerging trends in online activity over time. Its ability to provide insights by grouping search keywords into topics further short-circuited tedious tasks by far (Figueiredo et al., 2020).

2.1.1 Correlation Matrix and Pearson’s correlation coefficient

A correlation matrix is a table that displays the correlation coefficients between a set of variables. Correlation coefficients measure the degree and direction of the linear relationship between two variables. Correlation matrices are commonly used in statistical analysis to identify relationships between variables and to explore potential collinearity among them. A correlation matrix can be constructed for any number of variables, and each cell in the matrix displays the correlation coefficient between two variables (Gorard, 2013).

One commonly used correlation coefficient is Pearson's correlation coefficient, which measures the strength and direction of the linear relationship between two continuous variables. The coefficient ranges from -1 to 1, where -1 represents a perfect negative correlation, 0 represents no correlation, and 1 represents a perfect positive correlation. The closer the correlation coefficient is to -1 or 1, the stronger the linear relationship between the two variables. A correlation coefficient of 0 indicates that there is no linear relationship between the two variables. Pearson's correlation coefficient is widely used in statistical analysis and is particularly useful for identifying relationships between variables in large datasets (Pallant, 2016).

One advantage of Pearson's correlation coefficient is that it is easy to interpret and understand. The coefficient provides a measure of the strength and direction of the relationship between two variables, which can be easily interpreted by researchers and practitioners. In addition, Pearson's correlation coefficient can be used to identify potential outliers or influential observations that may affect the relationship between two variables (Field et al., 2012).

However, Pearson's correlation coefficient is only appropriate for measuring the linear relationship between two continuous variables. It may not be appropriate for variables that have a nonlinear relationship or for variables that are measured on a nominal or ordinal scale. In addition, Pearson's correlation coefficient assumes that the variables are normally distributed and that there are no outliers or influential observations that may affect the relationship. Pearson's correlation coefficient, also known as the Pearson product-moment correlation coefficient, is calculated as the covariance of the two variables divided by the product of their standard deviations:

$$r_{xy} = \frac{cov(X,Y)}{\sigma_x \sigma_y} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=}^{n}(y_i-\bar{y})^2}} \quad (1)$$

where r_{xy} is the Pearson correlation coefficient, $cov(X,Y)$ is the covariance of X and Y, while σ_x and σ_y are the standard deviations of X and Y, n is sample size, x_i, y_i are individual sample points of the same index i, and $\bar{x}, \bar{y}$ are sample mean of x and y respectively.

Generally, Pearson's correlation coefficient could be useful in measuring the linear relationship between two continuous variables. Its simplicity and ease of interpretation make it a valuable tool for researchers and practitioners in many fields, but its assumptions and limitations must be carefully considered when interpreting correlation coefficients (Dancey & Reidy, 2017).

2.1.3 QQ-Plot

As mentioned earlier, Pearson's correlation coefficient relied on linear relationship assumption which translates to normal distribution assumption. It is vital to test that the data meet this criterion in order to make use of the coefficient correctly. A QQ-Plot can be used to visually assess whether the distribution of the data is approximately normal, and this visual assessment is quick to determine normality, as well as any departures from normality, such as skewness or kurtosis, which can affect the validity of the correlation coefficient.

The QQ-Plot was first introduced by the Danish mathematician P. C. Mahalanobis in the 1940s and is based on the concept of quantiles, which were first introduced by Francis Galton in the late 19th century. To construct the QQ-Plot, we first sort the observations in ascending order $X_1 \leq X_2 \leq \ldots \leq X_n$. and calculate the corresponding quantiles q_i, using the rank order of the data:

$$q_i = \frac{i-0.5}{n}, \text{ for i = 1, 2, ..., n} \tag{2}$$

We can then compute the expected quantiles, p_i, for a normal distribution with the same mean and standard deviation as the data. These are given by the formula:

$$p_i = \Phi^{-1} q_i, \text{ for i = 1, 2, ..., n} \tag{3}$$

By using the inverse cumulative distribution function of the standard normal distribution Φ^{-1}. We plot the expected quantiles on the x-axis and the observed quantiles on the y-axis. If the data are normally distributed, the plot will show a straight line. Deviations from the straight line can indicate departures from normality.

If the QQ-plot indicates that the data are not normally distributed, alternative correlation coefficients may be more appropriate. For example, Spearman's rank correlation coefficient can be used when the variables are not normally distributed or are measured on an ordinal scale (Field et al., 2012).

2.1.4 Network Analysis

Network analysis is a branch of mathematics and computer science that is concerned with the study of complex systems of interacting objects, such as social networks, biological networks, and transportation networks. Network analysis uses mathematical tools and algorithms to analyse the structure and behaviour of these networks, and to identify patterns and relationships within them.

The graph is a fundamental tool in network analysis that provides a visual representation of a network. A graph is composed of a set of nodes or vertices that represent the objects in the network and a set of edges that represent the connections or interactions between the objects. The edges may be directed or undirected and may have weights that reflect the intensity or strength of the connection.

There are various types of graphs used in network analysis, including unweighted, undirected graphs, weighted undirected graphs, directed graphs or digraphs, and weighted, directed graphs that allow both edge weights and directions.

Graphs can represent various phenomena such as communication patterns, social interactions, transportation networks, and biological systems, and can be analysed using a variety of mathematical techniques such as clustering algorithms, centrality measures, and community detection methods to identify important nodes and patterns in the network (Newman, 2018).

2.1.5 Correlation Network Graph

According to Li et al. (2020), a correlation network graph is a subset of a network graph that represents the correlation relationships among a set of variables. In this type of graph, the nodes represent the variables, and the edges represent the correlations between them. The strength of the correlation is typically represented by the width or colour of the edge, with stronger correlations represented by wider or darker edges. The thresholding method is one of the most common methods for constructing correlation network graphs, in which a threshold is chosen to determine which correlations are significant enough to include in the graph. Once the threshold has been chosen, the graph can be constructed using a variety of software tools, such as Gephi, igraph in R, or network in Python. The resulting graph can provide valuable insights into the relationships among variables and the underlying structure of a complex system (Li et al., 2020).

2.1.6 Network Threshold

As mentioned earlier, the network threshold plays a major part in filtering elements in the graphs, and there are many methods to calculate network threshold (Udomwong, 2015), yet a decisive solution has not been decided. The choice remains subjective. Following are some methods used.

1) Visual inspection method: The network threshold is chosen based on the researcher's judgement of the graph's structure and the correlations between the nodes. This is a subjective trial-and-error method and is often used when the data is visual and easy to interpret (Davies & Bould, 2020).

2) Statistical significance method: The network threshold is chosen based on a statistical test of the correlation coefficients. This method is used when the researcher wants to control the false discovery rate or the family-wise error rate. The threshold is chosen by comparing the p-value of each correlation coefficient to a chosen significance level, such as the Bonferroni correction or the false discovery rate method.
Bonferroni correction threshold is calculated by following equation (Mylona & Polyzos, 2020):

$$threshold = \sqrt{\frac{1-\alpha}{n_k}} \qquad (4)$$

, where n_k is the total number of comparisons (i.e., pairs of variables) in the correlation matrix.
The FDR (false discovery rate) correction method is a statistical technique that is commonly used to adjust p-values for multiple comparisons, and to control the proportion of false discoveries among significant results. The FDR correction threshold is typically set at a certain level, which determines the maximum acceptable rate of false discoveries. The FDR threshold can be calculated using the following equation (Benjamini & Hochberg, 1995):

$$\frac{k}{m} \leq q \qquad (5)$$

where k is the rank of the p-value in a sorted list of all p-values, m is the total number of tests performed, and q is the desired FDR level. In this equation, $\frac{k}{m}$ represents the estimated proportion of false positives among all significant results, and q is the desired upper bound for this proportion.

To apply the FDR correction, one typically sorts all the p-values from smallest to largest, calculates the FDR threshold based on the desired level of control, and identifies all the p-values that are smaller than the threshold. These p-values are then considered significant, and any associated test statistics or effect sizes are reported with the corresponding adjusted p-values. Different FDR correction methods may use slightly different equations or algorithms to estimate the FDR threshold, but the basic idea is to control the rate of false discoveries while allowing for some flexibility in the number of significant results (Benjamini and Hochberg, 1995).

3) The Density of Network method is a technique used to select the optimal threshold for a network correlation matrix, based on the desired density of the resulting network. This method is used when the researcher wants to control the sparsity or density of the network. Density of network measures the proportion of edges drawn to nodes that can possibly be connected (Pavlopoulos et al., 2011) and could be derived by:

$$density = \frac{2|E|}{|V|(|V|-1)} \quad (6)$$

where |E| is the number of edges. |V| is the number of nodes excluding isolated nodes. |E| and |V| are a function of threshold level. Number of edges drawn drop when threshold rises while higher threshold leads more nodes to be isolated. As a result, density value starts from 1 when threshold remains 0, later reduces to the lowest network density. Then, the value rises again as the edge number is more stable while more nodes are being isolated. The procedure to find optimal threshold involves iterating threshold level from 0 to 1 which returns density level derived from the equation above. After each threshold, the density of the resulting network is calculated. The density of the network is defined as the proportion of actual edges (i.e., non-zero correlation coefficients) to the total number of possible edges (Newman, 2018).

Finally, Optimal threshold holds at the lowest value of the density network (Aoki et al., 2007, Ozaki et al., 2010). This threshold represents the optimal trade-off between sparsity and density and can be used as the threshold for the network correlation matrix (Alstott et al., 2014). It should be noted that the choice of the optimal threshold may depend on the specific data set and research question and may need to be validated using other techniques or sensitivity analyses (Newman, 2018).

4) The Information-theoretic criteria method is a statistical method used to select a threshold value for a network correlation matrix based on the amount of information contained in the network. This method is used to control the complexity of the model, and the threshold is chosen by comparing the fit of different models with different threshold values, based on an information criterion such as the Akaike information criterion (AIC) or the Bayesian information criterion (BIC) (Wasserman and Faust, 1994).

To apply the Information-theoretic criteria method to a network correlation matrix, several steps must be followed. First, the correlation matrix should be calculated by computing the pairwise correlation coefficients between all pairs of nodes in the network. Then, a linear regression model should be fit to the correlation matrix using the network density as the predictor variable and the correlation coefficients as the response variable. Next, the AIC or BIC should be calculated for the linear model using the formulas:

$$AIC = 2k + n\ln\left(\frac{RSS}{n}\right) \quad (7)$$

$$BIC = k * \ln(n) + n\ln\left(\frac{RSS}{n}\right) \quad (8)$$

$$RSS = \sum_{i=1}^{n}(y_i - f(x_i))^2 \quad (9)$$

where n is the number of observations (i.e., the size of the correlation matrix), RSS is the residual sum of squares, and k is the number of model parameters.

The next step is to vary the threshold value from 0 to 1 in small increments and for each threshold, calculate the density of the resulting network. For each threshold value, a linear regression model should be fit to the correlation matrix using the network density as the predictor variable and the correlation coefficients as the response variable.

The AIC or BIC should then be calculated for each linear model using the formula described above. Finally, the optimal threshold value is selected by identifying the threshold value that minimizes the AIC or BIC value. This threshold value represents the optimal trade-off between model complexity and goodness of fit and can be used as the threshold for the network correlation matrix.

Note that the Information-theoretic criteria method is computationally intensive and may require specialized software or programming languages to implement. Additionally, the optimal threshold selected by this method may depend on the specific data set and research question and may need to be validated using other techniques or sensitivity analyses (Wasserman and Faust, 1994).

5) Percolation thresholding method is another approach where the network threshold is chosen based on the critical threshold at which the network undergoes a phase transition from a connected state to a disconnected state. This method is used when the researcher wants to

identify the most important links in the network. The threshold is chosen based on the critical threshold value determined by the percolation theory (Strogatz, 2001). The basic idea of this method is to identify the threshold at which the network breaks into smaller components, while taking into account the size and connectivity of the components.

To apply the percolation thresholding method to a network correlation matrix, the threshold value is varied from 0 to 1 in small increments, and at each threshold, all edges (correlation coefficients) that are smaller than the threshold are removed, resulting in a sparse network. The connected components of the resulting network are then identified, and the size of the largest connected component is calculated as a function of the threshold.

The threshold at which the size of the largest connected component drops below a certain threshold, such as 5% of the total number of nodes, is then selected. This threshold represents the point at which the network breaks into smaller, disconnected components, and can be used as the threshold for the network correlation matrix. This method allows for the identification of the most important links in the network while taking into account the size and connectivity of the components (Strogatz, 2001).

2.2 Literature Review

2.2.1 Effect of Covid-19 on Human Behaviours

Jay J. van Bavel, Latherine Baicker with 43 co-authors published a paper in Nature Human Behaviour journal (2020) named "Using social and behavioural science to support COVID-19 pandemic response" (2020) provided a comprehensive review of the social and behavioural aspects of the COVID-19 pandemic, and how these aspects have contributed to the spread of the disease. The authors describe the various ways in which human behaviour has influenced the pandemic, including individual-level factors such as risk perception, social norms, and health behaviours, as well as larger structural and societal factors such as economic disparities and political factors. They also discuss the role of communication and messaging in shaping public perceptions of the pandemic and highlight the importance of a coordinated and evidence-based response that takes into account the social and behavioural dimensions of the pandemic. The paper provides a valuable resource for researchers, policymakers, and public health officials seeking to understand the social and behavioural aspects of the COVID-19 pandemic and to develop effective strategies for prevention and control. In a part of the work concluded that during a pandemic, one of the central emotional responses is fear. Animals, including humans, own a series of defensive systems for tackling natural threats.

LeDoux, J.'s book "Rethinking the emotional brain" (2012) discusses the neuroscience of emotions and argues that emotions are not entirely automatic or hard-wired in the brain. Instead, he contends that emotions are learned responses that can be modified through conscious effort and training. LeDoux proposes that emotions are constructed in the mind through a combination of automatic processing and higher cognitive functions, and that the brain's emotional circuitry can be consciously controlled and influenced by cognitive strategies such as reappraisal and mindfulness. Overall, the book challenges traditional views of emotions and provides a new perspective on how the brain processes and regulates emotions.

Mobbs, D., et al (2015) published "The ecology of human fear: survival optimization and the nervous system" propose that humans have evolved a sophisticated system for detecting and responding to threats in the environment. The authors argue that the experience of fear is not simply a product of cognitive processing, but rather involves complex interactions between the brain, the body, and the environment. They suggest that the brain has evolved to integrate information from multiple sensory systems to produce a rapid and adaptive response to perceived threats. The authors describe how this response involves a range of physiological and behavioural changes, such as increased heart rate, heightened arousal, and defensive behaviours. The paper also discusses the ways in which fear can be modulated by factors such as context, learning, and social cues, and highlights the importance of understanding these processes for improving our ability to cope with real-world threats. Overall, the authors propose a framework for understanding the ecology of fear that integrates multiple levels of analysis, from the molecular and cellular to the social and cultural. Fear makes threats perception to be distorted to the worst case based on Cole,S. et al (2013) and these negative feelings driven by threats can be communicable as supported by Kramer,A.D.I. et al (2014).

Strunk, D.R. et al. (2006) conducted a study to investigate whether optimistic people perceive negative information in a less threatening way compared to less optimistic people. Participants with varying levels of optimism were asked to rate the likelihood that negative events would happen to them, and to estimate the probability of negative events happening to them compared to others. The results showed that highly optimistic participants rated the likelihood of negative events happening to them as lower than the less optimistic participants. Additionally, highly optimistic participants also perceived the negative events as less threatening compared to less optimistic participants. The study concluded that highly optimistic people have an optimism bias, which leads them to underestimate the likelihood of negative events happening to them and to perceive negative events as less threatening. The authors suggest that this optimism bias could have both positive and negative consequences on decision-making and behaviour and should be considered in various fields such as health psychology and finance.

Sharot, T (2011) in "The Optimism Bias," explores the psychological phenomenon of the optimism bias, which refers to the tendency for people to overestimate their likelihood of experiencing positive events and underestimate their likelihood of experiencing negative events. Sharot examines research from neuroscience, psychology, and economics to provide insight into the mechanisms that underlie this bias and the potential consequences for decision-making and well-being. She suggests that the optimism bias serves a useful function in motivating people to take risks and pursue goals, but it can also lead to unrealistic expectations and poor decision-making. Sharot discusses strategies for managing the optimism bias, such as cultivating mindfulness and seeking out diverse perspectives. Overall, the book provides a fascinating exploration of a common cognitive bias and its implications for everyday life. This is also supported by Wise,T. et al (2020).

Jay, J., Willis, E., and J. Witherspoon's paper (2018) titled "Communication Strategies for Influencing Public Policy on Environmental Issues" focuses on identifying the most effective communication strategies for promoting environmental policies to the public.

The paper argues that understanding how to communicate environmental policies is crucial to making a positive impact on the environment. The authors reviewed the literature on the subject and found that effective communication strategies should take into account several factors, including the message content, the audience, and the medium used to convey the message. They identified four key communication strategies: fear appeals, efficacy messages, moral appeals, and framing. Fear appeals can be effective in drawing attention to environmental issues and encouraging individuals to take action, but overuse of fear can lead to desensitization or avoidance. Efficacy messages emphasize the ability of individuals to make a difference, while moral appeals focus on the ethical aspects of environmental issues. Finally, framing is the way in which an issue is presented and can impact how individuals perceive and respond to it. The authors also suggest that effective communication strategies should reflect the audience's values, beliefs, and attitudes, and should be tailored to fit the specific context and situation. The paper concludes that effective communication strategies are crucial to promoting environmental policies and that continued research in this area can lead to better policy outcomes. Main suggestion of Jay et al's paper in communication strategies is to strike a balance between breaking through the optimism bias barrier without causing too much anxiety. These works support the statement that COVID-19 induced negative emotional response which leads to different decisions of individuals and the statement that the event may have caused collective hysteria which ultimately proved that there exists some degree of correlation among people.

In "The COVID-19 Pandemic: Changing Lives and Lessons Learned" authored by Rod K. Rohrichm, MD, Kristy L. Hamilton, MD, Yash Avashia, MD, and Ira Savetsky, MD (2020) studied how COVID-19 change people's life in several aspects. Apart from medical and epidemiology findings and suggestions, the research points out how COVID-19 has changed plastic surgery which involved major behavioural changes toward the virtual environment. Another part is about societal changes after the crisis in the American context which suggests that the pandemic helps shape citizens to be more patient, more responsible to others, more disciplined, and more resilient. Overall, the pandemic affects people's core values and perception to evolve.

2.2.2 Utilizing Google Trends in Behavioural Studies

In the 2020 study, "Human-dog relationships during the COVID-19 pandemic: booming dog adoption during social isolation," Liat Morgan and co-authors examined the impact of the COVID-19 pandemic on the human-dog relationship, specifically the increased demand for dog adoptions. The authors conducted an online survey with dog owners to investigate the reasons behind this surge in adoptions, as well as the impact of the pandemic on the human-dog relationship. Interest in dog adoption is measured by Israeli dog adoption website visits and worldwide Google searches for adoptable dogs. This research implied that Google search volume can be utilized to measure interest and proved that the pandemic affects search interests in pet adoption. Further study in other hobbies could be done. The results of the study indicated a significant increase in dog adoptions during the pandemic, with many owners citing the need for companionship and a desire for a source of emotional support. The authors also found that the pandemic had a positive effect on the human-dog relationship, with owners spending more time with their dogs and reporting higher levels of attachment to their pets. Additionally, the study revealed that the relationship between dog owners and their pets was positively associated with the owner's mental health and well-being during the pandemic. The authors concluded that the human-dog relationship played a vital role in promoting mental health and well-being during the pandemic, and that the increased demand for dog adoptions highlighted the importance of companion animals in times of crisis. The study provides insight into the complex relationship between humans and animals, and emphasizes the potential benefits of pet ownership, particularly during times of social isolation and increased stress.

Kirsi-Marja Zitting et al (2021) found that Google Trends reveals increases in internet searches for insomnia during the 2019 coronavirus disease (COVID-19) global pandemic. The research tried to estimate the effect of COVID-19 on insomnia levels in global level as previous evidence from small samples suggest increased insomnia and other sleep disturbances. The result in United States showed 58% expanding search queries for insomnia in January through May 2020 compared to previous 3 years of the same month. Additionally, the search volume peaked around 3 am. This work showed that Google Trends can be used to extend the scope of the research toward global scale.

Simeon Vosen and Torsten Schmidt (2011) compared prediction power between survey-based indicators and Google indicators in predicting private consumption context. Survey-based indicators are the University of Michigan Consumer Sentiment Index (MCSI) and the Conference Board's Consumer Confidence Index (CCI). Google indicators are a collection of selected Google trends topics. Prediction power gain is measured by an increase R-squared from a simple autoregressive model as a baseline. The result showed that MCSI gave 1 percent incremental R-squared while CCI gave 2 percent and Google indicators gave 3 percent. This analysis shows that Google Trends is a very promising and convenient data source to use in prediction problems.

Amaryllis Mavragani & Knostantinos Gkillas (2020) studied a feasibility of Google Trends in predicting COVID-19 cases and deaths in global scale and the United States. The result showed the projected Google Trends models reveal powerful COVID-19 predictability.

In “Can Google Trends search queries contribute to risk diversification?” by Ladislab Kristoufek (2013) found an application of Google Trends in financial portfolio management. The intention to diversify risk is based on an idea that popularity of a stock measured by search queries is correlated with the stock riskiness. The result revealed that search queries-based strategy outperformed both the uniformly weighted portfolio and the benchmark index both in-sample and out-sample. There are more applications of Google Trends in finance context. Ilaria Bordino et al (2012) predicted stock market volumes and Hyunyoung Chio, Hal Varian (2012) forecasted near-term values of economic indicators.

2.2.3 From Relationships to Graphs

Correlational relationships among variables are often studied in various fields such as social sciences, economics, and psychology. These relationships can be challenging to understand and visualize as the number of variables increases. Network graphs provide a useful tool for transforming these complex relationships into a more understandable and visually appealing format (Boccaletti et al., 2006). Network graphs are a visual representation of relationships between objects, where objects are represented as nodes, and relationships between them are represented as edges (Newman, 2010). In the context of correlational relationships, nodes represent variables, and edges represent the correlations between them.

There are several approaches to constructing network graphs from correlational relationships. One common method is to use the Pearson correlation coefficient to measure the strength of the correlation between variables (Opsahl et al., 2010). This method has been used in various studies, including one that investigated the relationship between social network size and stress levels in older adults (Kang et al., 2014). In addition to providing a visual representation of correlational relationships, network graphs can also be used for statistical analysis. For example, network analysis can be used to identify key variables that play a crucial role in the network and can be targeted for interventions (Epskamp et al., 2018).

CHAPTER 3

Methodology

Methodology in this study will follow these steps. Firstly, researcher need to define population and sample of the study, then collect data accordingly. Upon data retrieval, next step is to combine and prepare data into the preferred format. Then, we take the normality test by utilising QQ-Plot and calculate appropriate correlation matrices. Network thresholds will need to be calculated and compared in this part. Lastly, Network graphs will need to be drawn.

3.1 Population and Sample

Population in this study referred to global citizens who search. Recalling that around 91 percent of searches are in Google's platform (Alex, 2021), with Google Trends, the authors can draw samples as nearly as population size, enabling the authors to gain a comprehensive understanding of the search patterns of global citizens in topics of interest and our search topics of interest are Collecting, Game, Sports, Music, Cooking, Arts, Crafts, Performing Art, Learning, and Pet.

Furthermore, the author has chosen to examine only 50 countries that possess the highest internet usage in the research. This decision is based on the understanding that countries with higher internet usage tend to have a more significant impact on global economic and political affairs, and therefore, their citizens' search behaviour may be more indicative of global trends. The countries included in the research are China, India, United States, Nigeria, Indonesia, Brazil, Japan, Russia, Bangladesh, Mexico, Philippines, Germany, Pakistan, Vietnam, Turkey, Iran, United Kingdom, France, Thailand, Italy, Egypt, South Korea, Spain, Argentina, Canada, South Africa, Saudi Arabia, Colombia, Poland, Malaysia, Peru, Australia, Netherlands, Romania, Chile, Belgium, United Arab Emirates, Sweden, Czech Republic, Switzerland, Portugal, Austria, Israel, Hong Kong, Denmark, Norway, Finland, Singapore, Ireland, and New Zealand

As mentioned, that this research aimed to study the changes from COVID-19, World Health Organization declared the disease as a pandemic on 11 March 2020 which separates the former timeframe into pre-pandemic, and the latter into post-pandemic.

3.2 Data Collection

This research collects weekly scaled Google search in 10 mentioned topics for each of 50 qualified countries from 1 January 2018 to 30 April 2022 utilising Google Trends Python API, returning 500 time-series tables in total. Data will be a scaled value between 0 to 100. Combining all tables in each topic together then separate the pre-pandemic for dates before 11 March 2020, and post-pandemic for dates after, resulting in 20 panels representing all topics for both time frames.

3.3 Normality Tests of Data with QQ-Plot

In this step, we test normality of data as a permission to use the simpler Pearson's correlation coefficient. For each of 20 panels and for each country represent by columns, separately start by sorting observations in ascending order and calculate the corresponding quantiles q_i, using the rank order of the data:

$$q_i = \frac{i-0.5}{n}, \text{ for i = 1, 2, ..., n} \tag{10}$$

then the expected normal distribution quantiles (p_i) are computed according to the formula:

$$p_i = \Phi^{-1} q_i, \text{ for i = 1, 2, ..., n} \tag{11}$$

Those series of pairs (q_i, p_i) are compared one by one by plotting a respective graph. For simplicity, 50 QQ-Plots of the same panel are grouped to view in the big picture. In the plot, the more it deviates from each other indicates, the more it departs from normality. If comparing pairs for most plots are aligned closely together, then Pearson's correlation coefficient is computed. If not then, we utilise one of the alternatives.

3.4 Correlation Matrix Computation

After the normality tests, we calculate 20 correlation matrices from those 20 panels with an appropriate correlation coefficient method. An example of the simplest Pearson's product-moment correlation coefficient, is calculated as the covariance of the two variables divided by the product of their standard deviations:

$$r = \frac{cov(X,Y)}{\sigma_x \sigma_y} \tag{12}$$

where r is the Pearson correlation coefficient, $cov(X, Y)$ is the covariance of X and Y, while σ_x and σ_y are the standard deviations of X and Y, respectively.

3.5 Network Compartments

Network compartments for this research will be represented by nodes in the graphs. Each graph should consist of 50 nodes, each representing one of the 50 selected countries and positioned accordingly to its real location on a typical world map. In this case, positioning the nodes using a fixed layout would be more intuitive than using an algorithmic approach. Research suggests that fixed positioning of nodes can help to improve the interpretability and usability of network visualizations. In a study by Ghoniem and Fekete (2005), participants found that manually positioned nodes were easier to understand and navigate than those positioned using an algorithm. Additionally, a review of network visualisation techniques by Hansen et al. (2015) highlights the importance of fixed positioning for creating clear and meaningful visualisations. The size of the nodes will be logarithmically scaled to reflect the number of internet users in each country, and the colour of the nodes represent one of the 15 regions which the country belongs to. Regions are east Asia, west Asia, south Asia, southeast Asia, east Europe, west Europe, south Europe, north Europe, central America, north America, south America, Oceania, north Africa, west Africa, and south Africa. Colour choices are chosen based on the author's preference.

3.6 Threshold Selection

Proceeding to draw graphs without appropriate thresholds will rend those “hard to create” network graphs into a useless mess that gives no information at all. Consider a network graph where each node is connected to every other node in the graph, irrespective of the type or strength of connection. This is arguably and obviously the most important part in creating any network graphs because it defines which connection to show or hide based on intensity of relationship or correlation coefficient value of any interested pairs. In this research, we utilise several of these threshold calculations listed below, repeatedly for each of 20 panels.

3.5.1 Bonferroni correction threshold

Using this method requires to set a predefined significance level (α), herein 5% (0.05), and then substitute the predefined α into equation (13) to acquire a threshold:

$$threshold = \sqrt{\frac{1-\alpha}{n_k}} \tag{13}$$

where n_k is the total number of possible pairs in the correlation matrix, which is 50x50 correlation matrices, there are (50 choose 2) possible pairs, where "choose" is the binomial coefficient. The possible pairs can be computed by $\binom{50}{2}$ which is $\frac{50!}{2!(50-2)!} =$ 1,225 pairs.

3.5.2 Density of network threshold

This threshold finding method is a way to find the best threshold value by testing all possible options. It involves simulating different results for each threshold value and keeping track of the outcomes. The outcomes will be evaluated by minimising the metric “density” which measures the proportion of edges drawn to nodes that can possibly be connected, it could be quantified as:

$$density = \frac{2|E|}{|V|(|V|-1)} \tag{14}$$

where |E| is the number of edges. |V| is the number of nodes excluding isolated nodes. Number of edges drawn drops when threshold rises while higher threshold leads more nodes to be isolated. As a result, density value starts from 1 when threshold remains 0, later reduces to the lowest network density. Then, the value rises again as the edge number is more stable while more nodes are being isolated. The procedure to find optimal threshold involves iterating threshold level from 0 to 1 which returns density level derived from the equation above. This research increases threshold level by 0.01 in each step. Optimal threshold holds at the lowest value of the density network.

3.5.3 Akaike Information Criterion (AIC) model fitness threshold

Given correlation matrices, set the threshold to 0 and calculate network density as defined earlier, then fit a linear regression model to the matrix and use network density as a predictor variable. Plug in following AIC formula:

$$RSS = \sum_{i=1}^{n}(y_i - f(x_i))^2 \tag{15}$$

$$AIC = 2k + n\ln\left(\frac{RSS}{n}\right) \tag{16}$$

where n is the number of observations, this case refers to countries variables which then equals to 50. Record the AIC value and increase the threshold by 0.01 and try all over again until it reaches 1. The optimal threshold is the one that minimises the AIC value, indicating the level of correlation between variables that best fits the observed data while minimising the complexity of the model.

3.5.4 Bayesian Information Criterion (BIC) fitness threshold

Just like the previous AIC part, set the threshold to 0 and calculate network density as defined earlier, then fit a linear regression model to the matrix and use network density as a predictor variable but this time plug in this formula instead:

$$BIC = k * \ln(n) + n\ln\left(\frac{RSS}{n}\right) \tag{17}$$

where everything remains the same, the optimal threshold lies in the one that minimises the BIC value.

3.5.5 Network percolation threshold

Vary the threshold from 0 to 1 in 0.01 increments, and for each threshold, remove all edges that are smaller than the threshold, just like in the density of network counterpart. Then identify connected components for each threshold choice and record the largest components. The optimal percolation threshold is the one that results in the largest component sizes.

3.6 Network Connectivity

A network graph would not be complete without connections. With thresholds provided, it enables connective edges to be created for each of the selected topics both pre-pandemic, and post-pandemic.

The edges of the graph connect pairs of countries with an absolute correlation coefficient value higher than the threshold value derived in the previous step. The thickness of the edges represents the strength of the correlation, with thicker edges indicating a stronger correlation. Additionally, the colour of the edges indicates the nature of the correlation, with navy blue edges indicating a positive correlation and pink edges indicating a negative correlation.

This visual representation of the correlations between countries provides a clear and intuitive understanding of the relationships between the hobby interest levels of the different countries. The size of the nodes and the thickness of the edges allow for the easy identification of countries with high levels of hobby interest and strong correlations, while the colour-coding of the edges and nodes makes it easy to identify regions with similar hobby interests and patterns of correlations.

CHAPTER 4

Results

Based on data collection methodology mentioned in Chapter 3, two periods of weekly time-series data for ten search topics in 50 countries are collected. First phase started from the beginning of 2018 to the official COVID-19 announcement date, March 11th in 2020. Another phase ranged from the week after until the end of April 2022. Fraction of raw data retrieved from Google Trends is shown in the Table 4.1 below. The data was scaled between 0 to 100 where 0 resembled the least search volume and 100 representing the peak.

Table 4.1: Part of scaled weekly search data in the Pets topic before the pandemic.

date	ARE	ARG	AUS	AUT	BEL	BGD	BRA	CAN	CHE	CHL	CHN	COL	CZE
1/7/2018	68	82	50	59	80	73	33	45	54	77	58	94	58
1/14/2018	73	87	49	55	84	75	35	46	58	80	81	85	57
1/21/2018	71	87	51	64	84	79	39	48	58	75	82	83	64
1/28/2018	75	83	53	59	87	76	35	44	53	80	64	75	67
2/4/2018	71	82	58	71	86	63	37	47	55	83	80	70	66
2/11/2018	68	93	60	69	97	70	35	48	64	83	69	73	69
2/18/2018	72	85	66	68	84	77	39	55	63	79	100	74	71

4.1 QQ-Plot Test Results

QQ-Plot tests for normality are calculated and visualised in this step from the combined data of both time periods. The result confirms majority of the dataset to be normal as most of the graphs in each of 10 topics depicted in straight line along with expected distribution by QQ-visualisation in Figure 4.1 to Figure 4.10.

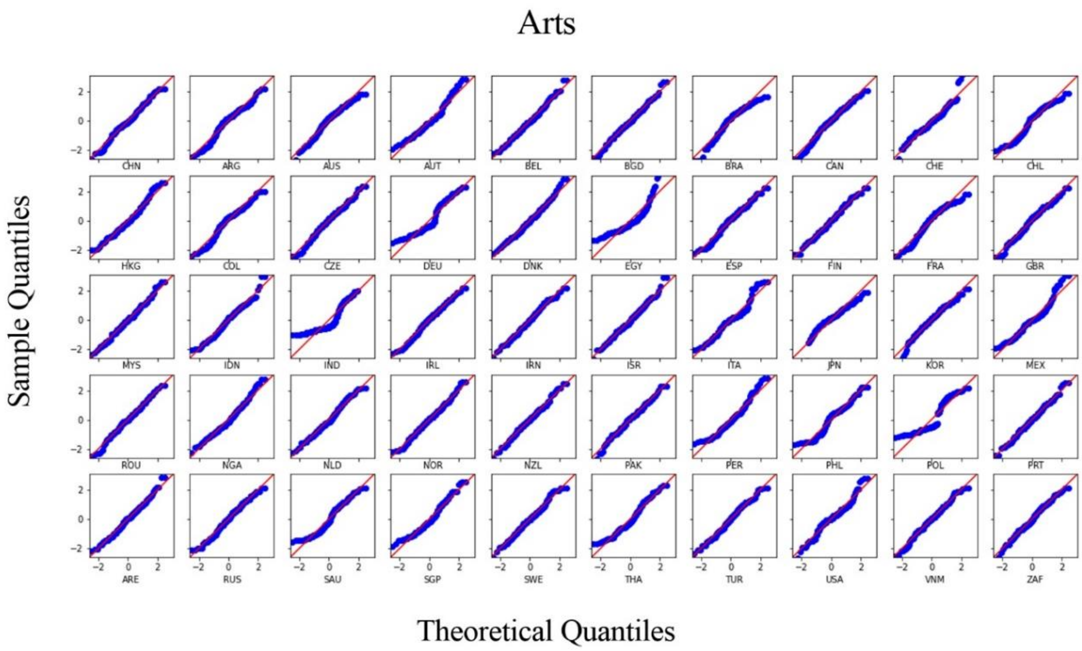


Figure 4.1 QQ-Plots of the Art topic for 50 countries

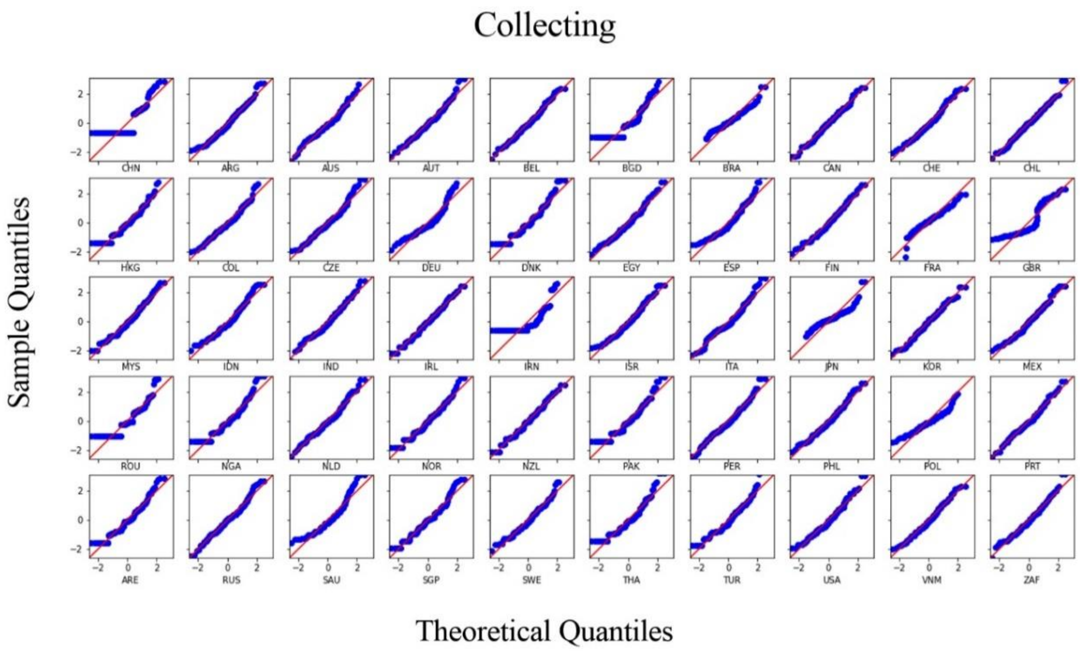


Figure 4.2 QQ-Plots of the Collecting topic for 50 countries

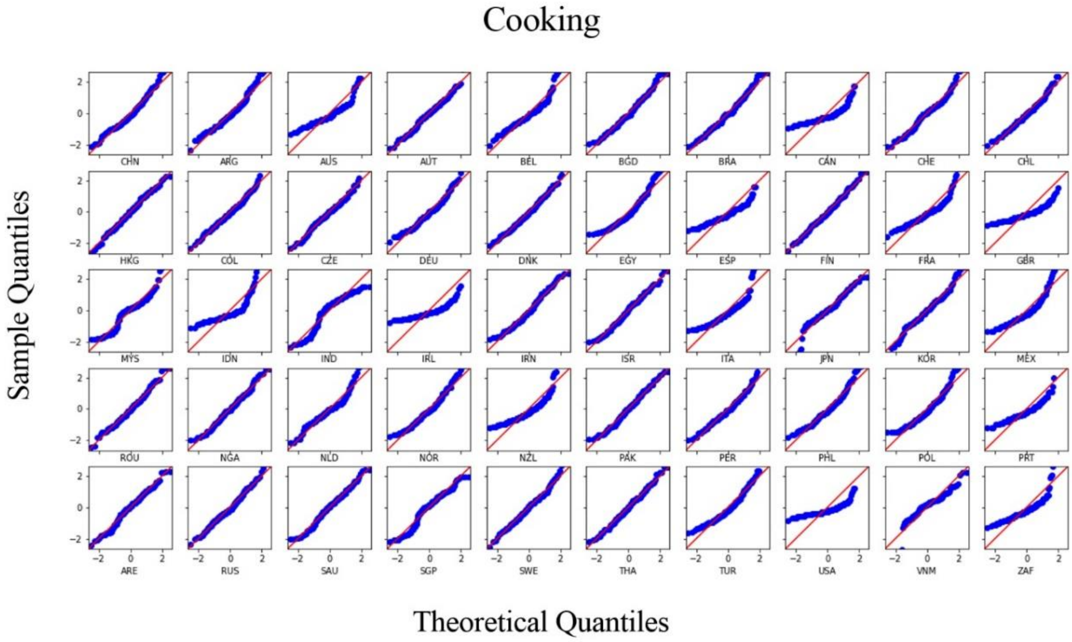


Figure 4.3 QQ-Plots of the Cooking topic for 50 countries

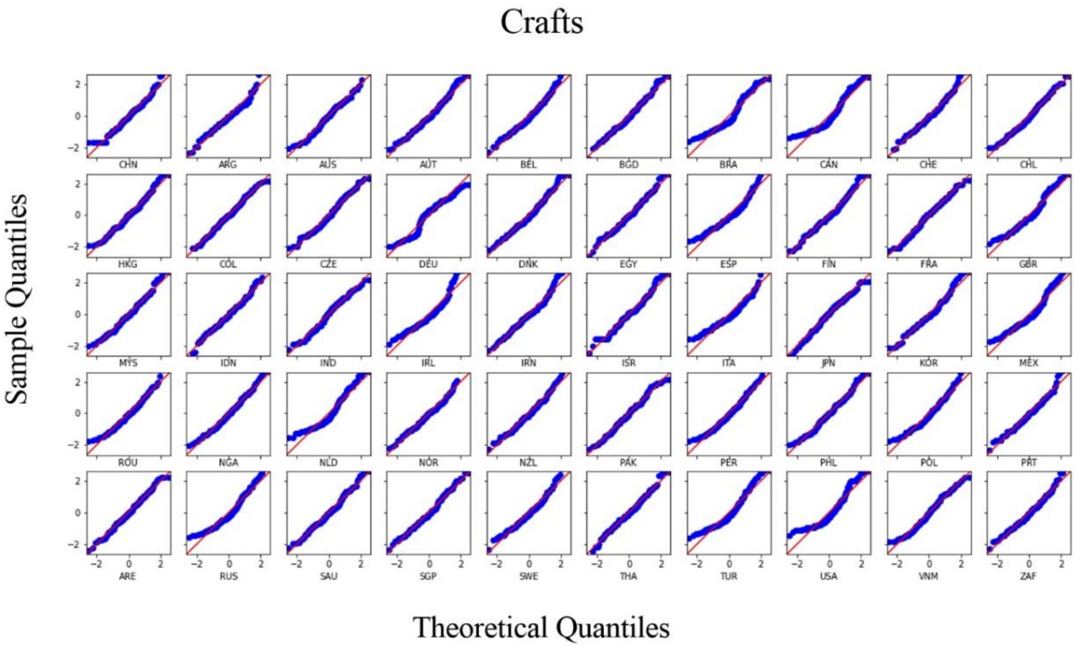


Figure 4.4 QQ-Plots of the Craft topic for 50 countries

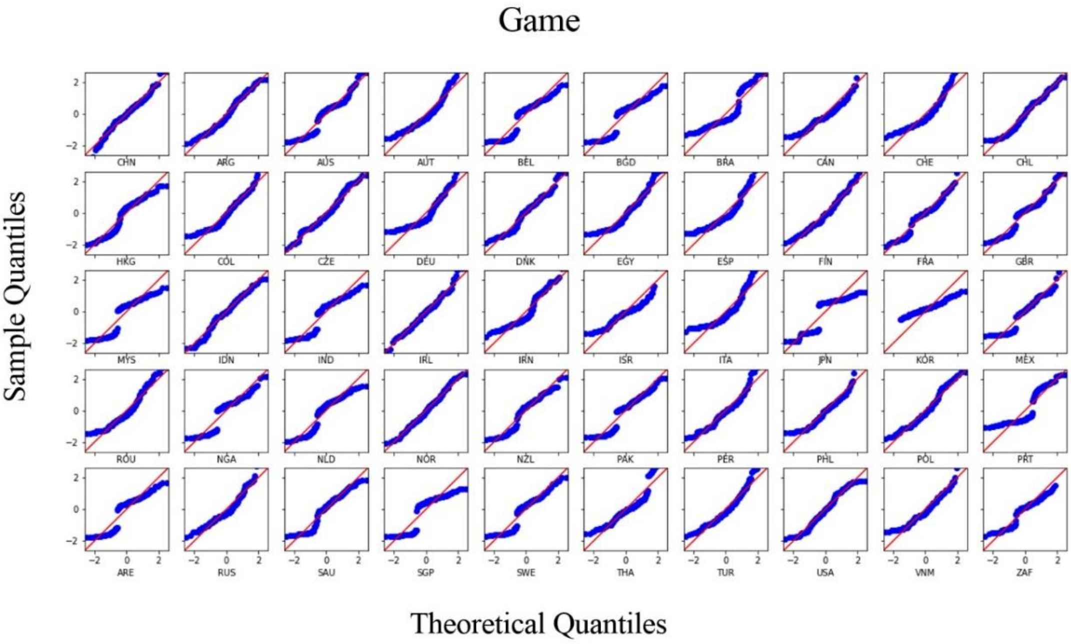


Figure 4.5 QQ-Plots of the Game topic for 50 countries

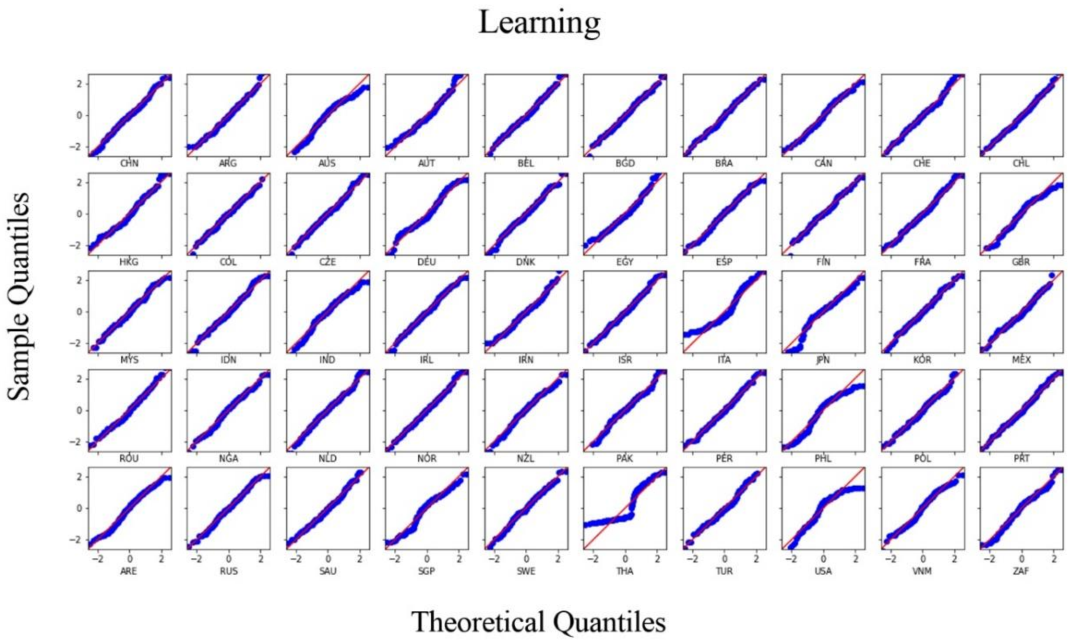


Figure 4.6 QQ-Plots of the Learning topic for 50 countries

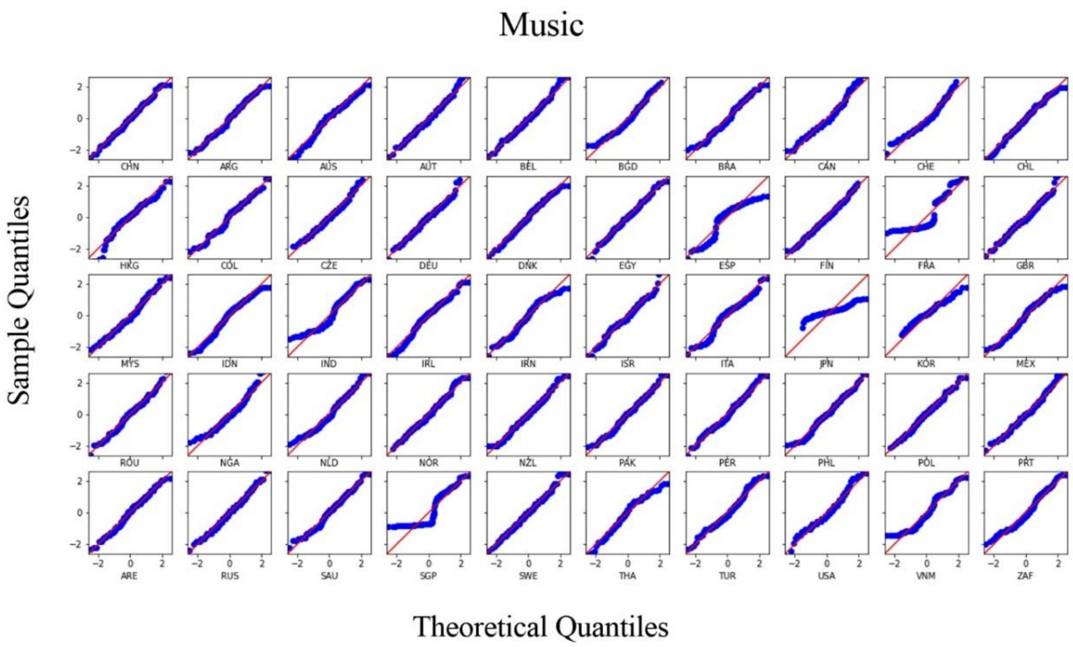


Figure 4.7 QQ-Plots of the Music topic for 50 countries

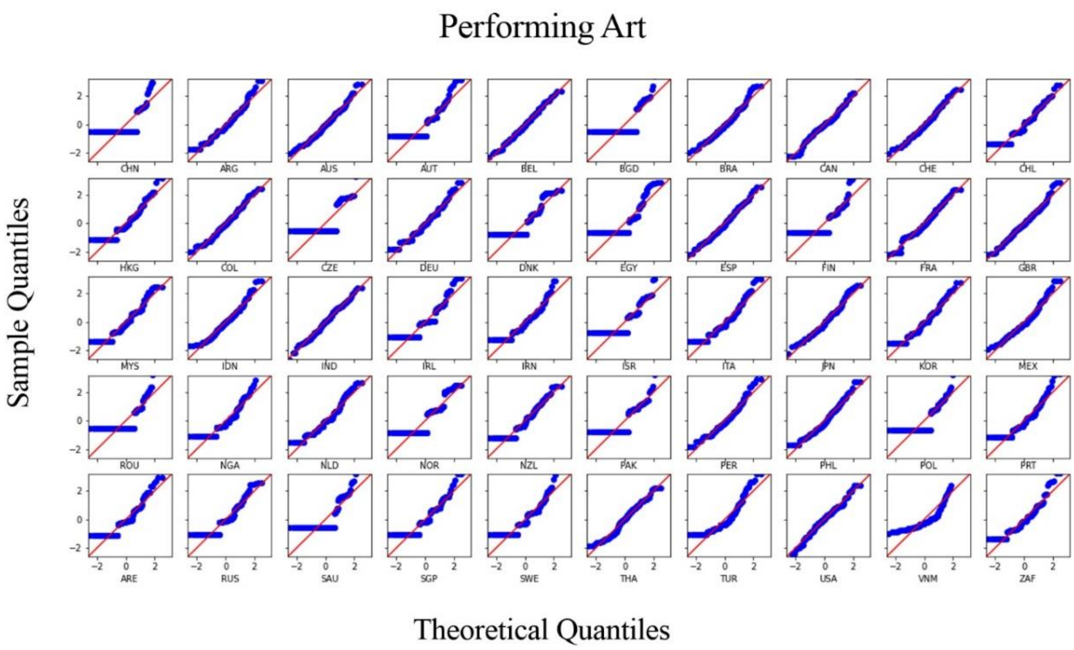


Figure 4.8 QQ-Plots of the Performing Art topic for 50 countries

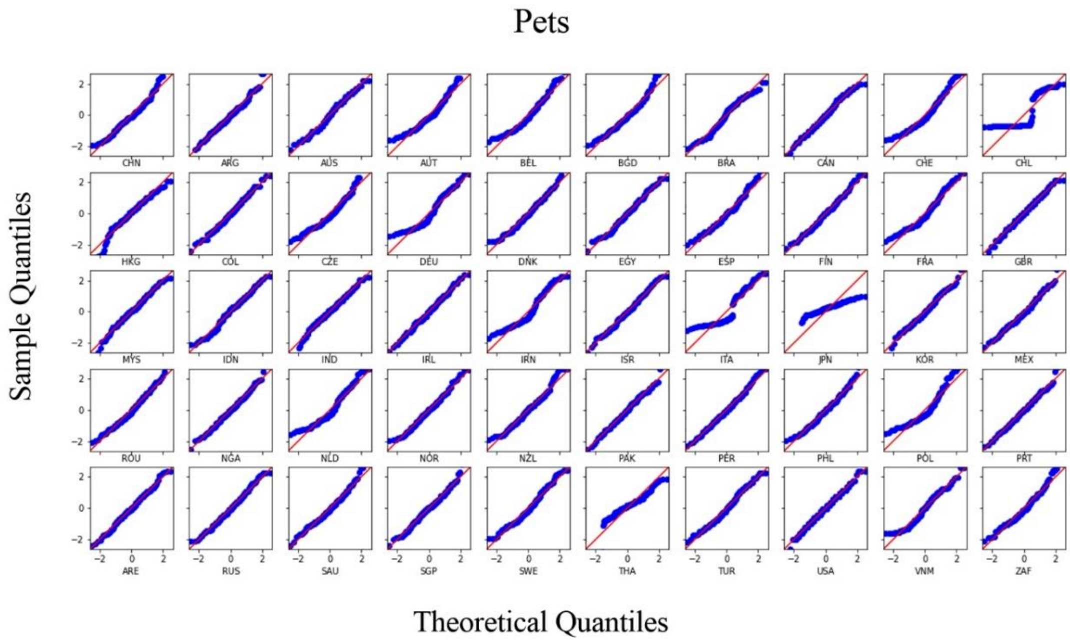


Figure 4.9 QQ-Plots of the Pets topic for 50 countries

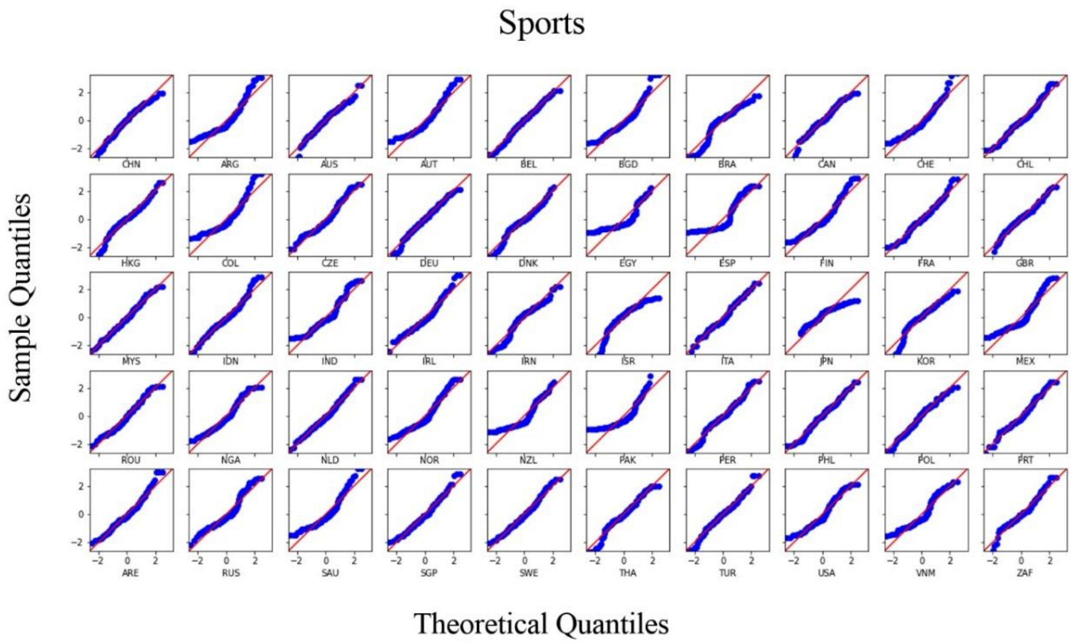


Figure 4.10 QQ-Plots of the Sports topic for 50 countries

The tests allow the author to use Pearson's correlation in calculating correlation matrices for 10 topics, in both pre-pandemic and post-pandemic, proceeding to the next step.

4.2 Threshold Finding Results

As there are no clear recipe on how to choose the threshold, the author tried all 5 methods and compare their compatibilities. Bonferroni method seems to be more defensive on cutting irrelevant edges and its value remains the same for all topics due to its formulation as parameters affecting calculation are only from the chosen significance level (α) and the total number of possible pairs in the correlation matrix (n_k) which will always be 1,225 for every 50 x 50 correlation matrices. By using Bonferroni threshold, the graphs will be very messy as it filters a very small portion of linkages in these cases. No information will be gained.

As well as using AIC, and BIC methods which give the value of 1 for every topic which mean that only perfectly correlated pairs are allowed to show, and there isn't exist. These predictor methods seem not to work well here as utilising these methods will give graphs with nodes without any connection, giving no useful information.

Leaving only density of network method and percolation method to be the remaining contestants. But again, after looking closely at both method thresholds and match with real correlation matrices, the percolation method returns a bit of too strict threshold. It allowed no connection to take place in the graph in topics like Collecting and Performing Art where correlations are generally low, while using density method allowed a few. Then, the only choice that is appropriate for this work is the density method. Thanks to its robust and adaptive formulation. Threshold values are shown below in Table 4.2 and Table 4.3

Table 4.2: Threshold Comparison for Pre-pandemic period

	Bonferroni	Density	AIC	BIC	Percolation
Arts	0.02785	0.48	1	1	0.88
Collecting	0.02785	0.21	1	1	0.62
Cooking	0.02785	0.34	1	1	0.87
Crafts	0.02785	0.39	1	1	0.86
Game	0.02785	0.68	1	1	0.89
Learning	0.02785	0.59	1	1	0.76
Music	0.02785	0.62	1	1	0.90
Performing Art	0.02785	0.19	1	1	0.70
Pets	0.02785	0.35	1	1	0.81
Sports	0.02785	0.54	1	1	0.78

Table 4.3: Threshold Comparison for Post-pandemic period

	Bonferroni	Density	AIC	BIC	Percolation
Arts	0.02785	0.62	1	1	0.73
Collecting	0.02785	0.33	1	1	0.49
Cooking	0.02785	0.75	1	1	0.90
Crafts	0.02785	0.35	1	1	0.78
Game	0.02785	0.95	1	1	0.98
Learning	0.02785	0.61	1	1	0.81
Music	0.02785	0.63	1	1	0.87
Performing Art	0.02785	0.36	1	1	0.60
Pets	0.02785	0.37	1	1	0.49
Sports	0.02785	0.89	1	1	0.89

As correlation matrices consisted of 50 countries crossing each other for both periods of all search topics were calculated in this step to act as the main ingredient to feed in network graphs. In fact, network graphs filter relevant information from correlation matrices to show useful insights. Prior to drawing the graphs, threshold methods were selected and calculated respectively. These important numbers dictated how strong of correlation pairs are required to enter valuable graphs. Pairs with weaker bond, lower correlation than the threshold were filtered out. Selected threshold values were reported in Table 4.2 and 4.3 based on density of network algorithm. Passing conditions varied due to competitiveness of pairs in the period. For example, in Collecting, threshold was 0.21 before COVID-19, then shifted to 0.25 later. In Sports, it was 0.54, then increased to 0.84. Only in Pets that the threshold number decreased with the pandemic. Between hobbies, the values were poles apart. It might be due to the different nature of each hobby.

Additionally, the following Figure 4.11 to 4.20 showed values of network density from the algorithm in the Y-axis from different levels of Pearson's correlation value in the X-axis. As its foundation stated, optimal thresholds were selected at the lowest point of Network density.

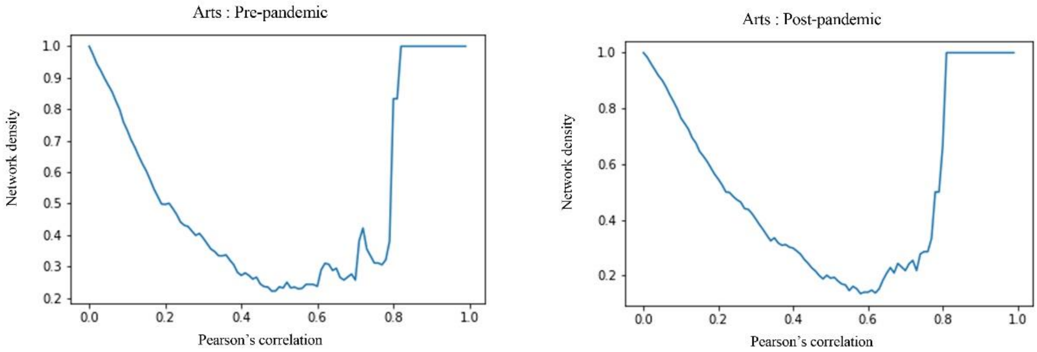


Figure 4.11 Density of network for the Art Topic

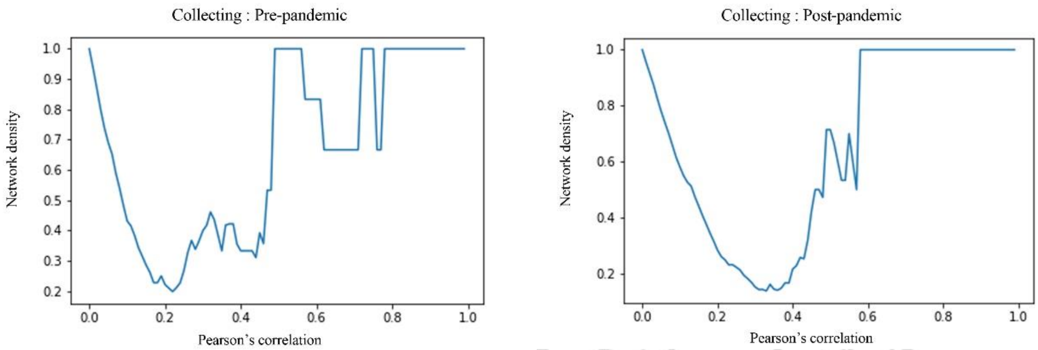


Figure 4.12 Density of network for the Collecting Topic

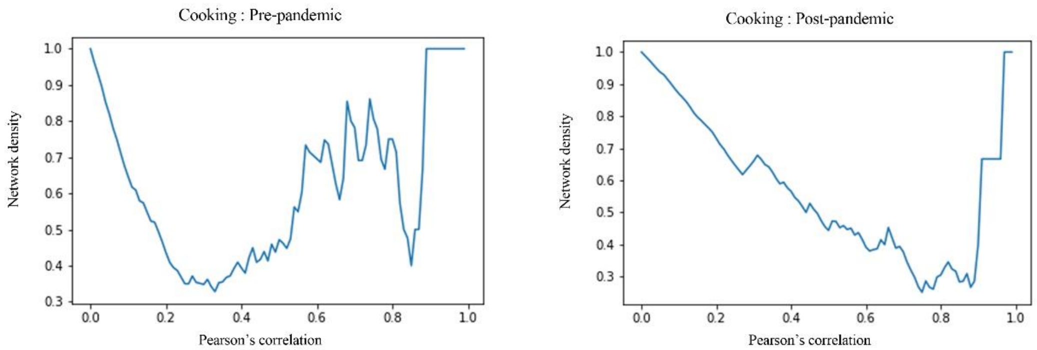


Figure 4.13 Density of network for the Cooking Topic

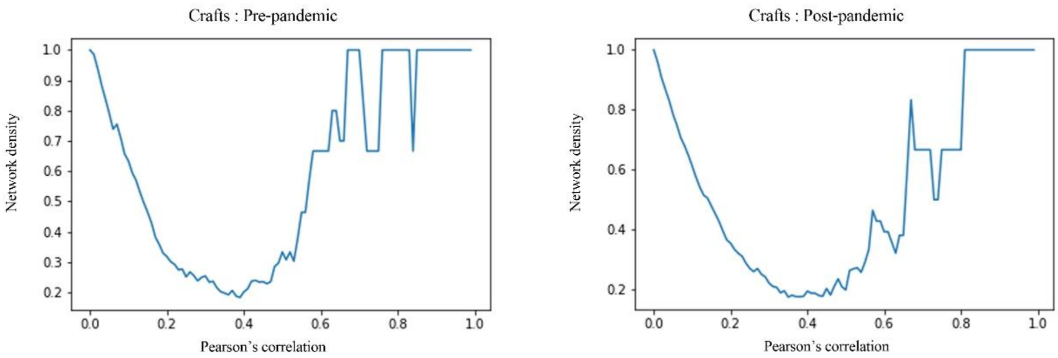


Figure 4.14 Density of network for the Craft Topic

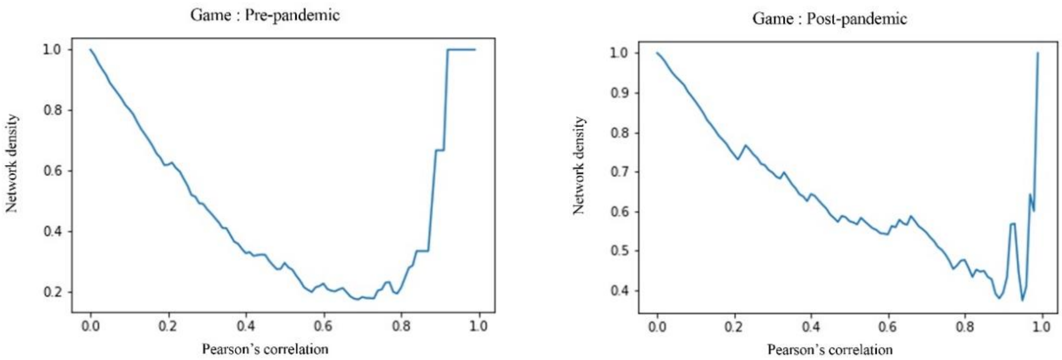


Figure 4.15 Density of network for the Game Topic

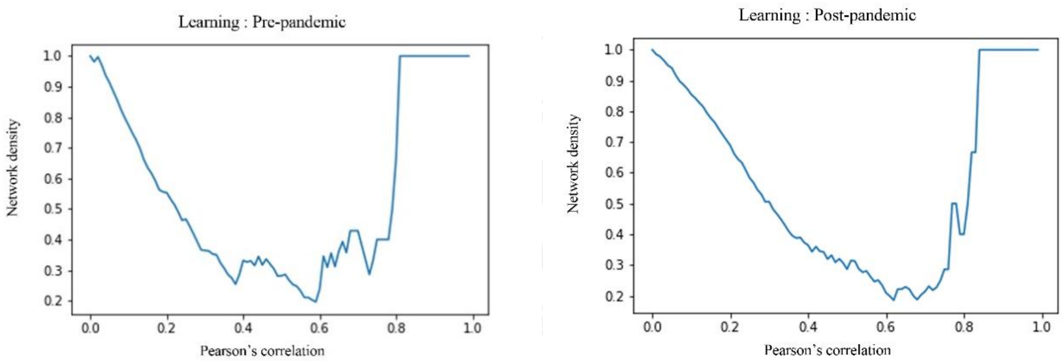


Figure 4.16 Density of network for the Learning Topic

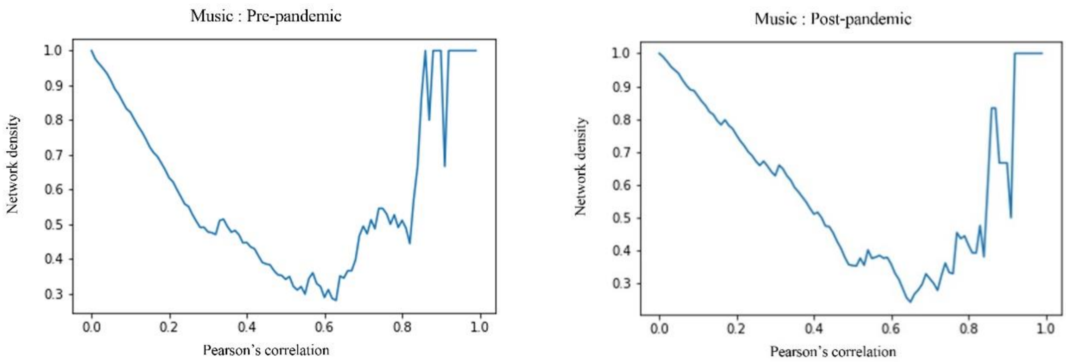


Figure 4.17 Density of network for the Music Topic

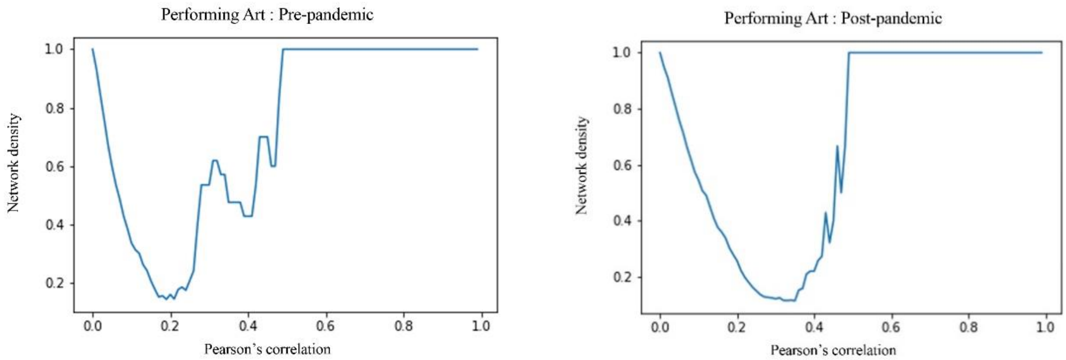


Figure 4.18 Density of network for the Performing Art Topic

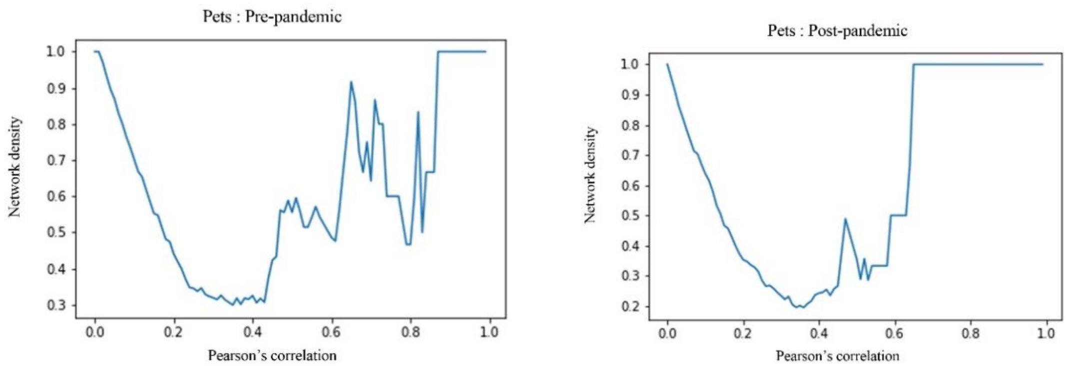


Figure 4.19 Density of network for the Pets Topic

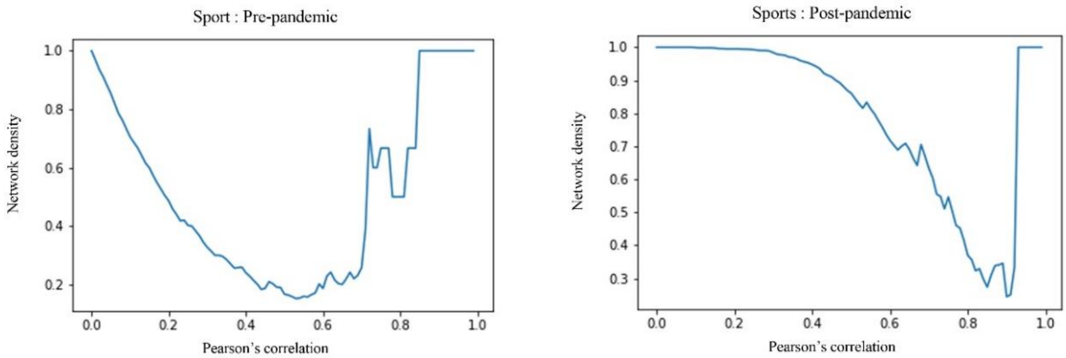


Figure 4.20 Density of network for the Sports Topic

4.3 Network Graphs Results

In this part, we aim to examine the interconnections between countries by analysing the number of connecting lines between them for each topic and the thickness of the edges to determine the strength of correlations. By creating network graphs for different topics, we can identify the patterns and relationships between countries. To determine the effect from the COVID-19 pandemic that has impacted the relationships between countries in hobbies, we will compare the network graphs of the same topics from the pre-pandemic period to the post-pandemic period. The changes in patterns and connections between countries before and after the pandemic will be investigated and to find out if there are significant differences. The findings should provide insight into how the pandemic has influenced the global relationships and interactions between countries in different areas, particularly in the context of hobbies.

As mentioned earlier, there will be 20 network graphs derived from 10 topics in 2 period, pre-pandemic, and post-pandemic. The nodes in each graph represents 50 countries and its size represent its logarithmically scaled internet users, while its colour will be assigned according to 1 of the 15 regions based on its geographical location in the typical world map, based on the author's preference. All correlations value above the threshold, will be presented in the graph with navy blue edges, its thickness will indicate stronger positive links. In the other hand, correlations value less than negative value of the threshold (-1 x threshold) will be depicted in pink, and its thickness will indicate stronger negative links. With these being said, Table 4.4 should give a clearer picture on what it has been done before mapping to graph drawing.

Table 4.4: List of Countries and its predetermined parameters.

Countries Code	Countries Name	Region	Colour	Xpos	Ypos	Internet Users
ARE	United Arab Emirates	West Asia	#FFABAB	17	-13.6	10082000
ARG	Argentina	South America	#D5AAFF	5.5	-21.7	41586960
AUS	Australia	Oceania	#6EB5FF	30	-18	21711706
AUT	Austria	West Europe	#F6A6FF	12.3	-10.5	7708997
BEL	Belgium	West Europe	#F6A6FF	9.8	-6	10857126
BGD	Bangladesh	South Asia	#BFFCC6	24	-10	111875000
BRA	Brazil	South America	#D5AAFF	6	-16	149057635
CAN	Canada	North America	#C5A3FF	2	-2	35477625
CHE	Switzerland	West Europe	#F6A6FF	14	-8	8066800
CHL	Chile	South America	#D5AAFF	3.5	-20	14108392
CHN	China	East Asia	#AFF8DB	26	-7.2	989080566
COL	Colombia	South America	#D5AAFF	2.3	-13.8	31275567
CZE	Czech Republic	East Europe	#FFB5E8	14	-6.2	9323428
DEU	Germany	West Europe	#F6A6FF	12.2	-5.8	79127551
DNK	Denmark	North Europe	#FF9CEE	9.8	-2.5	5649494
EGY	Egypt	North Africa	#FFFFD1	14.5	-15	54741493
ESP	Spain	South Europe	#FCC2FF	10	-10	42961230
FIN	Finland	North Europe	#FF9CEE	16	-2	5225678
FRA	France	West Europe	#F6A6FF	11.8	-8	60421689
GBR	United Kingdom	North Europe	#FF9CEE	7.7	-4	63544106
HKG	Hong Kong	East Asia	#AFF8DB	29.5	-8	6698252
IDN	Indonesia	Southeast Asia	#85E3FF	29.5	-15	196400000
IND	India	South Asia	#BFFCC6	22	-14	749342381
IRL	Ireland	North Europe	#FF9CEE	7.2	-7	4453436
IRN	Iran	South Asia	#BFFCC6	19.8	-9.8	67602731
ISR	Israel	West Asia	#FFABAB	15	-10	7002759
ITA	Italy	South Europe	#FCC2FF	12	-13.5	54798299
JPN	Japan	East Asia	#AFF8DB	30	-6	118626672
KOR	South Korea	East Asia	#AFF8DB	28	-4	49234329
MEX	Mexico	Central America	#B28DFF	2	-10	88000000
MYS	Malaysia	Southeast Asia	#85E3FF	26	-13	29161765
NGA	Nigeria	West Africa	#E7FFAC	12.5	-16.5	203168355
NLD	Netherlands	West Europe	#F6A6FF	10.5	-4	16383879

Table 4.4: List of Countries and its predetermined parameters. (cont.)

Countries Code	Countries Name	Region	Colour	Xpos	Ypos	Internet Users
NOR	Norway	North Europe	#FF9CEE	8	-1	5311892
NZL	New Zealand	Oceania	#6EB5FF	31	-20	4351987
PAK	Pakistan	South Asia	#BFFCC6	22	-9.5	76380000
PER	Peru	South America	#D5AAFF	3	-17.7	22000000
PHL	Philippines	Southeast Asia	#85E3FF	29	-12.2	86300000
POL	Poland	East Europe	#FFB5E8	15	-5	29757099
PRT	Portugal	South Europe	#FCC2FF	8	-11.5	8015519
ROU	Romania	East Europe	#FFB5E8	16	-8	14387477
RUS	Russia	East Europe	#FFB5E8	22	-2	116353942
SAU	Saudi Arabia	West Asia	#FFABAB	17.8	-11.8	31856652
SGP	Singapore	Southeast Asia	#85E3FF	25.5	-15	5173907
SWE	Sweden	North Europe	#FF9CEE	12	-1	9692227
THA	Thailand	Southeast Asia	#85E3FF	25.5	-11	57000000
TUR	Turkey	West Asia	#FFABAB	18.2	-7.7	69107183
USA	United States	North America	#C5A3FF	4	-6	297322868
VNM	Vietnam	Southeast Asia	#85E3FF	28	-11	71540000
ZAF	South Africa	South Africa	#FFF5BA	16	-19.7	34545165

In graph drawing, the author utilises networkX Python library along with pandas and numpy to transform correlation matrices, the threshold value only the part calculated by density of network method as shown in Table 4.2 for pre-pandemic graphs, Table 4.3 for post-pandemic graphs, and the labelled list of countries and its parameter as shown above in Table 4.4.

In general, Things have changed a lot here due to the pandemic, more countries were more connected in the global scale. Even though the thresholds are mostly higher except in Pets, countries seem to be more related in the term of preference. However, it is not safe to conclude that countries were more connected to each other in other context out of these hobby topics. But it could be considered that social distancing and stay home regulations which limit choices of activities might have caused sudden change in the same direction on some topics such as gaming, cooking, and learning. In these cases, the interest level increases for some obvious reasons. While some other hobbies have shown some interesting shift in relationship between countries. Followings are detailed explanation and the graph according to each topic.

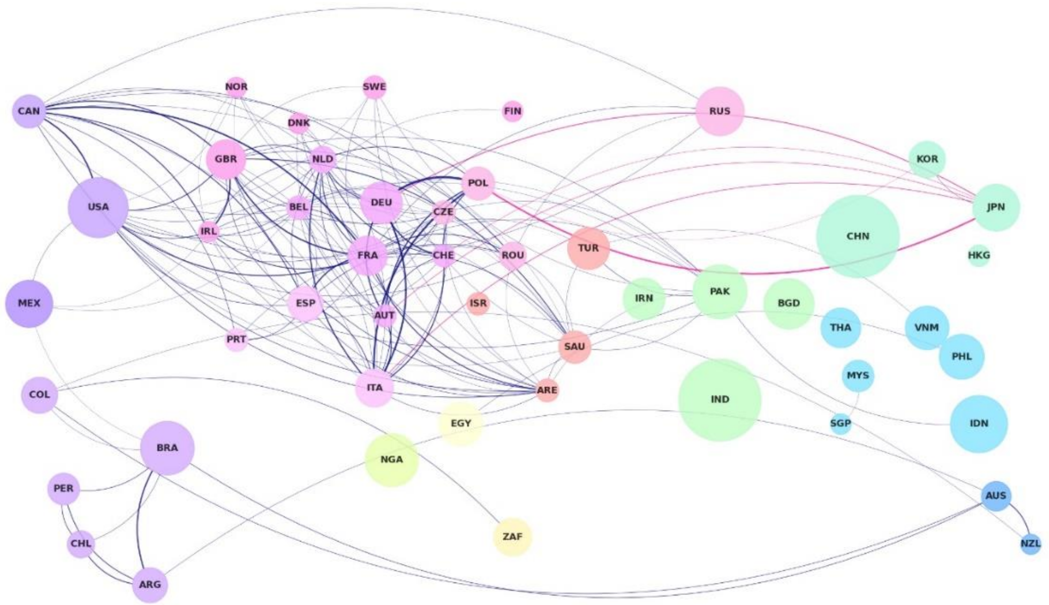
4.3.1 Arts

The relationship in art interest level before the pandemic is shown in Figure 4.21. European countries and north American countries with some of Arabian countries had formed the biggest cluster, clearly defined western world Arts connection in Arts. However, after the pandemic, which is shown in Figure 4.22, these linkages have been shaken. United Arab Emirates as depicted as ARE and Saudi Arabia (SAU) has loosened its bonds with many pre-pandemic countries, remains are bonds with Switzerland (CHE) and Netherlands (NLD) for UAE, and Saudi Arabia remains its bonds with the Netherlands, Ireland (IRL), and France (FRA), while forming a new strong bond with the Philippines (PHL). The bond between Germany (DEU) and Poland (POL) was very strong, but not for now. As well as the United States (USA) released its bond with Canada (CAN), United Kingdom (GBR) and so many countries, leaving only its weak bond with Mexico (MEX). However, Italy (ITA) has formed a much stronger bond with Spain (ESP). Argentina (ARG) is now connected to Colombia (COL) while weaken its strong bond with Brazil (BRA) who gained connection from South Africa (ZAF), Egypt (EGY), Hong Kong (HKG), and South Korea (KOR). Australia (AUS) has also strengthened its connection in Arts with Colombia (COL) as well and formed two more connections with Egypt (EGY) and South Africa (ZAF). Scandinavian countries are completely separated by the pandemic as well.

Japanese (JPN) negative bonds with Poland (POL), Italy (ITA), Austria (AUT), Germany (DEU), and Switzerland (CHE) depicted by pink lines and a little positive bond with South Korea (KOR) have been shattered by the pandemic, instead sharing positive taste with Thailand (THA), and Malaysia (MYS). Russia (RUS) is still connected to Canada (CAN) but have cut out every other relationship once had formed before the pandemic. Pakistan once connected to many countries now joined the lonely club consists of China (CHN), Bangladesh (BGD), Iran (IRN), India (IND). It is interesting to note that in Asia, bonds in Arts are already rare as most Asian countries are known to have its own distinctive culture as evidence suggests in languages, architecture, and art style. With COVID-19, they are less connected, even Malaysia

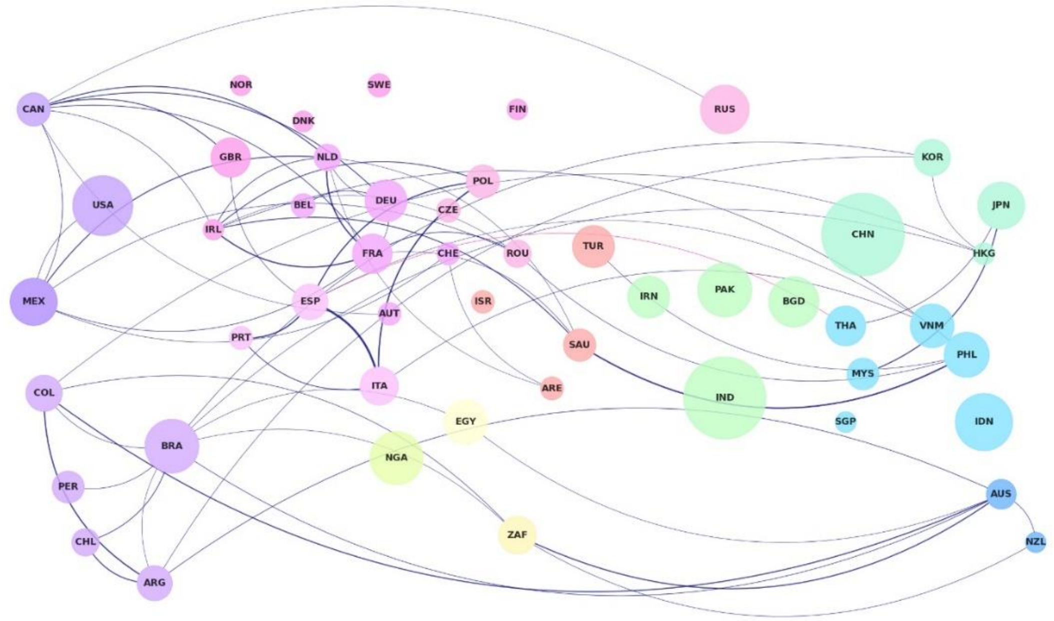
(MYS) and Singapore (SGP) where their culture was closely tied, are broken. Two countries that gained more connectivity is the Philippines (PHL), Hong Kong (HKG) and Thailand (THA).

Seeing these patterns without utilising network graph should be much more complicated and tedious.



Art : Pre-pandemic

Figure 4.21 Network Graph showing pre-pandemic relationship in Arts.

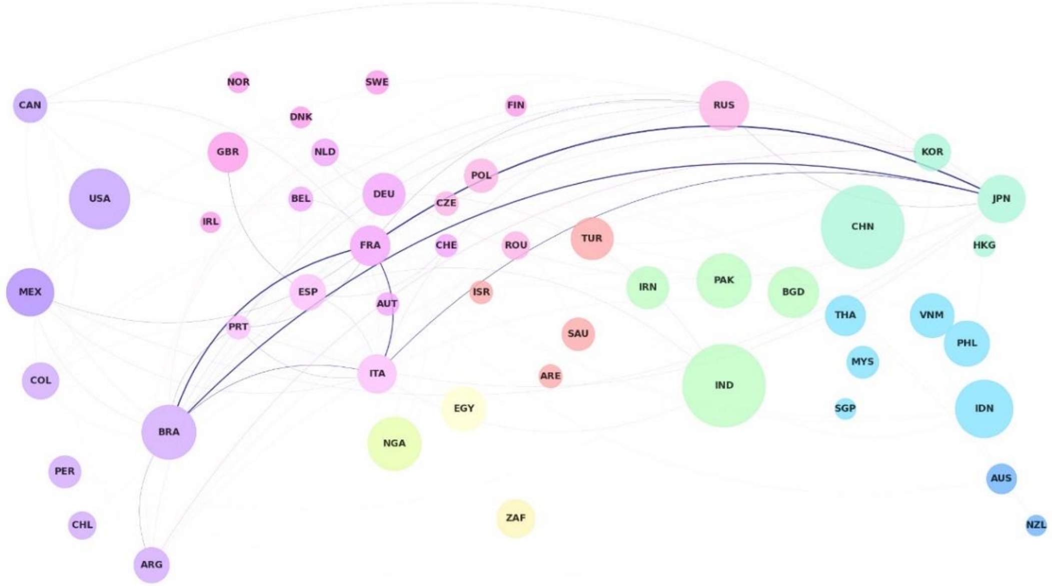


Art : Post-pandemic

Figure 4.22 Network Graph showing post-pandemic relationship in Arts.

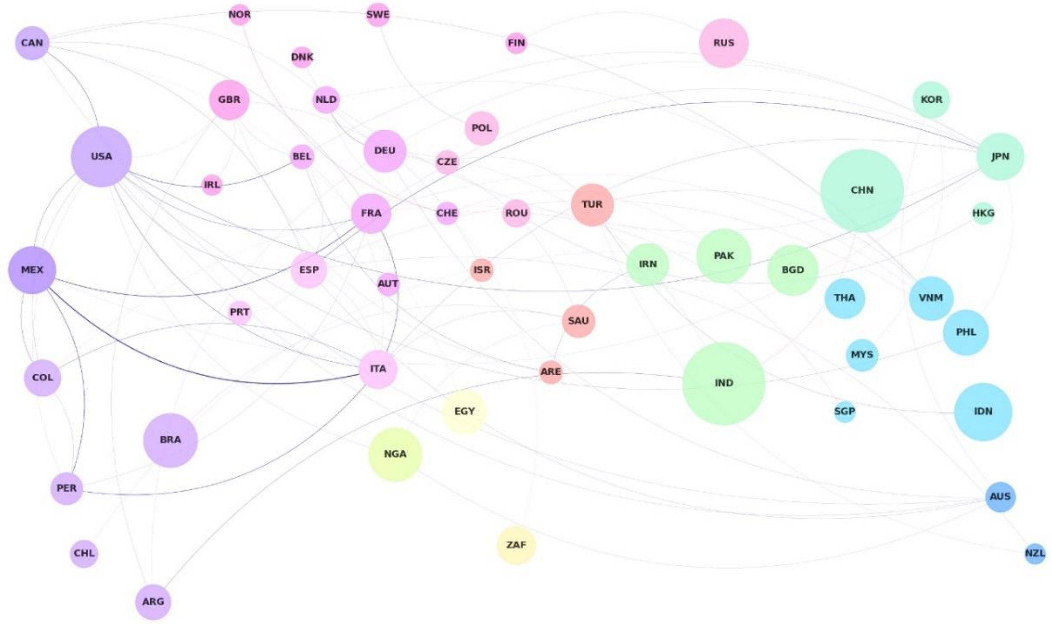
4.3.2 Collecting

In the collecting topic, connections have been totally altered. Before COVID-19, there was one strong cluster consisted of Japan (JPN) to France (FRA), Brazil (BRA), and Italy (ITA) as seen in Figure 4.23. None of them exist after the pandemic except France to Italy showed in Figure 4.24. The connection is weakened but still exist with 2 more members, Mexico (MEX), and Peru (PER). Many new weak connections started to grow worldwide. Australia (AUS), United States of America (USA), United Kingdom (GBR), Peru (PER) and Philippines (PHL) have gained more connections comparing to the rest of the world. India (IND) and China (CHN) were isolated, have turned into a slight negative connection. Most of other countries in Asia are still isolated, except a few.



Collecting : Pre-pandemic

Figure 4.23 Network Graph showing pre-pandemic relationship in Collecting.



Collecting : Post-pandemic

Figure 4.24 Network Graph showing post-pandemic relationship in Collecting.

4.3.1 Cooking

Cooking interest relationship landscape has also changed drastically with a few exceptions. China (CHN), Bangladesh (BGD), Israel (ISR), Iran (IRN), Poland (POL), Turkey (TUR), Norway (NOR), and Finland (FIN) was then isolated, is still isolated. Before the pandemic, strong connections were formed in a big clustered consists of countries in Europe except Scandinavian countries, North America, Oceania, and South Africa (Figure 4.25). It is noticeable that these countries are known as western world.

Nevertheless, COVID-19 has shaken things up by a lot (Figure 4.26). Weak bonds are either broken or strengthened. United States of America (USA), Peru (PER), Denmark (DNK), Romania (ROU), Russia (RUS), Sweden (SWE), South Korea (KOR), and Hong Kong (HKG) were once connected, have been disconnected. Stronger bonds between Brazil (BRA), Chile (CHL), and Argentina (ARG) are presented, while Colombia (COL) from the same region chose to form strong relationship with Egypt (EGY) and United Arab Emirates (ARE) instead of its neighbours. Australia (AUS), New Zealand (NZL), Mexico (MEX), South Africa (ZAF), Ireland (IRL), United Kingdom (GBR), and Belgium (BEL) managed to maintain and even strengthened their connections.

Interestingly, countries in Asia that were mostly stay on its own, have formed a very strong cluster with each other after the pandemic announcement. Exceptions are Bangladesh (BGD), Iran (IRN), and east Asian countries apart from Japan (JPN) mentioned earlier. Egypt (EGY) and Nigeria (NGA) once alone, have also gained several connections.

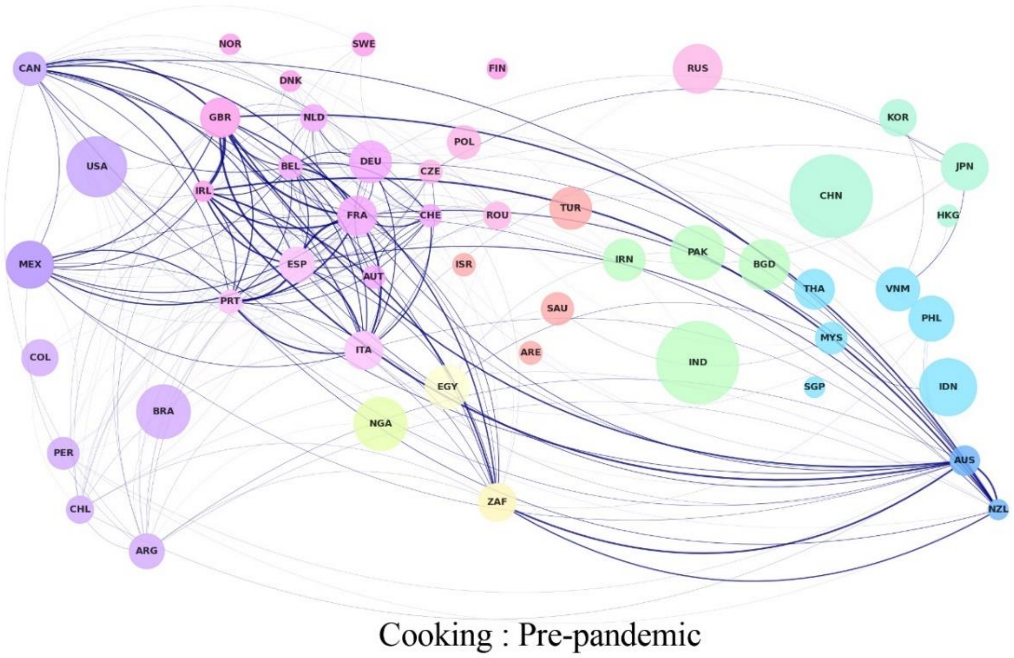


Figure 4.25 Network Graph showing pre-pandemic relationship in Cooking.

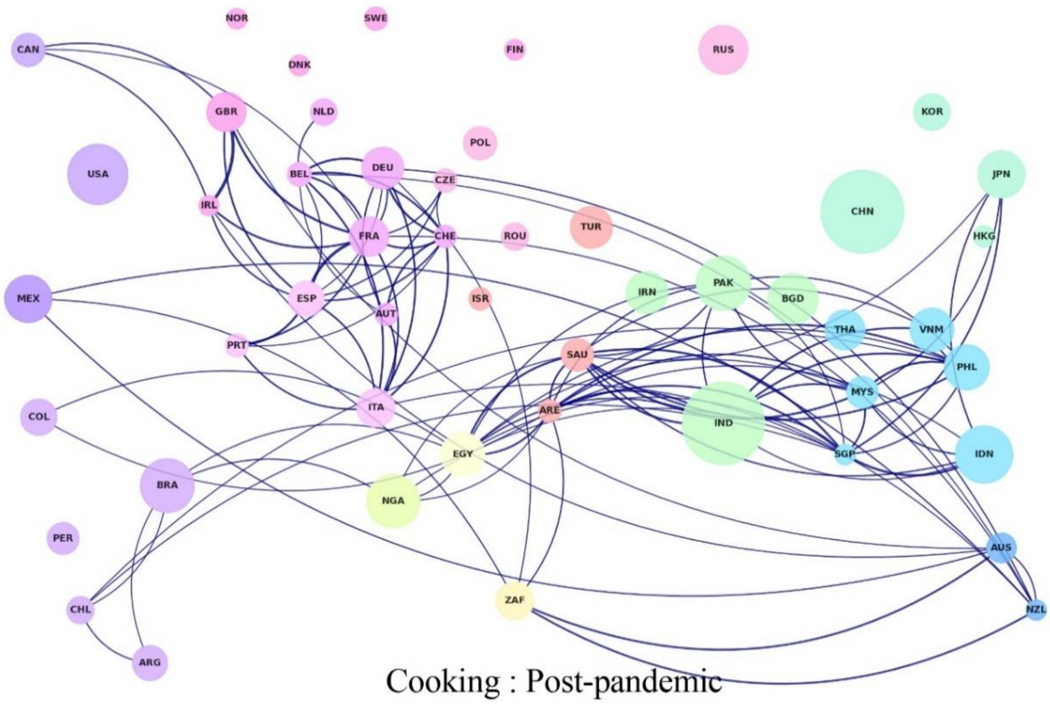


Figure 4.26 Network Graph showing post-pandemic relationship in Cooking.

4.3.4 Crafts

Crafts in overall has received minimal effect from the pandemic compared to other topics. As in the comparison between the pre-pandemic's Figure 4.27 and the post-pandemic's Figure 4.28 has showed little difference. Strongest cluster of Canada (CAN), United States (USA), United Kingdom (GBR), Ireland (IRL), and Australia (AUS) remained intact. Asian countries were mostly isolated in both periods except a few. All Indonesia's (IDN) existing links with several countries in Europe have been broken. India's (IND) weak positive link with Pakistan (PAK) have been replaced with South Africa (ZAF) and Brazil (BRA). Its weak negative link with Vietnam (VNM) have also been replaced by Philippines (PHL), France (FRA), Japan (JAP), Austria (AUT), and Canada (CAN). In the south American region, Brazil (BRA) has lost all its bonds with Turkey (TUR), the Netherlands (NLD), Sweden (SWE), Germany (DEU), Czech Republic (CZE), Poland (POL), Colombia (COL), and Indonesia (IDN). It instead formed several positive weak bonds with Argentina (ARG), India (IND), and Nigeria (NGA), and a negative weak relationship with Sweden (SWE). Russia (RUS) has maintained some of its connection while gaining a few more. Europe in overall has established linkages to each other while dropping some of the existing as well.

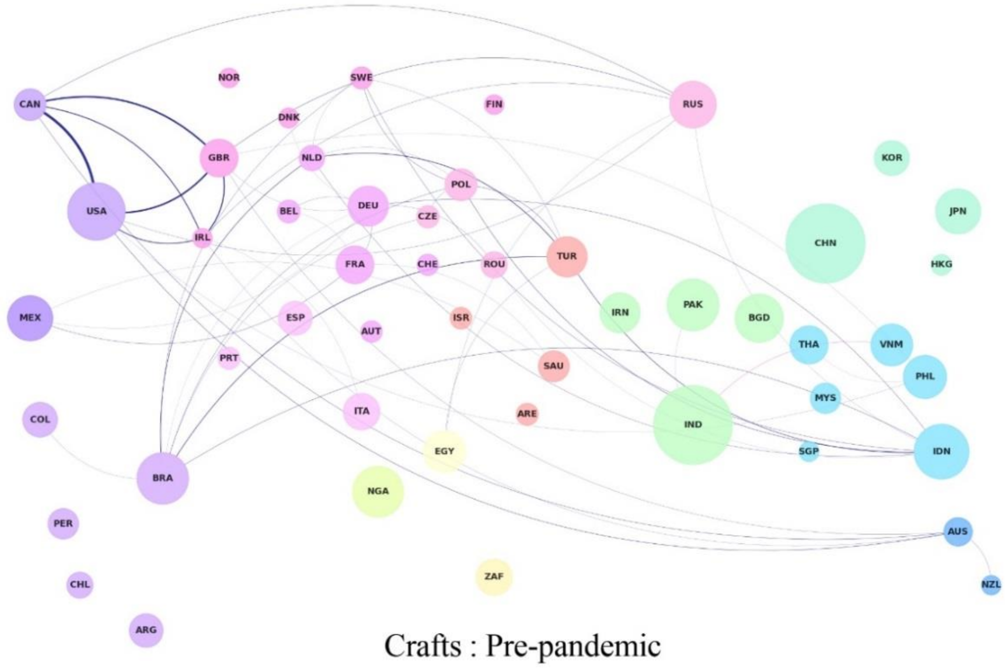
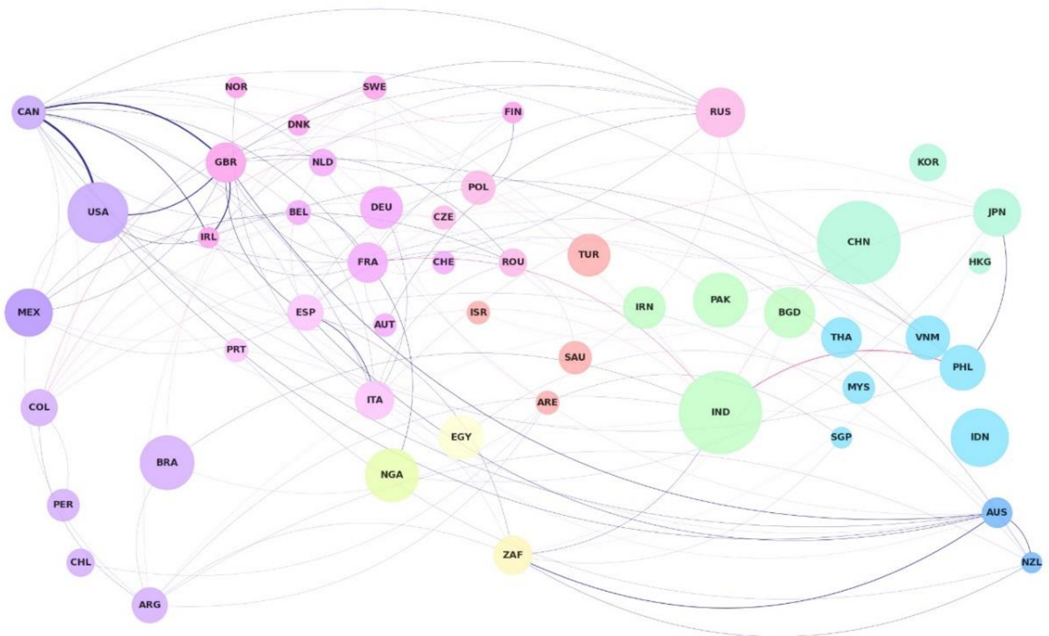


Figure 4.27 Network Graph showing pre-pandemic relationship in Crafts.



Crafts : Post-pandemic

Figure 4.28 Network Graph showing post-pandemic relationship in Crafts.

4.3.5 Game

As ones might expect interests in gaming as a hobby has increased worldwide due to obvious reasons of global lockdowns and social distancing. Though, there are some interesting patterns in its relationship landscape in either regional level, or world level. Network graph for pre-pandemic interest in Games as referred to Figure 4.29, showed clusters of countries from the same regions were tied with closer relationships than those far away. Spanish speaking countries in Latin America were tightly bound. So as European countries, middle east nations, Oceania, and east Asian countries except China. Distinctively, southeast Asian countries are own their own. China (CHN), Russia (RUS), India (IND), along with countries in South Africa, and North Americas were also unconnected.

Things have changed a lot here after the pandemic as referred to Figure 4.30. More countries are more connected in the global level even though the threshold was higher. Countries were more related in term of preference. The correlations are very strong as lockdowns limited choices of leisure, causing many countries to look for games at the same time. However, in the regional level, bonds were mostly broken as seen in south

America, Europe, and Middle East. Japan (JPN) once connected to Denmark (DNK) and South Korea (KOR) now became a hub connecting to many countries but without those two. Nigeria (NGA), Singapore (SGP), Bangladesh (BGD), and India (IND) were alone, now became hubs connecting many countries across the globe. Intriguingly, many big countries like United States (USA), China (CHN), Russia (RUS), Indonesia (IDN), Canada (CAN), Brazil (BRA), Egypt (EGY), Iran (IRN), France (FRA), Germany (GER), and Thailand (THA) are not connected to any other country in gaming interests.

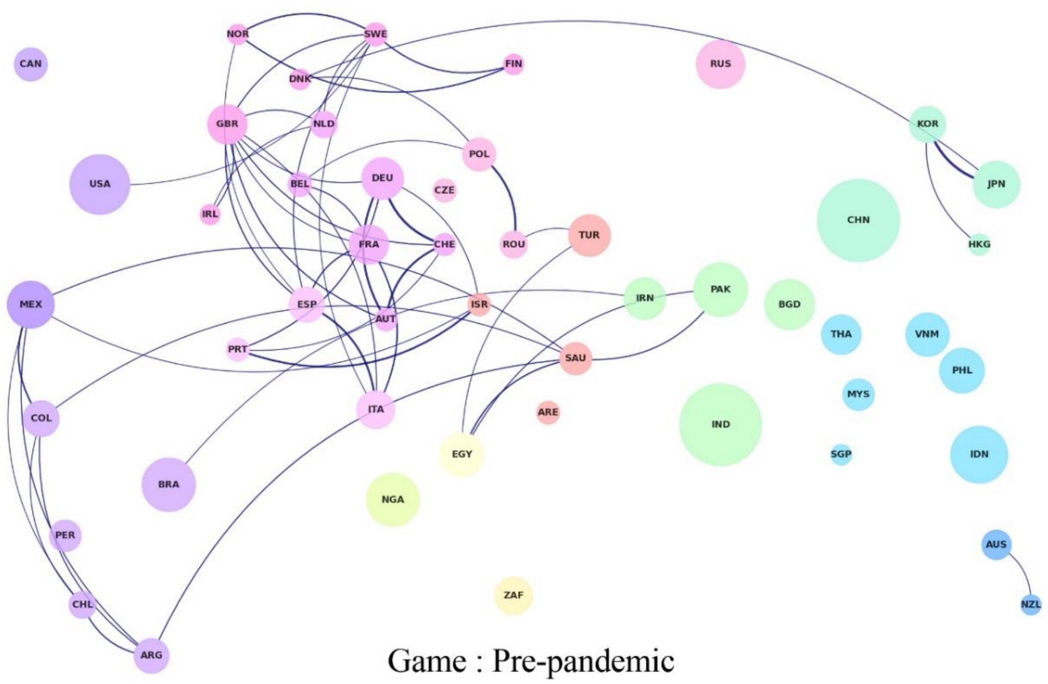


Figure 4.29 Network Graph showing pre-pandemic relationship in Games.

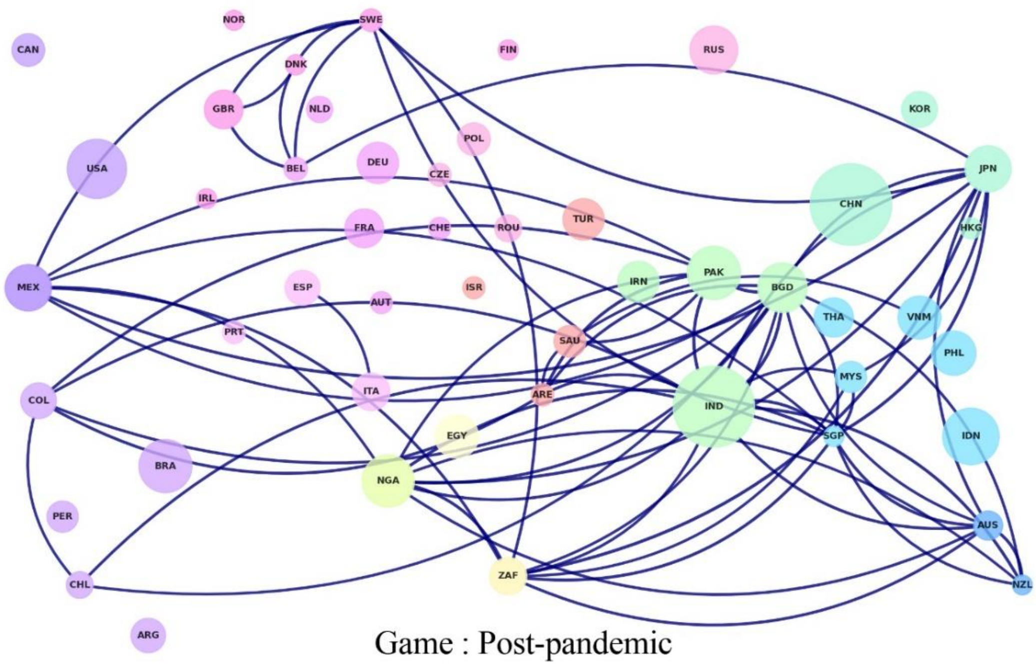


Figure 4.30 Network Graph showing post-pandemic relationship in Games.

4.3.6 Learning

Learning interest before the pandemic are shown in Figure 4.31. Countries in south America and Mexico (MEX), countries in South Asia, East Asia, Southeast Asia except Thailand (THA), Malaysia (MYS) and Indonesia (IDN), Russia (RUS), Scandinavian countries except Finland (FIN), and a few more countries in Europe had their own voluntary interest level in learning unrelated to other countries. While interest level of Malaysia and Indonesia were related to each other. The reason might lie in their languages have a lot of similarities. However, Thailand does not share language similarities with Germany and Italy but are correlated. It might be caused by other factors or just coincidence. Australia (AUS) and New Zealand (NZL) are closely tied in every hobby topic, and learning is not an exception. They are sometimes connected to South Africa (ZAF) and Nigeria (NGA) in several topics too. Some countries in Europe such as Germany (DEU), France (FRA), Spain (ESP), Italy (ITA), and Switzerland (CHE) are closely connected in learning interest, grouping as another cluster. Another cluster of United States (USA), Canada (CAN), United Arab Emirates (ARE), United Kingdom (GBR), and Ireland (IRL) were formed in learning as well. Noted that these countries have already formed a strong bond in Crafts hobby.

After the pandemic, most of those isolated countries mentioned in the last paragraph are still isolated as shown in Figure 4.32. Malaysia have switched its only pair from Indonesia to Singapore while Thailand lost its bond with Italy and Germany. South American countries are now connected to each other and to other parts of the world. United Arab Emirates (UAE), Australia (AUS), Singapore (SGP), Colombia (COL), United States of America (USA), and a few big countries in Europe have become hubs connecting many countries in term of learning interest. Observed that a big portion of those countries are leading education centres. Lockdowns and social distancing might limit citizen of the world from their local learning institutes, while online learning opportunities from the best are more accessible.

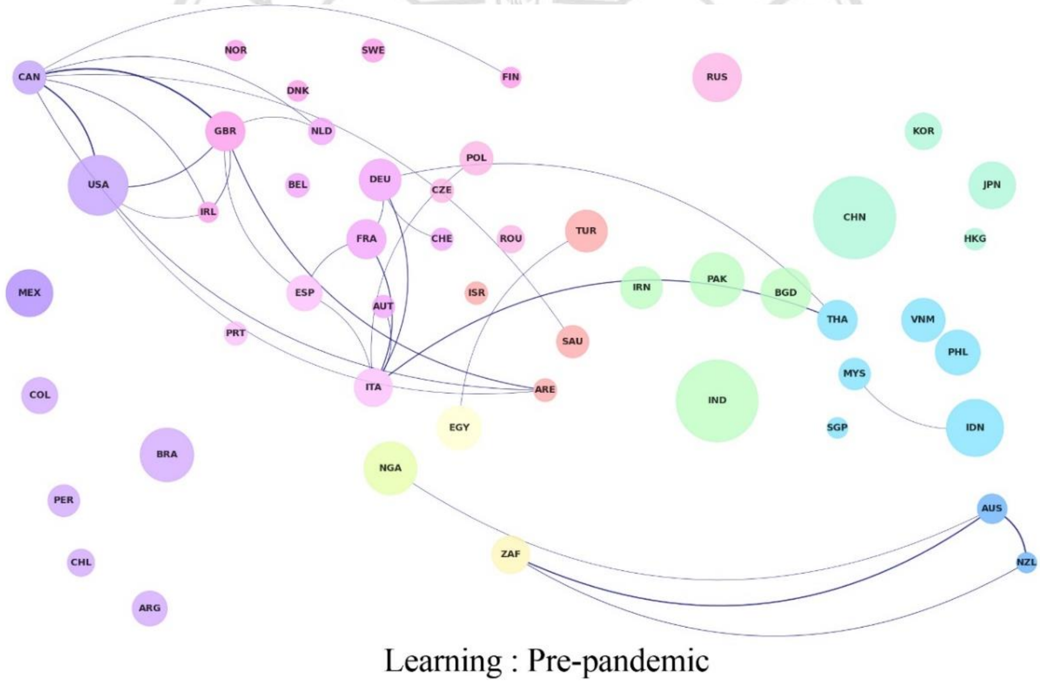
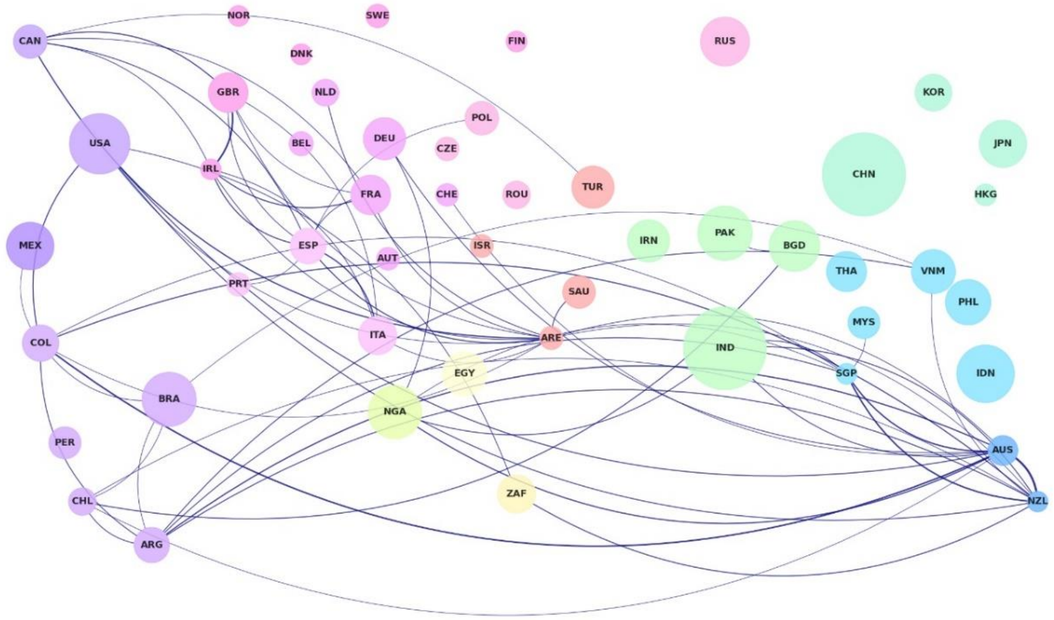


Figure 4.31 Network Graph showing pre-pandemic relationship in Learning.



Learning : Post-pandemic

Figure 4.32Network Graph showing post-pandemic relationship in Learning.

4.3.7 Music

Before the pandemic, the largest cluster consisted of Brazil (BRA), Colombia (COL), Mexico (MEX), Peru (PER), Chile (CHL), Argentina (ARG), Vietnam (VNM), Romania (ROU), Bangladesh (BGD), Turkey (TUR), and Russia (RUS). They were connected with positive correlations. Iran (IRN) is the only country that have formed negative connections with some of the big cluster members.

There were a few regional connections. In East Asia, Japan (JPN), South Korea (KOR), and Hong Kong (HKG) were connecting to each other without connecting to the rest of the world. In North America where United States (USA) and Canada (CAN) have formed a pair. In Europe, some relatively weak connections are found.

For the rest of the world, most countries were having their own voluntary interest level uncorrelated with others or at least connected with a few other countries as shown in Figure 4.34. Even for New Zealand (NZL) and Australia (AUS) that often paired together were not connected.

With COVID-19, much more connections are formed all over the world especially in European countries. New Zealand (NZL) and Australia (AUS) are now connected while the East Asia trio links have been broken. Iran (IRN) is no longer connected. Thailand (THA) now formed negative links with France (FRA), Italy (ITA), and Spain (ESP). India that was isolated turned to be a hub forming positive links with many countries, and a negative link with Philippines (PHL).

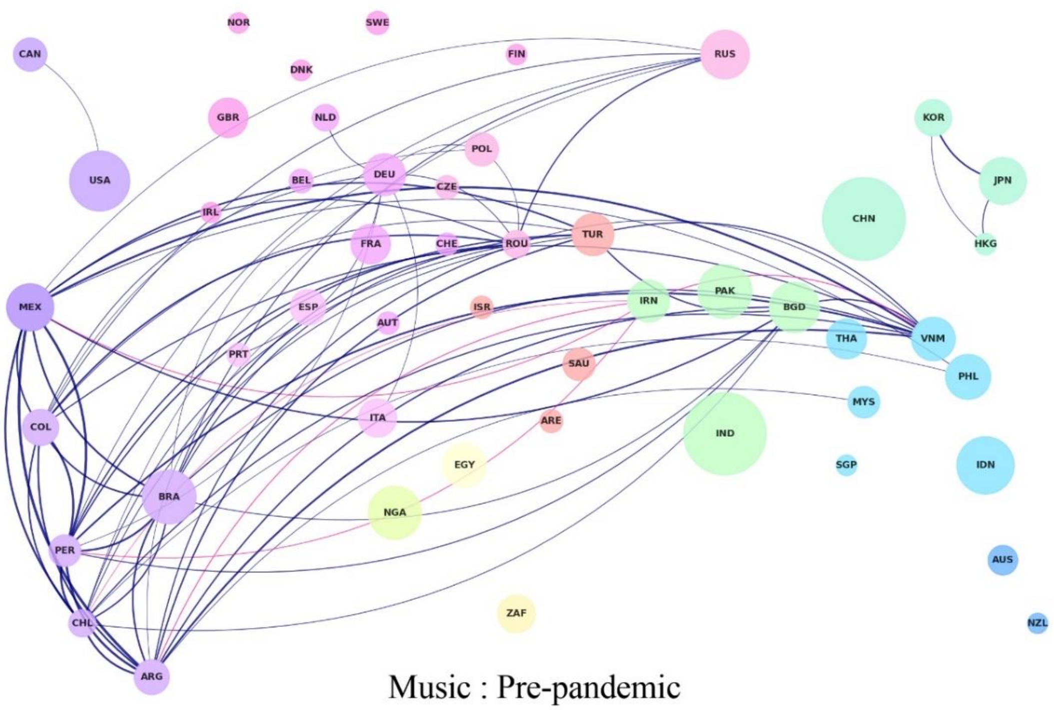
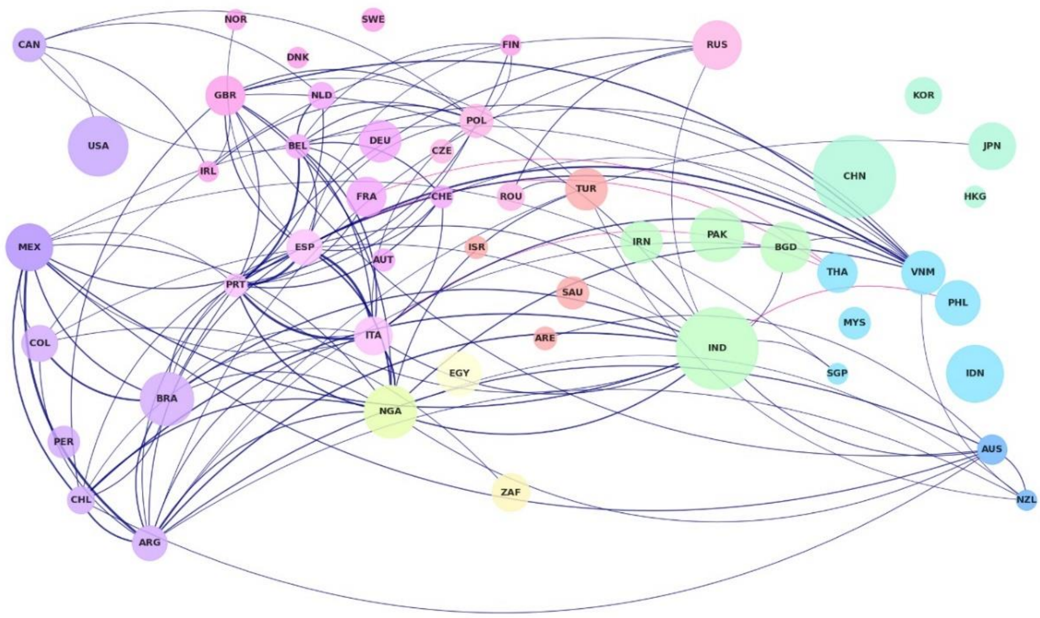


Figure 4.33 Network Graph showing pre-pandemic relationship in Music.



Music : Post-pandemic

Figure 4.34 Network Graph showing post-pandemic relationship in Music.

4.3.8 Performing Art

In this topic, there were very few connections before the pandemic as shown in Figure 4.35, and most of them are weak. The only strong pair was formed between Belgium (BEL) and France (FRA) who formed weaker links with Canada (CAN), Switzerland (CHE). With the pandemic, the only cluster mentioned does not exist anymore while random weak links emerged all over the world, presented in Figure 4.36.

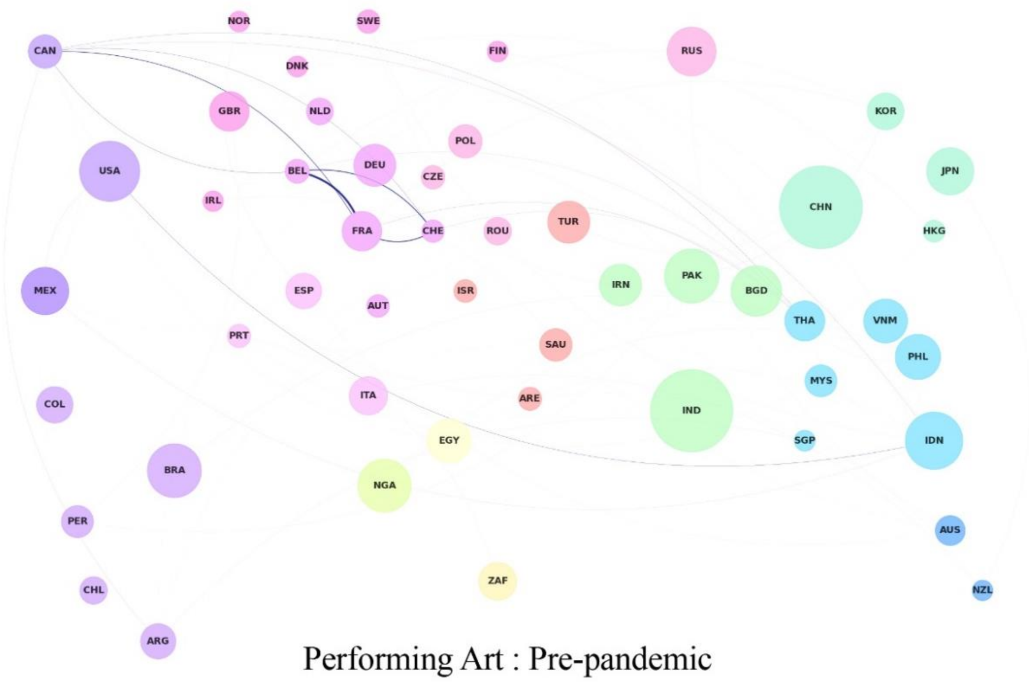


Figure 4.35 Network Graph showing pre-pandemic relationship in Performing Art.

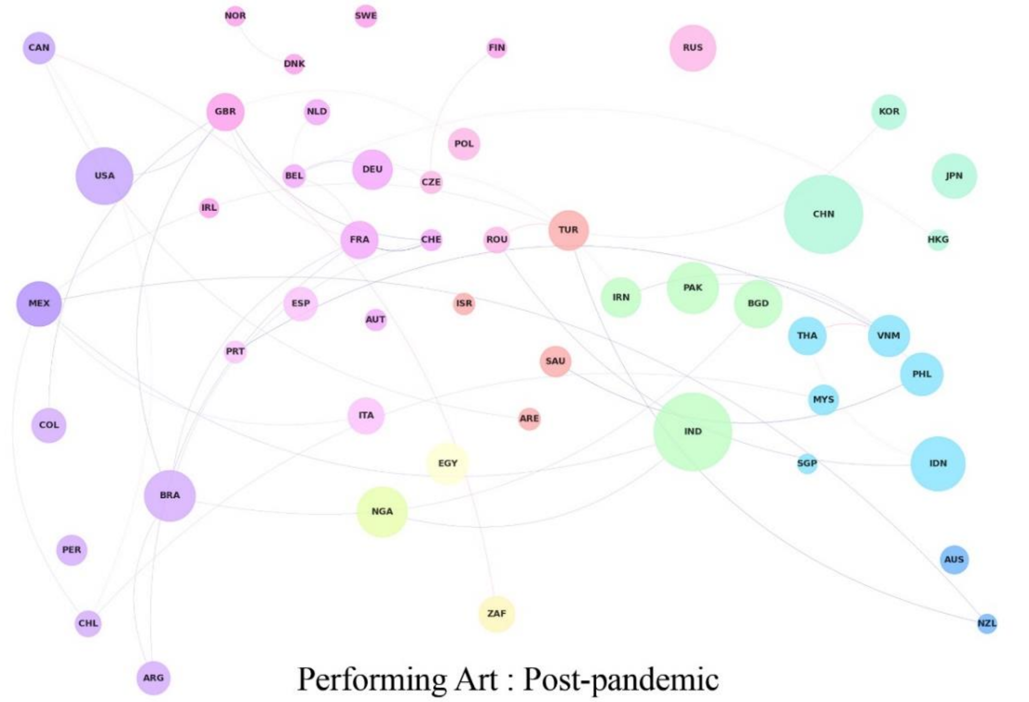


Figure 4.36 Network Graph showing post-pandemic relationship in Performing Art.

4.3.9 Pets

Pre-pandemic graph in Pets topic (Figure 4.37) has showed the most connections painted in pink compared to every other topic. A cluster consisted of Japan (JPN), Thailand (THA), and Hong Kong (HKG) has formed strong negative links to Italy (ITA), Chile (CHL) and members of another cluster in Europe. While countries in southeast Asia except Thailand, have formed relatively weaker connections with European countries, and South American countries. China (CHN), South Asian countries, and Middle East countries were separated from the world.

After the pandemic, strong relationship does not exist anymore. New weak connections has emerged worldwide, both negative and positive, presented in Figure 4.38. The relationship landscape has totally been changed.

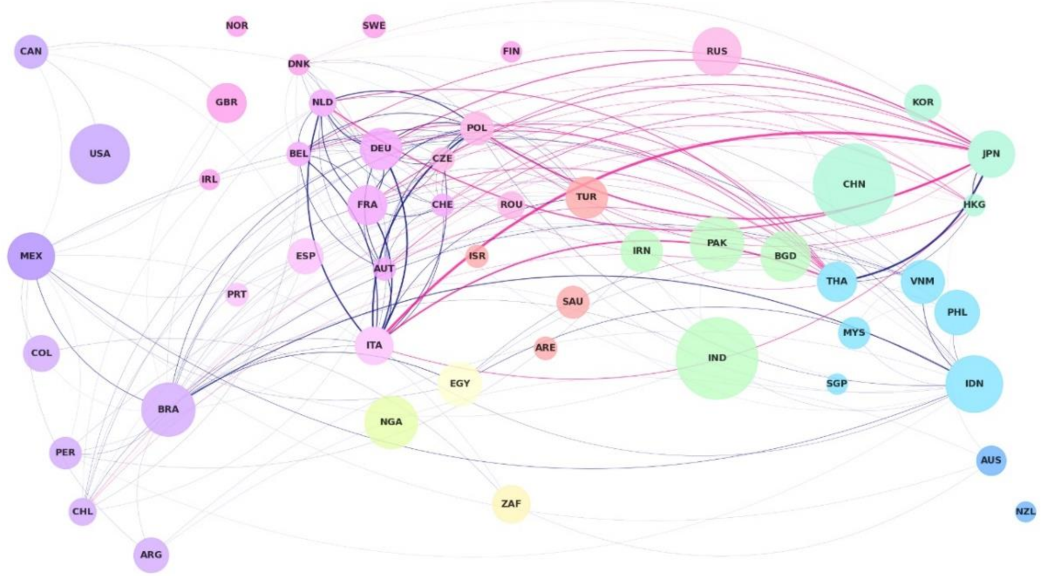
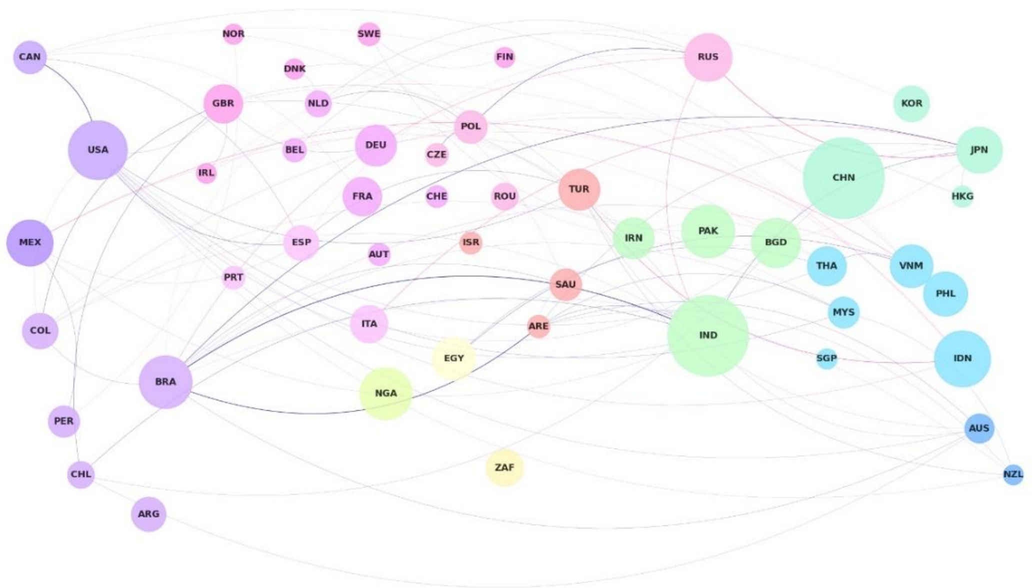


Figure 4.37 Network Graph showing pre-pandemic relationship in Pets.



Pets : Post-pandemic

Figure 4.38 Network Graph showing post-pandemic relationship in Pets.

4.3.10 Sport

Sports is a hobby that is expected to change tremendously from the pandemic, and its true. By comparing the pre-pandemic graph shown in Figure 4.39 with the post-pandemic counterpart shown in Figure 4.40, it could be said that the global landscape of relationship in Sports have been rewritten. There were regional links in some regions of the world, such as Europe, East Asia excluding China, Americas, Middle East, that connects to another region. A cluster of Japan (JPN), South Korea (KOR) and Hong Kong (HKG), have developed negative relationship with Spain (ESP). In general, connections were frequent.

After the pandemic, those connections are all gone. However, new relationship that emerged are quite strong. Norway (NOR) is connected to Austria (AUT). Brazil (BRA) is connected to Malaysia (MYS) who acted as the biggest hub node connecting to South Africa (ZAF), Thailand (THA), Nigeria (NGA), and Sweden (SWE). Israel (ISR) is connected to Portugal (PRT), Iran (IRN), and South Africa (ZAF). Lastly, Vietnam (VNM) is connected to Thailand (THA). There is no other connections.

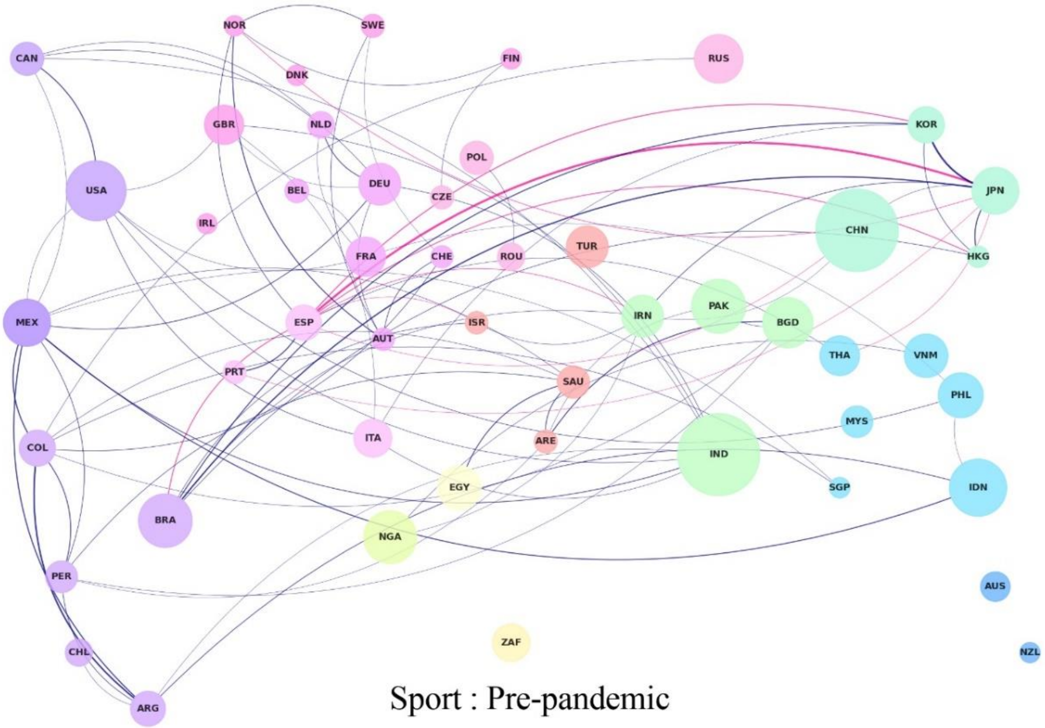


Figure 4.39 Network Graph showing pre-pandemic relationship in Sports.

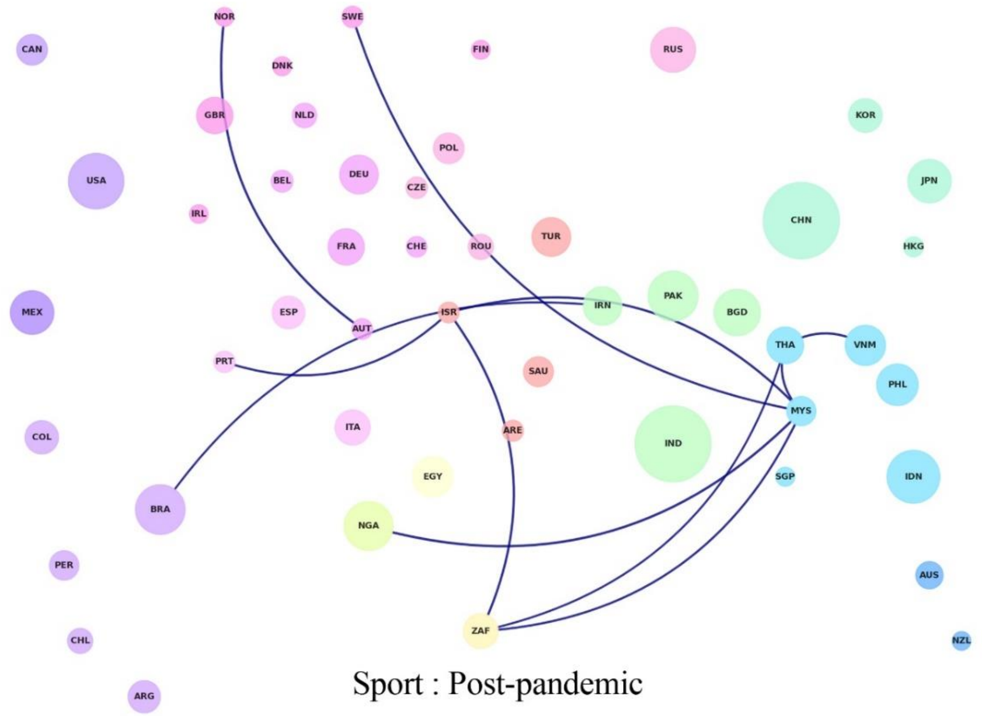


Figure 4.40 Network Graph showing post-pandemic relationship in Sports.

CHAPTER 5

Discussion

The purpose of this study was to explore the relationships among countries in terms of hobbies and interests before and after the COVID-19 pandemic. Recalling the study had four research objectives: to gain exploratory insights into the relationships among countries, explain the relationships among countries, create networks of the relationships among countries, and explain the networks of the relationships among countries. This chapter discusses the principal findings, interpretations of findings, discrepancies with other research, unexpected findings, implications, and limitations of the study.

5.1 Principle Findings

The findings of this study reveal significant changes in the relationships among countries in terms of hobbies and interests before and after the COVID-19 pandemic. The study focused on ten topics of interest. The findings of each topic are discussed below.

Art: The study found that the pre-pandemic relationships in art interests were clustered around European and North American countries with some Arabian countries. However, after the pandemic, these linkages have been shaken, and new connections have formed among countries such as the Philippines and Saudi Arabia. Countries in Asia, in general, were already known to have their own distinctive culture, and the pandemic seems to have further isolated them.

Collecting: The study found that the strongest cluster in collecting interests before the pandemic consisted of Japan, France, Brazil, and Italy. However, after the pandemic, many new weak connections started to grow worldwide, with Australia, the United States, the United Kingdom, Peru, and the Philippines gaining more connections.

Cooking: The study found that the cooking interests relationship landscape changed significantly after the pandemic, with weaker bonds either broken or strengthened. Countries in Asia were mostly isolated in both periods, except for a few. Europe, in general, has established linkages to each other while dropping some of the existing connections.

Crafts: The study found that the relationships in crafts interests received minimal effect from the pandemic compared to other topics. The strongest cluster of Canada, the United States, the United Kingdom, Ireland, and Australia remained intact. Most Asian countries were mostly isolated in both periods, except for a few.

Games: The study found that the interests in gaming as a hobby increased worldwide due to global lockdowns and social distancing. The correlations in gaming interests were very strong as lockdowns limited choices of leisure, causing many countries to look for games at the same time. Many big countries such as the United States, China, Russia, Indonesia, Canada, Brazil, Egypt, Iran, France, Germany, and Thailand were not connected to any other country in terms of gaming interests.

Learning: Before the pandemic, countries in South America and Mexico, South Asia, East Asia, and Southeast Asia had their own voluntary interest level in learning unrelated to other countries. After the pandemic, most of those isolated countries remained isolated, while a few countries formed hubs connecting many other countries in terms of learning interest.

Music: Before the pandemic, there were regional connections in East Asia, North America, and Europe, and a few strong pairs were formed between countries. After the pandemic, the strong relationships that existed before disappeared, and new weak connections emerged worldwide.

Performing Art: Before the pandemic, there were very few connections in this area of interest, and most of them were weak. After the pandemic, the only cluster mentioned disappeared, and random weak links emerged all over the world.

Pet: Before the pandemic, there were frequent connections among countries in terms of their pet interests. After the pandemic, strong relationships no longer existed, and new weak connections emerged worldwide.

Sports: Before the pandemic, there were frequent connections among regions of the world, and a few strong pairs were formed between countries. After the pandemic, those connections disappeared, and new strong connections emerged between previously unconnected countries.

5.2 Interpretation of Findings

The findings of the present study provide insights into the relationships among countries in terms of their hobbies and interests before and after the COVID-19 pandemic. The pandemic has brought significant changes in the way people interact with each other and spend their leisure time. The results suggest that promoting cultural exchange and understanding through hobbies and interests may be relatively resilient to the impact of the pandemic. However, the findings also reveal that some countries were already isolated in terms of their hobbies and interests before the pandemic. This suggests that there are underlying structural issues in terms of cultural exchange and understanding that could be addressed. The results demonstrate that the pandemic has significantly altered the patterns of relationships between countries. Each country has adapted to the pandemic in its own unique way, resulting in less dependence on other countries. Understanding which specific relationships persisted and formed during the pandemic could be particularly beneficial in marketing efforts. Furthermore, the results suggest that physical geographical factors such as countries' borders, seasons, and climates have become less important in determining the preferences and relationships between countries. With the shift towards online interactions and relationships, online presence has become a crucial factor in determining relationships between countries in the future.

Network graphs provided visual representations of the changes in the relationship between hobby interests in different countries. The results of this study show that eight out of ten hobbies experienced considerable structural changes due to the pandemic, while the other two remained unchanged. The changes in the relationships between countries can be attributed to a number of factors, including the impact of the pandemic on people's behaviour and the restriction of physical gatherings and international travel. The pandemic forced people to be more isolated, avoided gatherings, and narrowed their choices of hobbies. This led to a decrease in the linkages between countries in arts, collecting, and pets. Globally influenced cultures that required physical participation between countries were also restricted. However, this does not necessarily mean a decline in these interests globally, as people could simply enjoyed their own local culture more. Physical hobbies that were naturally more locally focused, such as crafts and performing arts, had always had weak relationships between countries and remained unchanged. The decline in international travel did not affect these hobbies, as the vast majority of participants were locals, determining its local trends.

5.3 Conflicting Results and Unexpected Findings

The study did not find any conflicting results. There are significant changes in the global landscape of relationship as expected. However, the findings related to the interests in crafts suggest that this topic has received minimal effect from the pandemic compared to other topics, which was unexpected given the overall impact of the pandemic on people's daily lives.

5.4 Discrepancies with another research

The findings of this study are consistent with some previous research on the impact of the pandemic on people's leisure time activities. A study by Schiavo et al. (2021) found that the pandemic has significantly affected people's leisure activities, leading to a shift towards online activities. However, the current study focuses specifically on the relationships among countries in terms of hobbies and interests, which is not presented in another research. Additionally, the finding in learning topic is also in line with previous studies that have suggested that the pandemic has led to a shift towards online learning and that countries with strong education systems are likely to benefit from this shift (Dehning et al., 2020).

5.5 Implication

Firstly, the findings of this study have the potential to have a significant impact on various fields. One potential implication is that it could provide additional insights into understanding geographical relationships between countries. By understanding the changes in relationships between countries due to the COVID-19 pandemic, it can help identify cross-cultural issues that may have emerged. The increased connectivity in gaming, for example, suggests that leisure activities such as gaming may serve as a form of global communication, connecting people from different parts of the world. This has implications for policymakers and international organizations in terms of promoting cultural exchange and understanding. It could be used as a supplement for companies and trade-related policymakers to refine their trade policies and make better informed business decisions. Companies that are selling products in their own country and looking for opportunities overseas might prefer to choose a country with a more similar culture or related interests as shown in the graph, rather than a more diverse country. This approach can result in lower costs of modifying products to blend into new markets. By selecting a country with similar culture or related interests, companies can expect fewer barriers to entry and greater acceptance of their products. For governments, there are many ways to use this information. For example, preserving existing industries or markets may require a new approach. The identification of broken bonds can signal potential threats, while new bonds can indicate opportunities. Policies can be developed to promote or ease the process of entering new markets, fix broken bonds with incentives, or create new bonds with countries that currently have weak relationships. In this way, governments can use this information to make more informed decisions when selecting trade destinations to support exporters.

Secondly, this study demonstrates the potential of network analysis as a tool for understanding the relationships among countries in various domains. Network analysis has proven to be a valuable method for exploring complex relationships and identifying patterns in large datasets. Our findings suggest that network analysis can be applied to a wide range of domains beyond hobbies and interests, including trade, migration, and political relationships.

5.6 Limitations

It is worth noting that these discussions are based on perceptible events and further in-depth investigations are required to establish their validity. Limitations of this study also include the reliance on publicly available data, which may or may not accurately reflect the true interests of individuals in each country as assumed. Additionally, the study did not take into account the cultural and social factors that may have influenced the relationships among countries in terms of their hobbies and interests. After all, the study did not explore the causal relationships between the pandemic and the shifts in the relationships among countries in terms of their hobbies and interests. Future research should investigate the underlying mechanisms that have led to these changes and explore the potential long-term effects of these changes on global relationships.

Moreover, the study only focused on ten topics of interest, and it is possible that the relationships among countries in other areas of interest may have also been affected by the pandemic. Future research could possibly explore the shifts in the relationships among countries in other areas of interest to provide a more comprehensive understanding of the impact of the pandemic on global relationships.

CHAPTER 6
Conclusion

The results of the study on the impact of COVID-19 on global hobby relationships showed a significant effect on the relationship between countries. The COVID-19 pandemic has disrupted the global landscape in terms of hobby relationships, as restrictions on travel and disruptions of internet-based solutions have had a major impact. Physical hobbies, such as art, collecting, and pets, where the internet was difficult to replace, showed weaker relationships between countries. On the other hand, hobbies where the internet could compensate, such as learning, cooking, sports, music, and games, showed a shift in relationships towards new destinations. Performing arts and craft, which had never been firmly globalized, remained unchanged.

The study also highlighted the effectiveness of network graphs in quickly identifying changes and strengths in relationships between countries. Traditional methods, such as correlation matrices, would have taken a significantly longer time to conduct and may not have captured the overall picture as effectively. The use of network graphs allowed for a clear understanding of the changes and relationships between countries, providing valuable insights into how the COVID-19 pandemic has affected global hobby relationships.

These findings have important implications for understanding cultural relationships in international marketing, as well as for trade policies and cross-cultural communication. Companies and governments can use this information to make more informed decisions when selecting trade destinations, promoting existing industries or markets, or creating new bonds with countries that currently have weak relationships. The results of this study provide valuable insights into how the COVID-19 pandemic has affected global hobby relationships and how these changes can be understood and navigated in the future. The use of network graphs in this study was found to be a valuable tool in quickly and efficiently identifying changes and the strength of relationships between countries.

Lastly, the results of this study provide valuable insights into how the COVID-19 pandemic has affected global hobby relationships and the use of network graphs as a tool for analysis. The findings have important implications for international marketing, trade policies, and cross-cultural communication, and can be used by companies and governments to make informed decisions in these areas. The use of network graphs was found to be a valuable tool in quickly and efficiently identifying changes and the strength of relationships between countries, making it a valuable tool for future research in this field.

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Appendix

Network Analysis of Relationship in Hobbies Interest Among 50 Countries and the Changes from COVID-19

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ABSTRACT

While the uncertainty from COVID-19 persists throughout the globe, the impact it triggered is not only limited to physical health issues. The pandemic forced people to adapt in many aspects. People's behaviours and perceptions has shifted throughout the pandemic. Though, inhabitants of distinct culture perceive and react to things differently. There are findings that culture strongly influences both individuals and society perception of events and this pandemic is not an exception. Leisure is one of an autonomous way to express culture. This research is intended to spot global connection patterns in hobby interest and learn how the patterns has changed by the occurrence of COVID-19 with network graphs visualization. In the last decade, Google Trends has been proven to be a promising tool in behavioural science studies. It allows researchers to draw summarized time-series data from the sample size of global Google users for free. One of its tools accumulates different search queries that belong to the same topic in different synonyms and languages as a topic which is essentially useful. This research has collected scaled data of ten selected hobbies, in fifty top GDP (2020) countries from January 1st, 2018 thru March 31st, 2021 with Google Trends topics. This work marks the period before March 11th,2020 as pre-pandemic and the period from this date as post-pandemic according to the World Health Organization's announcement. This paper then calculate correlation matrices and visualize with network graphs. The analysis shows significant adjustments in global relationship patterns affected by the pandemic in most search topics.

Keywords: COVID-19, pandemic, behaviour, perception, culture relationship, leisure, hobby, Google Trends, network graphs

1. INTRODUCTION

The novel coronavirus disease which was later renamed as "COVID-19" emerged in China in late 2019. The disease quickly spread overseas, and its trend continued to grow. On 11 March 2020, the World Health Organization (WHO) publicly announced COVID-19 as a pandemic. At that time, there were 4,291 deaths from approximately 118,000 cases in 114 nations (WHO. 2020). The number was surprising but incomparable to the figure of a year later. On 11 March 2021, the world had lost more than 2.8 million lives from the disease which has infected more than 130 million people. The pandemic has not only caused health issues to those infected but also posed challenges to public health administrators around the globe (Van Bavel et al. 2020). Several measures have been imposed ranging from lockdown, isolation, quarantine to local confinement to protect the world population. Apart from direct effects, the pandemic has forced people to adapt in many aspects (Cole et al. 2013). Recently, researchers from around the world have studied both direct and indirect effects from COVID-19. In behavioural science, key focus in this phenomenon has been on how people perceive the pandemic and then shift actions due to the shock and also what are the reasons behind those changes (Kramer et al. 2014).

There are findings that culture strongly influences both individuals and society perception of events and this pandemic is not an exception (Biddlestone et al. 2006). Different perceptions often lead to different behaviours, together with peers gradually reinforcing the culture. In social sciences, family, work, and religious beliefs are generally considered to shape an individual's behaviour (Markus et al. 1991). Leisure is not commonly included (Triandis & H. 2018). Yet growing leisure investigations under modernism, recreation practice and cultural consumption are at least as essential. Normally, hobbies are activities people choose to do in their spare time relative to their core values (San Martin et al. 2018). Hobby preference might be influenced by peers in any community, but the bottom line is that, no one would or could effectively force others to take interest in a hobby in the long term. This makes hobbies an interesting topic to study freewill cultural expression. and how culture transmits.

Studying human behaviour often involves conducting surveys, interviews, or observing subjects. However, doing so can be costly and prone to be biased which makes these methods impractical on a global scale. Nevertheless, in the digital era, the internet has solved and eased countless issues including research (Makhortykh et al. 2020). When people are interested in something, people inquisitively search (Zitting et al.2020). Google is the largest search provider in the world with more than 90% share in 2021 (Alex Chris 2021) which makes its free Google Trends service quite powerful in research. This allows behavioural science studies to have significantly more sample size than ever (Vosen 2011) and allowing researchers to conveniently extend their experiment worldwide (Kristoufek 2013) Google Trends has also proven to be a promising data source improving explanation power in prediction problems (Choi et al. 2012).

This work sees an opportunity to utilize Google Trends in studying cultural expression with 10 hobbies among 50 countries and their relationships in both before and after the official COVID-19 pandemic announcement. The work then visualizes the preference linkage between countries to give exploratory insights of cultural relationship in network graphs comparing between pre and post pandemic to examine the effect of COVID-19. Based on our knowledge, this paper is the first empirical research attempt to study the effect of COVID-19 on the preference of hobbies between countries. This work attempts to show empirical linkages but not to be confused with influential power. This research is not designed to prove any causal relationship and cannot claim that one country has an influence over another country even if true. This work is only interested in the patterns involving which countries are trending together and how it changes along with the pandemic.

2. LITTERATURE REVIEW

2.1 Effect of Covid-19 on individual's behaviour and society perception.

Jay J. van Bavel, Latherine Baicker with 43 co-authors published a paper in Nature Human Behaviour journal (2020) named "Using social and behavioural science to support COVID-19 pandemic response". The paper discusses evidence from a range of research issues related to pandemics. The work focuses on navigating threats, social and cultural influences on behaviour, moral decision-making, science communication, leadership, and stress and coping. A part of the work concluded that during a pandemic, one of the central emotional responses is fear. Animals, including humans, own a series of defensive systems for tackling natural threats. As supported by LeDoux, J. (2012) in the study "Rethinking the emotional brain" and Mobbs, D., et al (2015) in "The ecology of human fear: survival optimization and the nervous system". Fear makes threats perception to be distorted to the worst case based on Cole,S. et al (2013) and these negative feelings that are driven by threats can be communicable, as supported by Kramer,A.D.I. et al (2014). Another emotional response is that people might present an 'optimism bias', which is the belief that unpleasant things will not happen on oneself than others. Optimism bias has proven to be useful in avoiding pessimistic feelings as researched by Strunk, D.R. et al (2006). This has lead people to underestimate their chance of getting a disease and ignore warnings as stated in "The optimism bias" composed by Sharot,T in 2011 and also in Wise,T. et al's work in 2020. The main suggestion of Jay et al's paper in communication strategies was to strike a balance between breaking through the optimism bias barrier without causing too much anxiety. These works support the statement that COVID-19 induced negative emotional response, which lead to different decisions by individuals and the statement that the event may have caused collective hysteria. This ultimately proved that there exists some degree of correlation among people.

In "The COVID-19 Pandemic: Changing Lives and Lessons Learned" authored by Rod J. Rohrichm, MD, Kristy L. Hamilton, MD, Yash Avashia, MD, and Ira Savetsky, MD (2020) studied how COVID-19 change people's life in several aspects. Apart from medical and epidemiology findings and suggestions, the research points out how COVID-19 has changed plastic surgery which involved major behavioural changes toward the virtual environment. Another part is about societal changes after the crisis in American context which suggests that the pandemic helps shaping citizens to be more patient, more responsible to others, more disciplined, and more resilient. In overall, the pandemic affects people's core value and perception to evolve.

There are cultural factors related to COVID-19, such as in M Briddlestone et al (2020)'s work "Cultural orientation, power, belief in conspiracy theories, and intentions to reduce the spread of COVID-19". This work investigated cultural and psychological factors associated with intentions to reduce the spread. In cultural context, the research referred to Markus, H.R., and Kitayama, S. (1991) who showed cultural variation of countries. North American and Western European cultures are considered independent due to their individualism endorsement supported by Triandis,H.C. (1995), while Asian and other societies are considered interdependent or collectivism. The citizens of the latter are more committed to country, tribe, and family based on San Martin, A. et al (2018) and Kitayama, S. (2009). The result suggests that social-oriented countries' citizens tend to prioritize social responsibility over personal desires. The paper further suggests that promoting collectivism might be a tactic to improve engagement to stop spreading the disease. These papers demonstrated that culture of countries is diverse while interconnected in some degree which in turn might show insightful patterns if the pattern could be visualized, especially in this period.

2.2 Utilizing Google Trends to measure interest level.

The paper "Human-dog relationships during the COVID-19 pandemic: booming dog adoption during social isolation" written by Liat Morgan and 7 more co-authors (2020) investigated how people recognized and behaved during the pandemic social isolation. Previous studies showing that having a pet benefits mental health. Playing with animals helps with depression and anxiety, particularly in stressful conditions. The paper found that social isolation raised dog adoption interest and the adoption rate also rose significantly during pandemic while abandonment numbers stayed the same. Interest in dog adoption is measured by Israeli dog adoption website visits and worldwide Google searches for adoptable dogs. This research implied that Google search volume can be utilized to measure interest and proved that the pandemic affects search interests in pet adoption. Further study in other hobbies could be done.

Kirsi-Marja Zitting et al (2021) found that Google Trends reveals increases in internet searches for insomnia during the 2019 coronavirus disease (COVID-19) global pandemic. The research tried to estimate the effect of COVID-19 on insomnia levels at global level as previous evidence from small samples suggest increased insomnia and other sleep disturbances. The result in the United States showed 58% expanding search queries for insomnia in January through May 2020 compared to previous 3 years of the same month. Additionally, the search volume peaked around 3 am. This work showed that Google Trends can be used to extend the scope of the research toward global scale.

Simeon Vosen and Torsten Schmidt (2011) compared prediction power between survey-based indicators and Google indicators in predicting private consumption context. Survey-based indicators are the University of Michigan Consumer Sentiment Index (MCSI) and the Conference Board's Consumer Confidence Index (CCI). Google indicators are a collection of selected Google trends topics. Prediction power gain is measured by an increase R-squared from a simple autoregressive model as a baseline. The result showed that MCSI gave 1 percent incremental R-squared while CCI gave 2 percent and Google indicators gave 3 percent. This analysis shows that Google Trends is a very promising and convenient data source to use in prediction problems.

Amaryllis Mavragani & Knostantinos Gkillas (2020) studied the feasibility of Google Trends in predicting COVID-19 cases and deaths in global scale and the United States. The result showed the projected Google Trends models reveal powerful COVID-19 predictability.

In "Can Google Trends search queries contribute to risk diversification?" by Ladislab Kristoufek (2013) found an application of Google Trends in financial portfolio management. The intention to diversify risk is based on an idea that popularity of a stock measured by search queries is correlated with the stock riskiness. The result revealed that search queries-based strategy outperformed both the uniformly weighted portfolio and the benchmark index both in-sample and out-sample. There are more applications of Google Trends in finance context. Ilaria Bordino et al (2012) predicted stock market volumes and Hyunyoung Chio, Hal Varian (2012) forecasted near-term values of economic indicators.

2.3 Methodology Review

Bishara, A. J., & Hittner, J. B. (2012) conducted research titled "Testing the significance of a correlation with non-normal data: Comparison of Pearson, Spearman, transformation, and resampling approaches". It is known that when data is not normally distributed, Pearson's significance tests might cause excessive Type I error rate and reduce its power. Repeated attempts in the past decades found several alternatives to Pearson's correlation. However, those alternatives did not have a clear performance comparison. This study compared 12 methods including Pearson, Spearman's rank-order, and other approaches with two simulation studies. Among transformation approaches, a general-purpose rank-based inverse normal transformation was most beneficial. However, when samples were both small ($n \leq 10$) and extremely nonnormal, the permutation test often outperformed other alternatives, including various bootstrap tests. The research confirmed that if the data is not normally distributed, Pearson correlation test should not be used.

A test for normality often needs to be interpreted by statisticians or experts. However, M.B. Wilk & R.Gnanadesikan (1968) discusses graphical techniques based on cumulative distribution function. Quantile to quantile plots (Q-Q plot) are also useful for normality tests, by benchmarking cumulative distribution function of normal distribution in comparison to original data. There are more possible applications of Q-Q plot discussed in the paper. Areas of application include: the comparison of samples; the comparison of distributions; the presentation of results on sensitivities of statistical methods; the analysis of collections of contrasts and of collections of sample variances; the assessment of multivariate contrasts; and the structuring of analysis of variances; mean squares. Many of the objectives and techniques are illustrated by examples. This paper showed another way of visualizing statistical tests.

In "Handbook of Graph Theory" by Gross, J. L., & Yellen, J, (2003) described the principle of network graphs. Network Graph consists of nodes, and edges. While nodes are points representing variables or entities, edges are connections between nodes. Connections often correspond with correlation coefficient. Many works use the thickness of the line to depict a degree of correlation. The handbook also gives a guide on types of network graphs. Conclusively, there is more freedom on how to visualize network graphs to meet aesthetic desire than restrictions, but the graph should be designed to give as much precise message to viewers as it could.

Chapter 3 of Udomwong, P. (2015)'s dissertation "Association of genes in bacterial population genomics" presented several network threshold selection techniques. First method is density of networks as utilized by Pavlopoulos et al., (2011). Density off the network is calculated by an equation to measure the proportion of edges drawn to nodes showing if edges can possibly connect. Threshold searching process involved iterating threshold level from 0 to 1. In each iteration, density of the network is calculated by the equation. The optimal threshold is the one which gives the minimum value of density based on Aoki et al. (2007) and Ozaki et al (2010). Another method is the connected component by Fukushima et al. (2011) which selects the threshold at the level with sharp transition in the number of linking components. Barabasi et al. (2004) in the third method of clustering coefficient measures the tendency of a node to form a cluster. The tendency is measured with an equation for each node pair and then average the value with the number of the whole network. Potential threshold is again observed at sharp transitions based on Gupta et al. (2006) and Elo et al (2007). Lastly, the spectral graph theory method by Perkins et al. (2009) calculates eigenvectors and eigenvalues of the largest component in the network to find spectral clusters which feed in the Laplacian matrix. There will be an algebraic connectivity which is the smallest non-zero eigenvalues in the matrix. Potential threshold is identified at the algebraic connectivity as mentioned by Ding et al (2001). The dissertation's chapter gave an overview on how to select ideal threshold level.

3. METHODOLOGY

3.1 Population and Sample

Population in this study referred to global citizens who search. Recalling that around 91 percent of searches are in Google's platform, with Google Trends, the authors can draw samples as nearly as population size. Following Table 1 shows countries included in the research, the top 50 countries with highest GDP.

China	India	United States	Nigeria	Indonesia
Brazil	Japan	Russia	Bangladesh	Mexico
Philippines	Germany	Pakistan	Vietnam	Turkey
Iran	United Kingdom	France	Thailand	Italy
Egypt	South Korea	Spain	Argentina	Canada
South Africa	Saudi Arabia	Colombia	Poland	Malaysia
Peru	Australia	Netherlands	Romania	Chile
Belgium	United Arab Emirates	Sweden	Czech Republic	Switzerland

Portugal	Austria	Israel	Hong Kong	Denmark
Norway	Finland	Singapore	Ireland	New Zealand

Table 1: List of top 50 countries with highest GDP

3.2 Data Collection

This research collects weekly Google search topics data of 10 selected hobbies topics in 50 highest internet users in the world from 1 January 2018 to 31 August 2021 from Google Trends. Selected topics are Collecting, Game, Sports, Music, Cooking, Arts, Crafts, Performing Art, Learning, and Pet. Search topics are not search terms or keywords. Topics are a collection of search terms which will include all search terms related to it while search terms are specific which will only show the relative value of that keyword. Time-series tables of 50 countries are then combined for each topic and separated into two timeframes, pre-pandemic for dates before 11 March 2020, and post-pandemic for dates from 11 March 2020.

3.3 Testing Normality of Data with Q-Q Plot

Q-Q Plot compares the data sorted in ascending order with theoretical cumulative function by plotting their quantiles against each other (Wilk, M.B. & Gnanadesikan, R. ,1968). If the two counterparts being compared are similar, then data points will sit approximately at the line x=y. It is handy in testing normality by fixing normal distribution as a theoretical benchmark. If the plot shows data sitting tightly on the line, then the data is considered normal, and if most data is normal, Pearson correlation would be sufficient for the task.

3.4 Correlation Matrix

Correlation Matrix is simply a table of correlation coefficients between items, in this case countries. There are several ways to calculate the value. One of the most popular methods is Pearson correlation coefficients. It was developed by Karl Pearson in 1895 with inspiration from Francis Galton's works in the 1880s. Mathematical formula is as followed

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \qquad (1)$$

where n is sample size, x_i, y_i are individual sample points of the same index i, and $\bar{x}, \bar{y}$ are sample mean of x and y respectively. While Pearson's correlation is useful, it comes with a caution. It is well known that if data is not normally distributed, Pearson's correlation may inflate Type I error rates (Bishara, A. J., & Hittner, J. B. ,2012). It would be more careful to test if most of the data is normal or this work should opt for another method.

3.5 Correlation Network Graph

Correlation Network Graph consists of two main components, nodes, and edges (Gross, J. L., & Yellen, J, 2003). Nodes are points often depicted by a circle. Edges are lines connecting nodes. In this study, a graph represents a topic in a timeframe, whether it is pre-pandemic or post-pandemic. Nodes represent countries while edges correspond to correlations between hobby interest levels of two countries. However, every connection should not be drawn otherwise the graph would be messy and less informative especially in network analysis which relies heavily on visual interpretation. To resolve this issue, threshold is the quantity to decide which connection to draw.

3.6 Threshold

Threshold is an important decision indicator governing which connection to be shown. Correlations less than the threshold are hidden. Setting too low a threshold will show too many irrelevant relationships. These false interactions are unwanted noise disturbing interpretation. In contrast, setting too high a threshold might filter out important relations. Graph-based topology technique, density of network is utilized to find optimal thresholds.

3.7 Density of Network

Density of network (Pavlopoulos et al., 2011) measures the proportion of edges drawn to nodes that can possibly be connected.

$$\text{density} = \frac{2|E|}{|V|(|V|-1)} \qquad (2)$$

where |E| is the number of edges. |V| is the number of nodes excluding isolated nodes. |E| and |V| are a function of threshold level. Number of edges drawn drop when threshold rises while higher threshold leads more nodes to be isolated. As a result, density value starts from 1 when threshold remains 0, later reduces to the lowest network density. Then, the value rises again as the edge number is more stable while more nodes are being isolated. The procedure to find optimal threshold involves iterating threshold level from 0 to 1 which returns density level derived from the equation above. This research increases threshold level by 0.01 in each step. Optimal threshold holds at the lowest value of the density network (Aoki et al., 2007, Ozaki et al., 2010).

3.8 Network Graph Drawing

In this step, we draw a network graph for each topic. There will be 50 nodes representing 50 selected countries at the spot corresponding to each country location in a typical world map. Nodes size scales with the number of internet users of a consequent nation and the colour will match with members of the same region. Edges connect pairs of countries with absolute correlation coefficient value higher than threshold derived previously. Thickness of edges represent strength of correlations while the colour shows either the relationship between the couple is positive as depicted in navy blue or negative as depicted in pink.

3.9 Interpretation

This research will show if countries are related or not by numbers of connecting lines in each topic and the thickness of the edges to show strength of correlations. Then, the work will compare network graphs of the same topic between pre-pandemic period and post-pandemic period to satisfy the second hypothesis. If there are significant changes in patterns, then the research concluded that COVID-19 affects the relationship between countries in hobbies.

4. RESULTS

Based on the methodology, two periods of weekly time-series data for ten search topics in 50 countries are collected. First phase started from the beginning of 2018 to the official COVID-19 announcement date, March 11th in 2020. Another phase ranged from the week after the report until the end of August 2021. Fraction of raw data retrieved from Google Trends is shown in Table 2 below. The data was scaled between 0 to 100.

date	ARE	ARG	AUS	AUT	BEL	BGD	BRA	CAN	CHE	CHL	CHN	COL	CZE
1/7/2018	68	82	50	59	80	73	33	45	54	77	58	94	58
1/14/2018	73	87	49	55	84	75	35	46	58	80	81	85	57
1/21/2018	71	87	51	64	84	79	39	48	58	75	82	83	64
1/28/2018	75	83	53	59	87	76	35	44	53	80	64	75	67
2/4/2018	71	82	58	71	86	63	37	47	55	83	80	70	66
2/11/2018	68	93	60	69	97	70	35	48	64	83	69	73	69
2/18/2018	72	85	66	68	84	77	39	55	63	79	100	74	71

Table 2: Part of scaled weekly search data in the Pets topic before the pandemic

QQ-Plot normality test results in Figure 1 showed seemingly diagonal lines in most series, suggested simple Pearson's correlation to be sufficient.

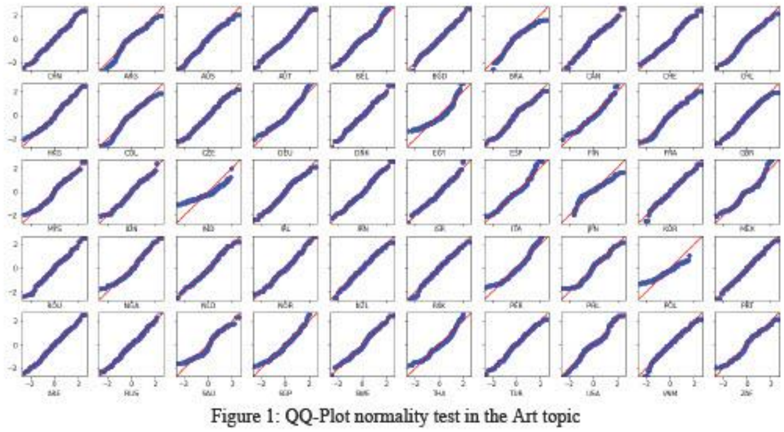

Figure 1: QQ-Plot normality test in the Art topic

Correlation matrices consisted of 50 countries crossing each other for both periods of all search topics were calculated in this step to act as the main ingredient to feed in network graphs. In fact, network graphs filter relevant information from correlation matrices to show useful insights. Prior to draw the graphs, threshold values were calculated. These important numbers dictated how strong of correlation pairs are required to enter valuable graphs. Pairs with weaker bond, lower correlation than the threshold were filtered out. Threshold values were reported in Table 3 based on density of network algorithm. Passing conditions varied due to competitiveness of pairs in the period. For example, in Collecting, threshold was 0.21 before COVID-19, then shifted to 0.25 later. In Sports, it was 0.54, then increased to 0.84. Only in Pets that the threshold number decreased with the pandemic. Between hobbies, the values were poles apart. It might be due to the different nature of each hobby.

Topic	Pre-pandemic	Post-pandemic
Collecting	0.21	0.25
Game	0.70	0.83
Sports	0.54	0.84
Music	0.58	0.77
Cooking	0.45	0.68
Arts	0.53	0.61
Crafts	0.29	0.42
Performing Art	0.22	0.26
Learning	0.37	0.69
Pets	0.33	0.28

Table 3: Threshold values calculated by density of network

Additionally, the Figure 2 below showed values of network density from the algorithm in the Y-axis from different levels of Pearson's correlation in the X-axis. Example below featured the Game search topic for pre-pandemic and post-pandemic, respectively. Thresholds were selected at the lowest point.

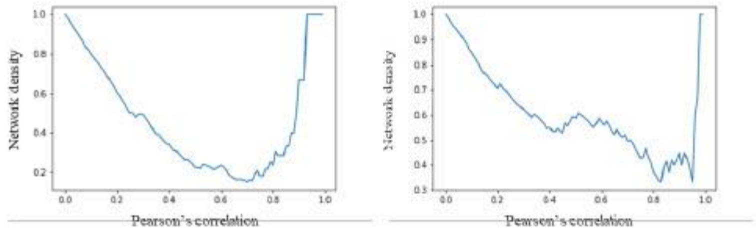

Figure 2: Density of network for the Game topic in pre-pandemic (left), and post-pandemic (right) period

The research promised pre-post pandemic network graphs for ten hobbies, however due to publishing limitations, only network graphs for games topic are depicted as examples here. Other topics could be seen in the appendix part. As presented in Table 3 and Figure 2, threshold value for games is 0.70 for pre-pandemic, and 0.83 for post-pandemic. Network graphs components details could be found in the methodology, but to recall in a nutshell, nodes are countries, colour of nodes represent regions, size of nodes are internet population, lines are edges, thickness of edges correspond with strength of relationship. Navy-coloured edges show positive relationship while pink stand for negatives.

Network graph for pre-pandemic interest in Games as referred to Figure 3, showed clusters of countries from the same regions were tied with closer relationships than those far away. Spanish speaking countries in Latin America were tightly bound. So as, European countries, middle east nations, Oceania, and east Asian countries except China. Distinctively, southeast Asian countries are unbounded. China, Russia, India, South African countries, and North Americas were also unconnected. The result showed the countries that were more connected, shared language, or had close culture, tended to be more related in Gaming interests. While countries with more unique culture, and language, tended to be isolated.

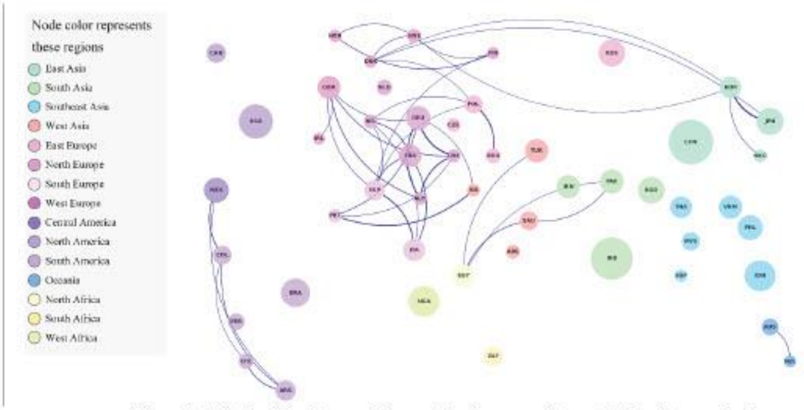

Figure 3: Relationship between 50 countries in games interest before the pandemic

Things changed a lot here after the pandemic, more countries were more connected in the global level even the threshold was higher. Countries were more related in term of preference but, it could not be concluded that countries were more connected. If considered, social distancing and stay home regulations which limit choices of activities might have caused sudden change in the same direction on gaming interests worldwide, in this case it could be implied that the interest level was increasing.

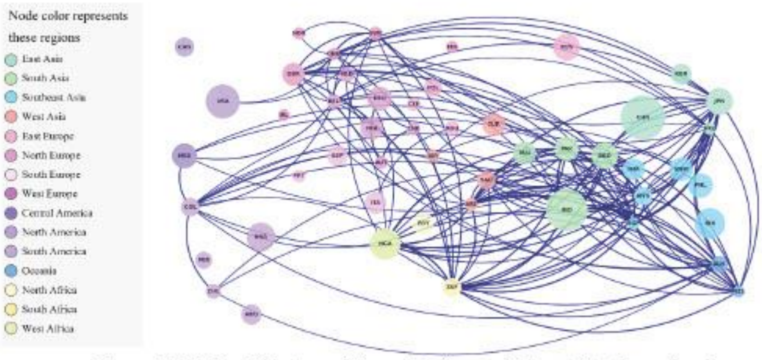

Figure 4: Relationship between 50 countries in games interest after the pandemic

For the other topics, the relationship in art interest level before the pandemic for European countries and north American countries were the biggest cluster. There were some pink lines linking Japan to few countries in Europe, suggested negative relationship between those pairs. Then after the pandemic, those bonds were completely broken apart. Linkages were rarer. However, a few relationships were formed such as Thailand-Malaysia-Singapore and Canada-Ireland-Mexico.

There was only one strong pair between France and Japan in Collecting before the pandemic which did not remain after the pandemic. Other connections were very weak.

Relationship before the COVID-19 for cooking interest were more tied in English speaking countries, and Hispanic. The connection structure after COVID-19 consisted of two big clusters, European countries plus Canada, and countries in the equatorial and southern hemisphere.

In craft, changes were insignificant around the world. The only strong group consisted of Canada, United States, and Britain in both before and after the pandemic.

Learning interest in pre-pandemic graph showed strong linkages from United Arab Emirates to Britain, United States and Canada. Turkey to Indonesia. South Africa to Australia and New Zealand. There were plenty of weaker links around the globe shown in the graph. However, those weak links were removed in post-pandemic. Strong linkages were stronger in overall. First group mentioned gained more members from west European nations. Turkey broke the bond with Indonesia and attached to Spain instead. Saudi Arabia formed a new link with UAE. Lastly, Australia and New Zealand aligned their interest to Singapore and Vietnam instead of former South Africa.

Music relationship structure have changed from the pandemic largely except for Latin countries. The Korea-Japan-Hong Kong bond broke. India, Nigeria, and Australia were not connected before the COVID, later formed several links to the world.

Performing Art interest resulted in no substantial change. Strong connections were from France to Canada, Belgium, and Switzerland in pre-pandemic. Same connections remained except for Canada.

Pets interest main connections were centred around central and south Europe before the COVID. Indonesia was another hub connecting Brazil, Egypt, Vietnam, and Italy. Japan was again on the opposing side with Italy and Poland with strong negative relationship, and with a few more European countries with moderate negative relationship. After the announcement, not any strong relationship remained. The only moderate link was between Canada and United States.

Lastly, the relationship in sports interest before the global pandemic were random with stronger bond in local regions especially in Latin America, Africa-middle east, and Europe. Japan, Korea, and Hong Kong were in the same group with positive correlation, formed a strong negative relationship with Spain. After the pandemic, Latin countries and east Asian connections were not exist while Europeans were stronger and formed new bonds with southeast Asian countries. Russia switched its only pair from Mexico to Australia.

5. DISCUSSION

Network graphs showed globally changes of hobby interest relationship formation in a glance. The results were varied. Eight out of ten hobbies showed considerable structural change from the pandemic while the other two remained unchanged. Massive changes in relationship in general might occurred by these following reasons. The pandemic undeniably forced people to be more isolated, avoided gathering for many activities including most group hobbies, narrowed choice of the people. Linkages in arts, collecting, and pets, between countries had been removed in overall. Once globally influenced cultures which required physical participations between countries were restricted. Unconnected International trends did not mean globally decline in these interests, if that happened it would show stronger bonds, people just enjoyed their own local culture more. In physical hobbies that were naturally more locally focused such as crafts and performing arts, the relationship had always been weak between countries remained unchanged. Big drop in international travellers did not affect, the vast majority of participants were locals, determining its local trends.

Learning perspective had known to be changed. In-person education were heavily shifted to virtual education. Schools and universities were faced with sudden change, some could adapt, some could not. The disruption caused some relationship to emerge, some to fade. Music and games are hobbies that internet could easily replace traditional way of enjoying. Physical venues were cancelled, internet is vital for these hobbies. Like any disruptions, new player came with better solution, the former obsoleted, pushing global relationship landscape to shift. Cooking and sports are similar in a point of view, these hobbies required physical execution. They could not be appreciated virtually like music and games. However, it is not an excuse for disruption. More people were influenced globally by the internet while making their own dinner and exercise at home. Seasons might play a lagging role in cooking relationship, separating two clusters between northern hemisphere and the south. These discussions were based on perceptible events and not claimed to be true. In depth investigation are required.

Possible implications from the findings might grant additional insights to better understand geographical relationship, spot cross-cultural issues, or polish trade policies. The patterns of relationship shown have changed massively due to COVID-19. Countries adapted to the pandemic with their own unique ways. Therefore, countries are less dependent. Knowing that most relationship before the pandemic broke and knowing which specific pairs persisted and formed could be beneficial, especially in marketing. The findings have proved that physical geographical factors such as countries' borders, seasons and climates have been playing less important roles to determine preferences relationship between countries as relationships are heavily restricted to be formed online more than ever. Online presence will be more crucial.

Elongated persistence of COVID-19 has been shaping culture as well. Short-term behavioural changes have turned to be permanent. It is reasonable to say that culture have been evolving in a much faster pace. In many cases, difference in culture between two or more parties could cause issues which leads to conflicts. Knowing that the previous cultural bonds of two countries are breaking apart could signal for immediate intervention, especially in sensitive areas. Ensuring peace before it is too late.

The research findings could also be used as supplement in trade policies planning. Companies that are selling products in their own country and looking for opportunity overseas might prefer to choose and give a try on the country with more similar culture or more related as shown in the graph than the other more diverse countries. The products might need less modifications which resulted in lower cost to blend in new market. For governments, there are many ways to use the information. Saving existing industries or markets might require new approach. Broken bonds could signal threats while new bonds could signal opportunities. Policies could be promoting or easing the process to new market opportunities, fixing broken bonds with plethora of incentives and attractiveness, or try creating new bonds to countries that possess no strong relationship to others. In the bottom line, policy makers could use the information to better select trade destinations to support exporters.

6. CONCLUSION

Results showed that COVID-19 strongly affecting global landscape in hobbies relationship between countries for most cases. Restrictions in travelling and disruptions of internet-based solutions were expected to play part. Physical hobbies like art, collecting, and pets where internet was hard to replace, relationship between countries were shown weaker. If internet could compensate like in cases of learning, cooking, sports, music, and games, the relationship in overall shifted to new destinations. While in performing arts, and craft where it had never been firmly globalized remained unchanged. Network graphs were proved to be useful in spotting changes and strength in relationship in no time. Imagine if ones need to conduct the same study with correlation matrices, it will take much more time and might not be able to capture the big picture. The research could be useful for cultural understanding in international marketing.

7. ACKNOWLEDGEMENT

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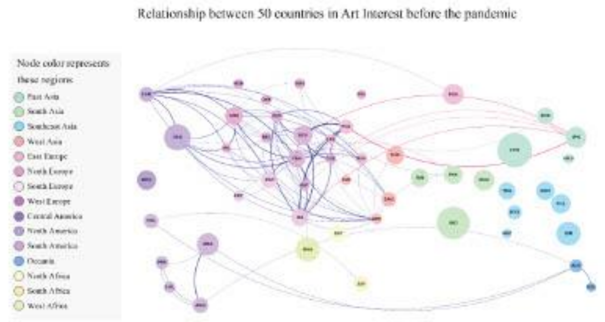
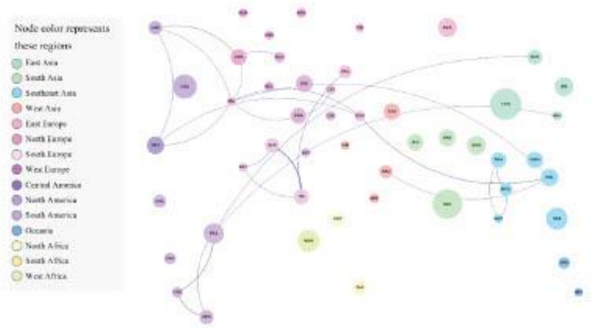
9. APPENDIX

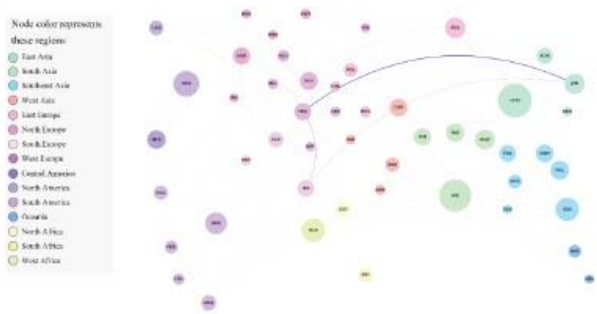


13

Relationship between 50 countries in Art Interest after the pandemic



Relationship between 50 countries in Collecting Interest before the pandemic



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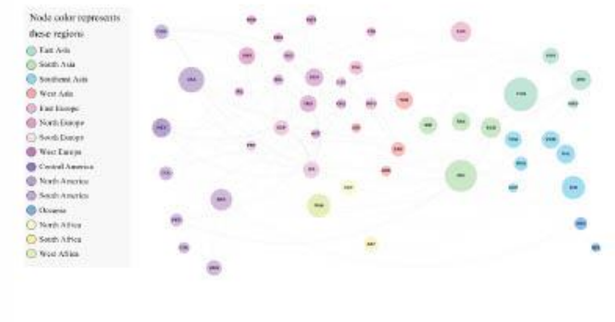
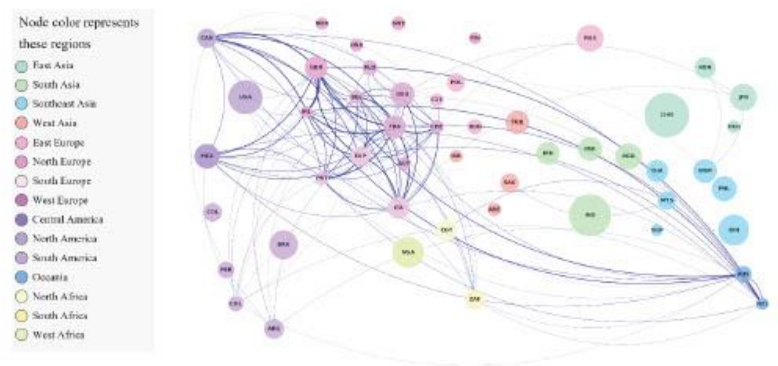
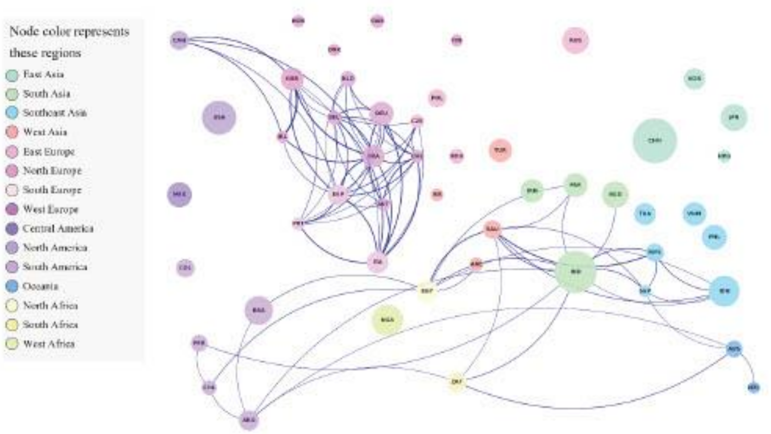
Relationship between 50 countries in Collecting Interest after the pandemic



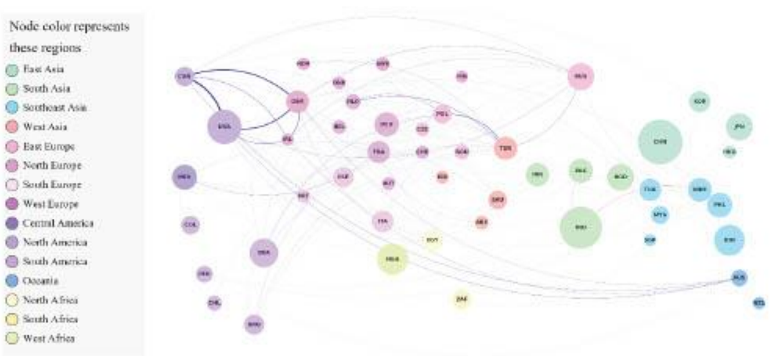
Relationship between 50 countries in Cooking Interest before the pandemic



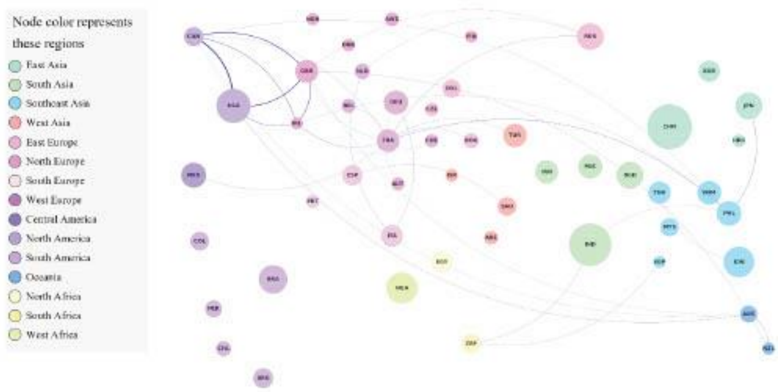
Relationship between 50 countries in Cooking Interest after the pandemic



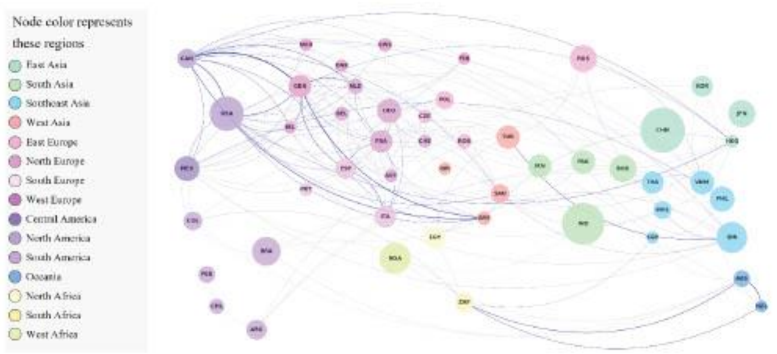
Relationship between 50 countries in Craft Interest before the pandemic



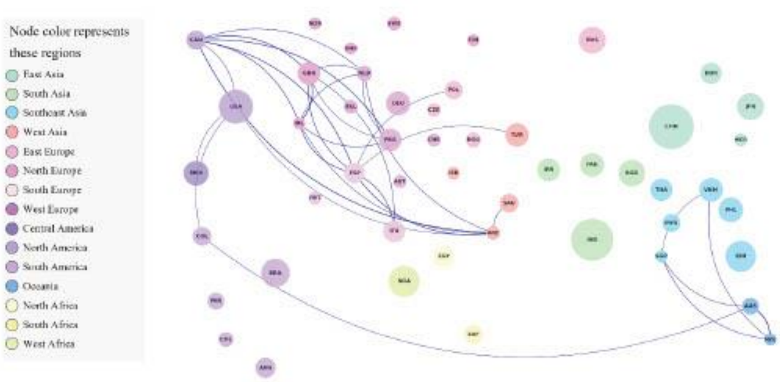
Relationship between 50 countries in Craft Interest after the pandemic



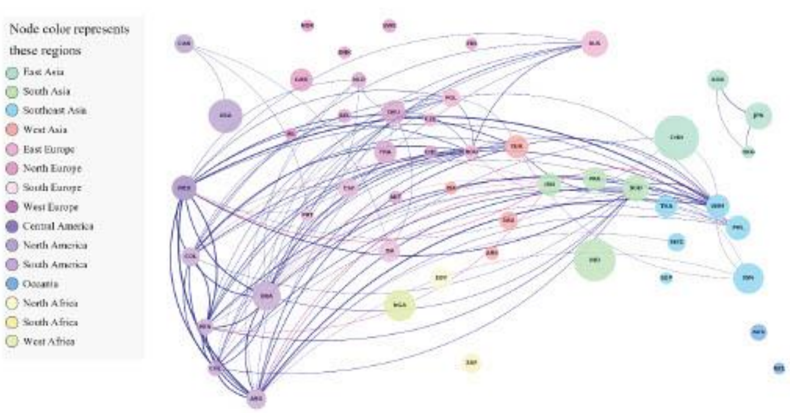
Relationship between 50 countries in Learning Interest before the pandemic



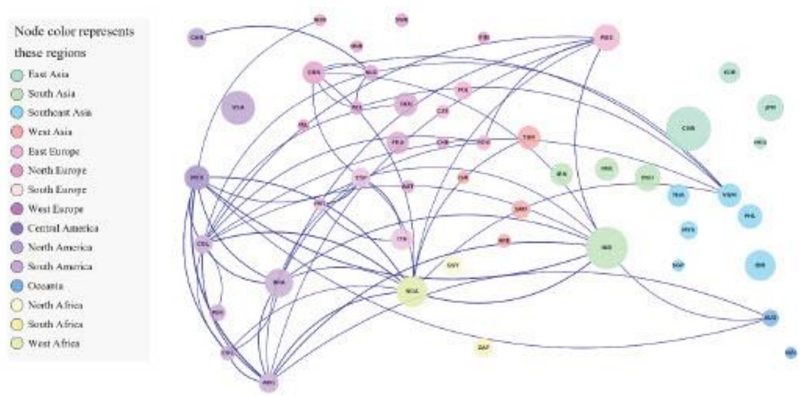
Relationship between 50 countries in Learning Interest after the pandemic



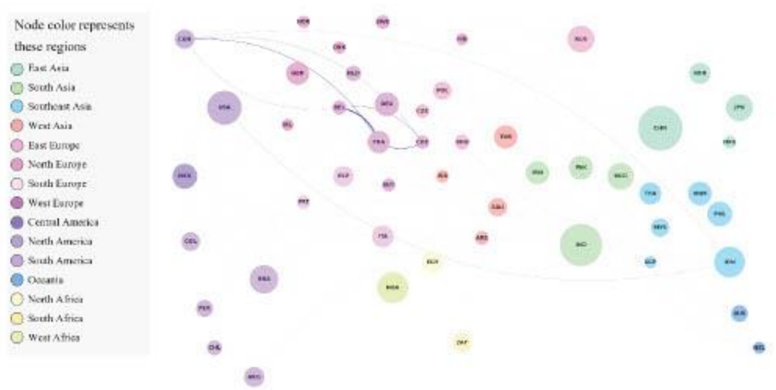
Relationship between 50 countries in Music Interest before the pandemic



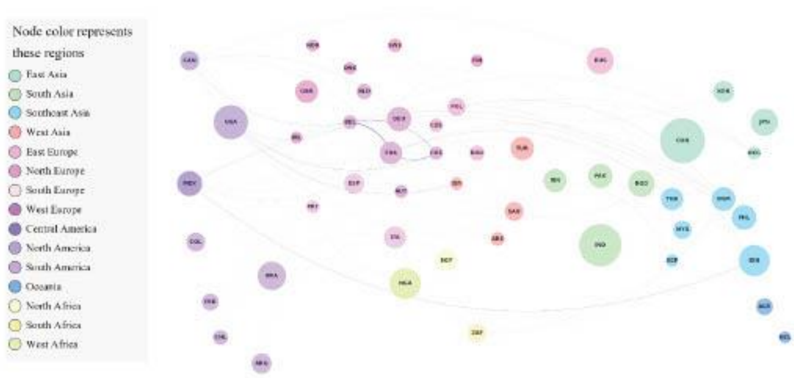
Relationship between 50 countries in Music Interest after the pandemic



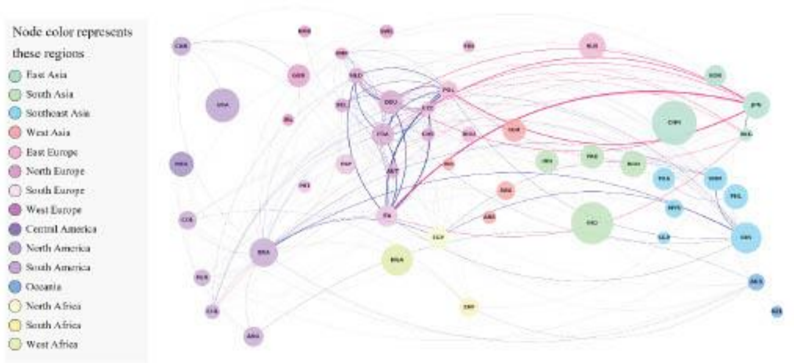
Relationship between 50 countries in Performing Art Interest before the pandemic



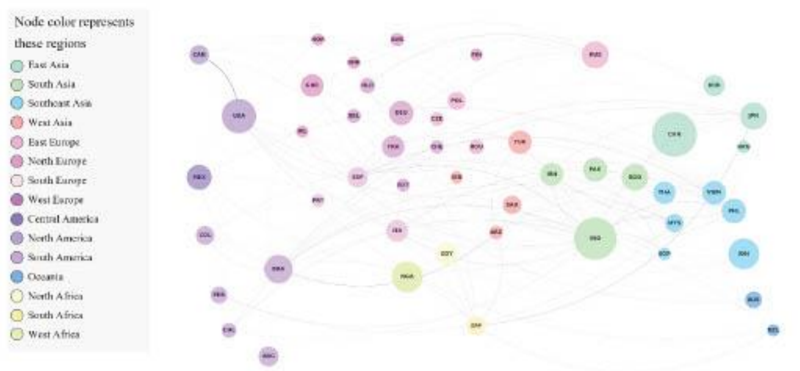
Relationship between 50 countries in Performing Art Interest after the pandemic



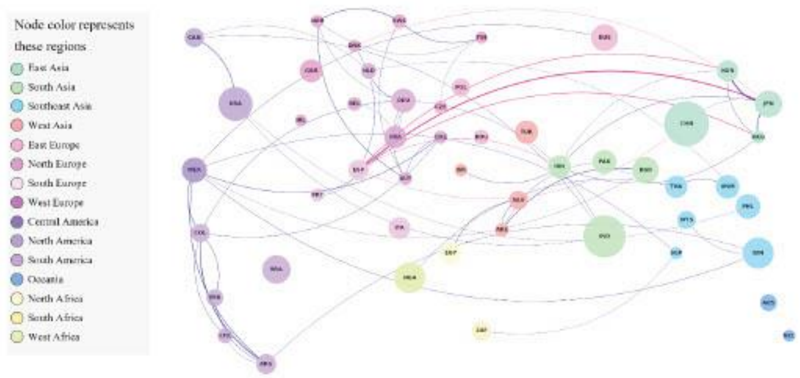
Relationship between 50 countries in Pets Interest before the pandemic



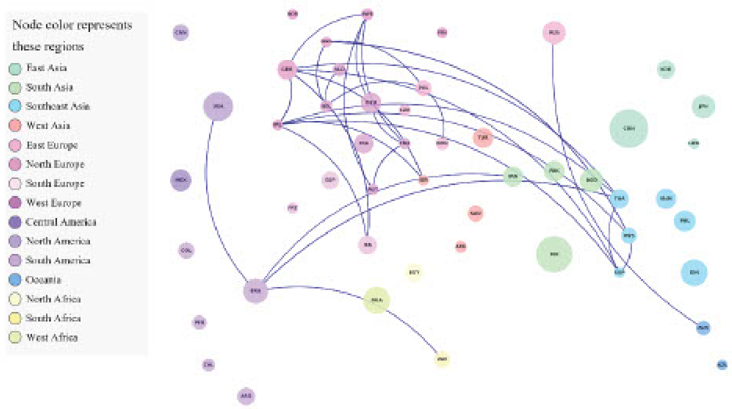
Relationship between 50 countries in Pets Interest after the pandemic



Relationship between 50 countries in Sports Interest before the pandemic



Relationship between 50 countries in Sports Interest after the pandemic



ประวัติผู้เขียน

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ผลงานตีพิมพ์ Thamprasert, Y., Udomwong, P., Chanaim, S., & Thamprasert, K. (2021). Network Analysis of Relationship in Hobbies Interest Among 50 Countries and the Changes from COVID-19. Review Process, 2.

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