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Bibliometrics analysis of mHealth and AI to discover the concept of AI in the field of mHealth

Kota Kodama

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2020 FFJ/Air Liquide Fellow

January 2022

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Abstract

Smartphones have become an integral part of our lives with a diverse selection of apps. The continuous upgrade of information technology has enabled smartphones to display potential in the field of health care. First, we analyzed the research trends and the latest research hotspots in mobile health to understand the global trends. This chapter collected mHealth-related literature published between 2000 and 2020 from the Web of Science database. We constructed visualization network maps of country collaborations and author-provided keyword co-occurrences, as well as overlay visualization maps of the average publication year of author-provided keywords to analyze the hotspots and research trends in mHealth research. In total, 12,593 mHealth-related research papers were extracted. The research trends revealed a gradual shift in mHealth research from health policy and improving public health care to the development and social application of mHealth technologies. To the best of our knowledge, the most current bibliometric analysis dates back to 2016. The results of this study shed light on the latest hotspots and trends in mHealth research. These findings provide a useful overview for researchers in the digital health field.

Keywords

Mobile health, Digital health, Digital medicine, Artificial Intelligence, Bibliometric analysis, Research trends

Acknowledgement

We would like to express our gratitude to Ritsumeikan University for providing access to the Web of Science database, which allowed us to access and collect the latest information related to mHealth. We would also like to thank all study participants for their constructive advice and guidance for this research. This work was supported by the FFJ/Air Liquide Fellowship. The authors gratefully acknowledge the generous support and assistance of the Fondation France-Japon (FFJ) de l'École des Hautes Études en Sciences Sociales (EHESS) and Air Liquide.

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“Bibliometrics analysis of mHealth and AI to discover the concept of AI in the field of mHealth”

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1. Introduction

With the rapid increase in the penetration rate of mobile phones over the past 10 years, almost each person in developed countries owns mobile phone (Donner 2008), and the lifestyle of carrying the device around has become more common and it has become ordinary to use various services such as e-commerce and finance. There are increasing opportunities for health promotion, especially in the medical field, due to the abundance of smartphone application functions and the ability to operate anytime, anywhere. The health services for medical and public health supported by such mobile devices are defined as mobile health (mHealth).

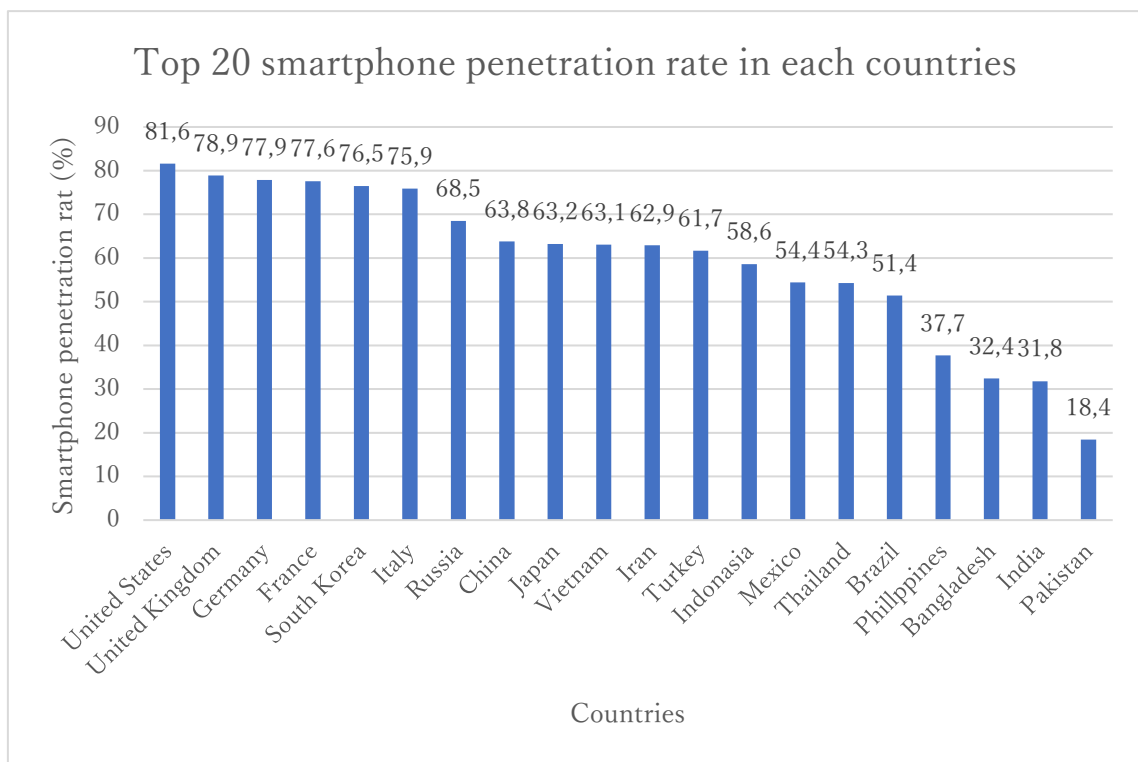


Fig. 1.1 The top 20 smartphone penetration rate in each country. Replicated by the author. Source (BankMyCell)

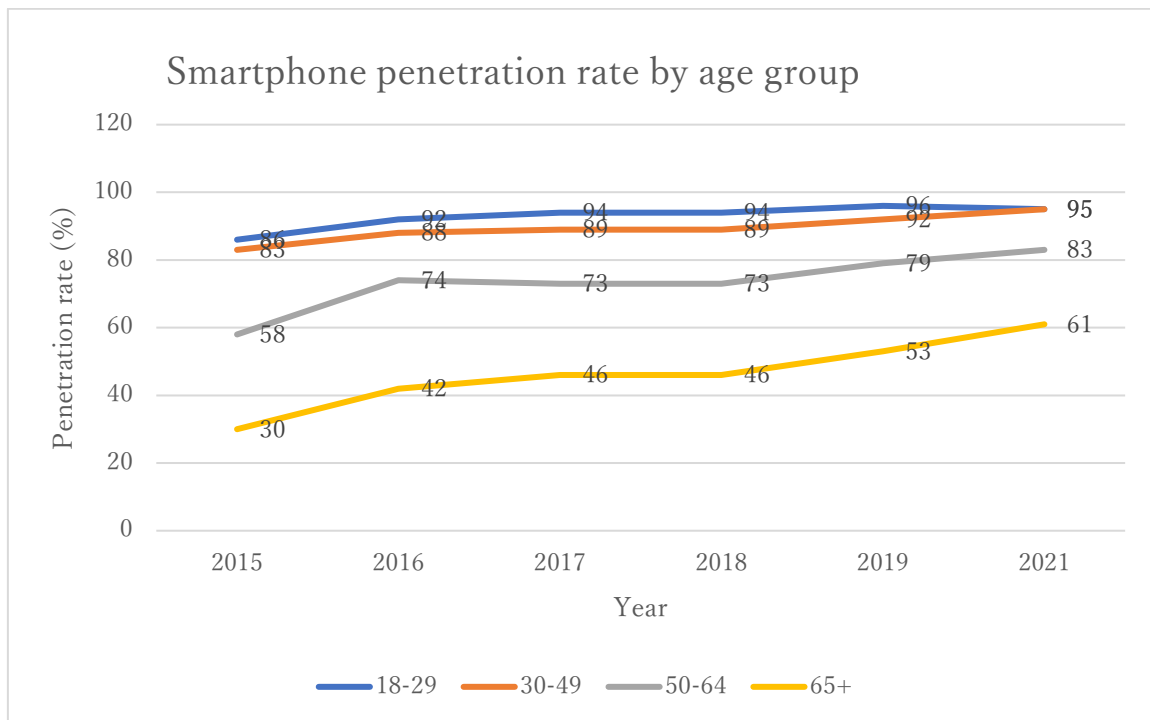


Fig. 1.2 Smartphone penetration rate by age group. Replicated by the author *Source* (Statista)

The introduction of mHealth has transformed our management style of our health. Also, mHealth device and services have allowed us to communicate and cooperate through multiple sectors in the society (Hoque and Sorwar 2017). The global pandemic of coronavirus 2019 (Covid-19) in 2020 reveals a shortage of medical resources in each country. Under these circumstances, the mHealth application can monitor various physical information such as heart rate and behavioral information such as acceleration (ACC) in real time through mobile devices such as smartphones and smart watches. This allows people to check their health at any time and provide a reference data to their medical staff. Therefore, mHealth development can alleviate medical resource shortages to some extent.

Through this phenomenon, to seamlessly link health and medical services has been the initiated by integrating and centrally managing health information and medical information. However, the institutional design requires the intervention of a doctor worldwide for disease diagnosis, and significant deregulation is required to apply IoT and AI technologies to this field of mHealth. For this reason, the introduction of AI in the mHealth field had been failing to replace existing medical services. Under these circumstances, from the beginning of 2020, with the worldwide epidemic of the new coronavirus, general citizens practical use of AI technology in the healthcare has progressed as an emergency measure such as telemedicine and tracking of close contacts.

The challenge to harmonize the conventional regulation to implement AI in the field of mHealth will occur in the future worldwide. In addition, the recent progress in mobile technology, represented by smartphones and smart watches, has been remarkable. The mHealth service, which utilize mobile technology to manage health is becoming to a reality. Although the accuracy of medical devices is not as accurate as those used in medicine, the biometric information such as heart rate and SpO2 can already be monitored over a long period of time. The mHealth technology is maturing to the point where it can be implemented in the society, however, the implementation still remains unapproved as a service of medical care in most countries.

The development and acceptance by the people with the use of mHealth is most active in the US, however, in other countries, the progress is a gradual (Hoque and Sorwar 2017). Researchers from various countries are paying attention to the great potential of mHealth in the medical field. Also, how to rationally develop the mHealth services and products while creating social value is a significant interest to researchers. Therefore, it is necessary to have a deep understanding of current mHealth research trends and hotspots.

In this article, we will first discuss what kind of harmonized regulations are desirable in the global scale by comparing the regulatory reforms necessary to increase practicality and acceptance of mHealth. Since mHealth raises privacy concerns in the US because the usual behavior and biometric information of subjects is utilized by private companies (Joo et al. 2021).

Therefore, it is worth shedding lights on to the regulations to assess the development of AI in the mHealth field. This is because while there are number of health-related apps with the mHealth services have been utilized in the daily life however, there is only small number of apps which are approved by the government according with regulations. In addition to this, the focus of this paper is to identify the factors which can mitigate the challenge faced by the process of implementing regulations appropriate for novel AI technology in the mHealth field effectively and efficiently. While comparatively analyzing the factors including the status of mHealth development, the national regulations, and the social background of each nation including Japan, South Korea, and China with the United States and the European Union as well as analyzing the current research trends in mHealth field. Therefore, the purpose of this article is to bring awareness of safety for general public to utilize AI technologies into daily lifestyles in the future. This article will support the policymakers, researchers and practitioners as well as students who will initiate in developing AI in the field of mHealth.

2. Definition of AI handled in this Paper

The term artificial intelligence (AI) was explicitly proposed at the Dartmouth Conference in 1956. At that time, the proposal for the conference included this assertion: "every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it" (McCarthy et al. 2006). With the recent increase in the amount of data that can be handled, the sophistication of algorithms, and the development of related technologies such as computer performance and storage technology, and cloud computing, the abbreviation AI has become more widely known. AI utilize the behavior and biometric information of subjects collected by smart devices is automatically analyzed by AI technology, mainly machine learning, which is the analysis of a black box. Through many years of technological development, it has led to the realization of decision support systems and smart search systems aimed at complementing and strengthening human abilities. In parallel with the widespread penetration of AI technology into society, the story of robots and systems equipped with AI in Hollywood movies and science fiction novels conquering human society is also depicted. In addition, there are many reports in the media that AI will rob humans of their jobs in the future. However, the current evolutionary stage of AI technology has not reached such level. In this way, in modern society, the word "AI" has various meanings, so the definition of "AI" used in this paper is strictly defined as AI technology. We also want to clarify the scope of applicable medical fields. First, I will briefly outline the word "AI". However, the author specializes in health care, and of course he does research using AI in this specialized field, however, he is not an expert in information engineering or AI. In addition, in the current situation where "AI" has a wide range of meanings and is being defined including philosophical discussions, I will not give an authoritative definition, but only a brief overview of the term "AI" for ease of explanation in this paper.

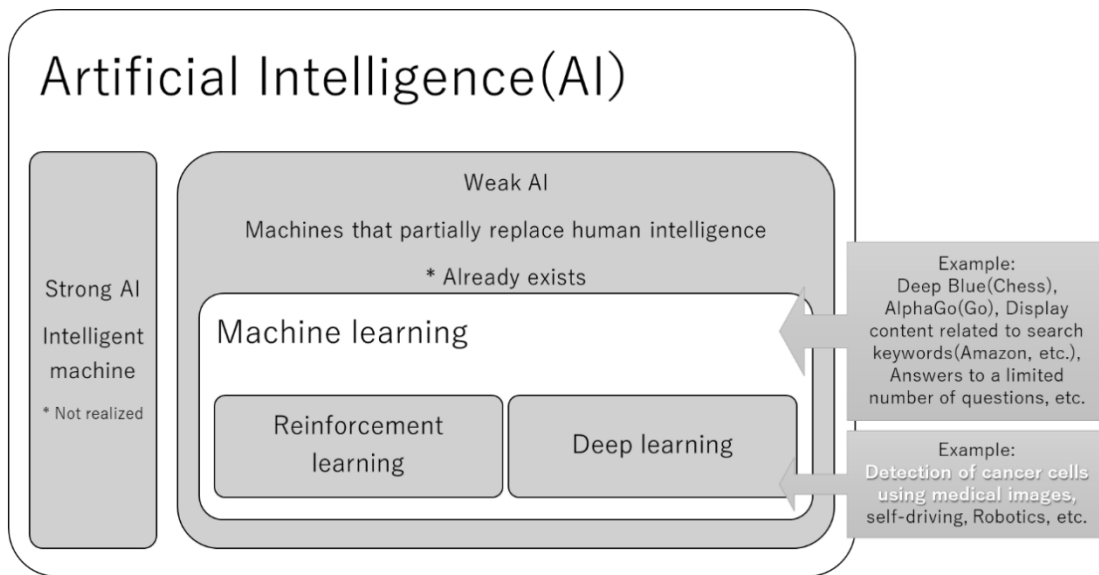


Fig. 1.3 Positioning of AI and related terms in this paper. *Source* Reproduced from McCarthy (2007)

Here, we define the contents of "AI" handled in this paper and outline of the contents. The definitions of "Strong AI" and "Weak AI" in Fig. 1.3 are terms coined by John Rogers Searle, and it is Strong AI that comes to mind when the public, as non-specialists, hear the term "artificial intelligence"(McCarthy 2004) (Searle 1980). From the influence of science fiction novels and movies, it seems that computers that can do human work and have a wide range of knowledge and some self-consciousness are generally regarded as "artificial intelligence". Such "artificial intelligence" ("artificial intelligence" here means Strong AI) has not been realized as of 2021. Currently, the "artificial intelligence" that is being used in society is the Weak AI in Fig. 1.3, and the "artificial intelligence" in this paper, which is a specialized paper, all means Weak AI. The most important technical term in Weak AI is "machine learning".

Machine learning is to identify potentially complex relationships among data, and to use the identified relationships to make predictions about new data (Mohr et al 2017). Machine learning algorithms calculate to support with development of the models with the information called "learning data" that enables predictions and decisions without being explicitly programmed. In the healthcare world, which is the subject of this paper, this characteristic of machine learning is one of the factors slowing down the acceptance of AI in this field.

In the medical field discussed in this paper, AI technology is truly starting to be used in various fields such as treatment, medication, and roentgen image diagnosis. One of the areas where the acceptance of AI technology in the medical field has initially taken place was the use of AI in diagnostic imaging. When radiologist utilize medical images as one of the factors to diagnose a disease, AI can support this process by raising a possible disease from the medical image to support the radiologist. However, it is only used to support the diagnosis, and the final diagnosis

is made by the doctor. In addition, except commercialized products such as pacemaker and implantable defibrillators, it is considered inappropriate from the technical and ethical points of view to replace doctors and medical professionals diagnose with an AI autonomous decision of diagnosing a disease in the current medical system.

For this reason, our discussion area will focus on AI used for disease prevention and health promotion outside of the current medical practice of the healthcare system, or for daily biometric information that cannot be monitored by doctors and other medical professionals, especially AI used in mobile devices.

Interest in application that apply machine learning called AI continues to grow worldwide. The machine learning seeks to atomically learn meaningful relationships and pattern from problem-specific training data to automate the process of analytical model building and solve associated tasks. On the other hand, deep learning is a machine learning concept based on artificial neural network which outperform the shallow machine learning models and traditional data analysis approaches. Deep learning has strength with the large and high dimensional data including text, image, video, speech and audio data. There is a shift from machine learning and deep learning being (Janiesch et al. 2021).

With the addition of the situation where it is becoming easier to collect consumer / patient data from smartphones, etc., there are increasing interests in utilizing these technologies to evaluate the effects and side effects of medicines and to improve the accuracy and adaptability of medical devices.

The AI has potential with the transformation of conventional public health management. According to Khan and Alotaibi, health professionals have the benefits of improving their gathering the data. For instance, the conventional reporting methods for patients were through communication and questionnaires. Which were self-administered. On the other hand, utilizing mobile devices can successfully monitor the patient's behavior which enhance the quality with assessing the clinical data (Khan and Altoibi 2020).

Practical case study has revealed the possibility of dramatical change with the Parkinson's disease (PD) in the upcoming years. Worldwide implementation of the patient-controlled electronic health record (EHR) and the technology-based home monitoring system will be the cornerstones of this revolution. This research has raised the future direction with combining the digital database's location to be homes, hospitals, doctors' practices, and research institutions. These phenomena will achieve in personalized care at an entirely new level (Hansen et al. 2018). The combined data will provide personalized diagnosis and improve knowledge about individual disease course and treatment response. According to mHealth HUB, AI has multiple benefits from different aspects. For medical experts, mHealth allow monitor and measure the patient's heart rate and glucose levels, early prediction of medical conditions such as heart attacks from the data

collected 24/7 on person's heart rate, sleep cycle, breathing data, active level and blood pressure. For the patients, it allows them to manage their health and gain healthcare support through providers with solutions. Also, getting a hospital appointment reminder (mHealth HUB). There are number of benefits through AI in the mHealth sector. The practical use is still in the early stage of its development process. The research and assessments will be crucial for this dramatical transformation for public health care to be generally utilized in the daily lifestyle.

3. Expected Market Size and Utility of mHealth

mHealth is the abbreviation for mobile health. mHealth utilize mobile devices, such as a cellphone or a tablet to support with healthcare. While utilizing mHealth services, it is possible for the patients to monitor their health records with their devices (SBMA). This is useful in improving the effectiveness of health care delivery. Additionally, there are number of health-related apps. The global related market is also growing and according to the medical devices market report published by Lucintel in April 2018, the medical devices market is expected to grow at a CAGR of 4.5% from 2018 to 2023 (Cision 2018). The market size is estimated to reach \$ 409.5 billion in 2023, creating investment opportunities and progress prospects in this area. However, medical products have traditionally been developed under very strict regulations because they have a direct impact on human health and life. In mHealth, which is a medical system that utilizes mobile wireless devices, it is possible to approach patients without going through a medical staff, and the AI algorithm used for that judgment.

Many countries have yet to determine how to regulate the fact that algorithms are continually updated based on the existence of new data sets by their nature and cannot be dealt with by traditional management methods. This makes it difficult for new entrants to comply with regulations. To overcome this challenge, governments have already started working on special legislative systems for AI-based medicine. One of the key initiatives in this area is the activities of the US, Food and Drug Administration (FDA), which began its consideration in April 2019.

The FDA advocates a Total Product Life Cycle (TPLC) that includes post-implementation monitoring to accommodate AI-based medical services that could adapt and improve using user data (FDA 2019). This approach enables product reviews and monitoring from pre-market to post-market launch, allowing continuous review to match the operator's internal policies and level of operational excellence. The FDA has set up a Breakthrough Devices Program in the 2016, 21st Century Cures Act to promote the practical use of the innovative devices, as well as clarifying the distinction between types that should be treated as truly medical devices and those that do not require regulation. It shows the intention to eliminate the innovation hindrance due to its ambiguity.

The mHealth are gaining attention by the mental health sector since mental health is the serious illness with effective treatment methods have been provided with mental health cure application for all the stages of clinical needed, from immediate crisis intervention, prevention, diagnosis, primary treatment, supplement to in-person therapy and post treatment condition management (Chandrashekar 2018).. According to the research, in the United States alone tens of millions of people are affected by the mental health disorders and only half of those receive treatments (Sort 2017). Even though, mental illness is curable disease, only half of the people actually receive the care needed. Utilizing mHealth, it will effectively overcome challenges to receive treatment with mHealth. The factors such as ease of habit, low effort expectancy and high hedonic motivation as well as cost effective can provide scalable solution to address the mental health solutions (Chandrashekar 2018). Fig. 1.4 shows the number of clinical trials started in Clinicaltrials.gov., But the number of clinical trials for psychiatric disorders is increasing year by year. According to the World Health Organization (WHO), depression alone affects at least 300 million people worldwide and causes hundreds of billions of dollars in economic losses each year in the United States (WHO 2017).

Despite treatments and social services, many people with mental illness tend to avoid seeing them for fear of degrading their social reputation. To support such patients with mental illness, mobile applications are being developed to perform therapeutic intervention while maintaining the privacy of patients (Depp et al. 2010). In these services, a 24-hour automated conversation program listens to patients and provides support and advice as needed. These are highly dependent on machine learning, deep learning, etc., and there are concerns among regulators in terms of the above-mentioned continuous change and the delicacy of the value provided.

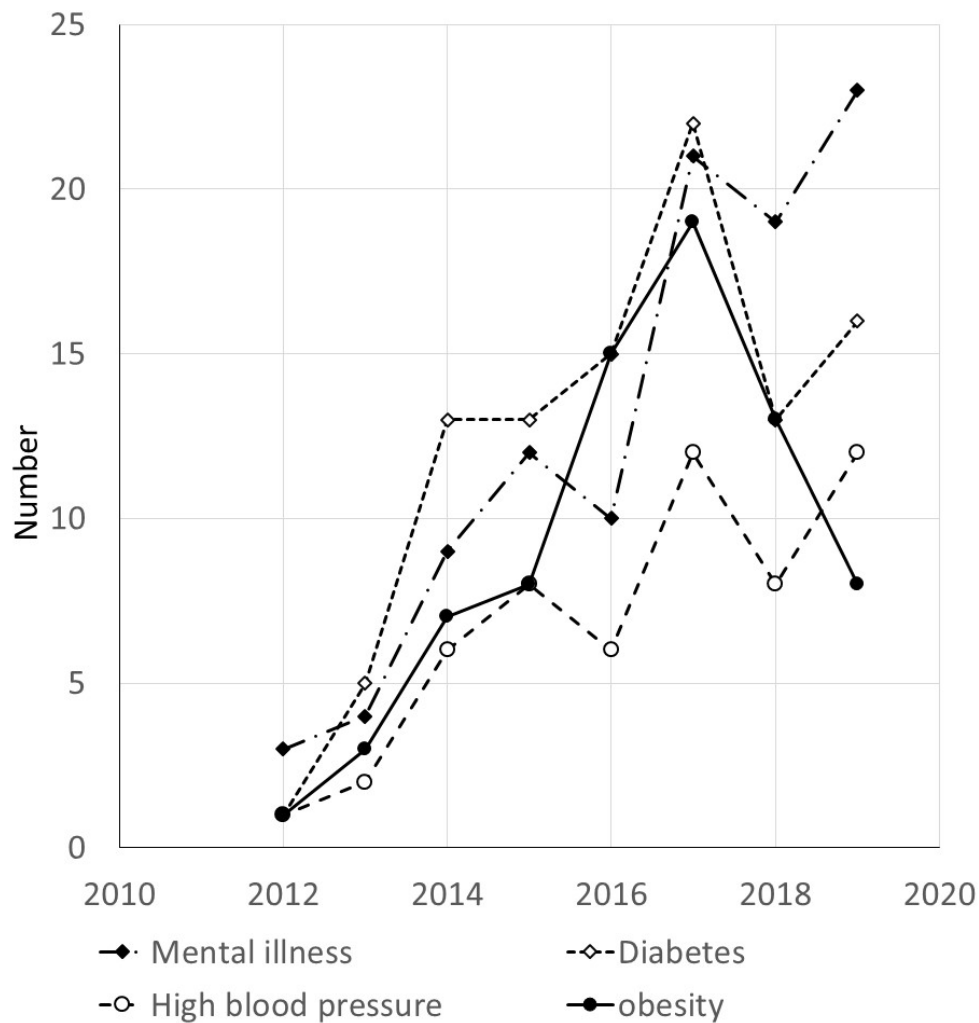


Fig. 1.4 Number of mHealth-related clinical trials initiated by disease. Replicated by the author from ClinicalTrials.gov *Source* (Clinicaltrials.gov)

4. Literature Review

Currently there are few papers on bibliometric analysis of mHealth-related literature. Among the few, Sweileh searched Scopus for articles on mHealth published between 2006 and 2016, analyzed the increase in publications and citations by data visualization, and used bibliometric indicators to clarify research efficiency (Sweileh et al. 2017). As a result of the research, it was found that among the related papers on mHealth, there are many keywords related to diabetes, medication adherence, and obesity. The study also found that the mHealth literature has grown exponentially.

As of 2016, Shen collected 2,704 mHealth-related papers from the Web of Science database (Shen et al 2018). Although different from the database Sweileh searched, the results of the two

studies were similar in that the United States was found to be the most active country which regarded from the number of the publication in the mHealth research field published worldwide. There was also an exponential growth trend in the papers on mHealth in Web of Science database. By identifying keywords, mHealth research hotspots were categorized into four main areas: (1) Patient Engagement and Patient Intervention, (2) Health Monitoring and Self Care, (3) Mobile Devices and Mobile Computing, (4) Security and Privacy.

The results of a bibliometric analysis of mHealth-related literature by Peng were recently published in 2020. Peng focused on a treatise related to the mHealth app (Peng et al 2020). They collected a total of 2,802 papers published between 2000 and 2019 from the Web of Science. The status of research on mHealth apps, research trends, hotspots, co-authored networks have been clarified.

However, there are still gaps in the bibliographic analysis of mHealth research from 2017 to 2020. Both Sweileh's and Shen's studies point to an exponential growth trend in publications on mHealth studies (Sweileh et al. 2017), (Shen et al. 2018). Therefore, we can predict that the number of mHealth-related publications will increase exponentially from 2017 to 2020. In fact, the number of publications from mid-2017 to 2020 is higher than ever. For this reason, we thought it is necessary to re-examine the bibliographic analysis of mHealth studies from 2000 to 2020. Another reason for choosing 2000-2020 as the analysis period, not just 2017-2020, is that the 2000-2020 period analysis is to identify research hotspots and research trends in this area. This is because the average publication year of the author keyword can be grasped more intuitively.

5. Methods

5.1. Bibliometric Analysis

Bibliometrics can quantify comprehensive textual information and provide a variety of numerical statistics on the evolutionary process of a particular topic (Daim 2006). The quantified information also helps scholars identify future trends in the subject. Bibliometrics is widely used in academia, especially for detailed analysis of journal articles. In recent years, researchers have developed many bibliographic analysis tools that meet the needs of bibliographic analysis and enrich bibliographic processing. For example, analysis of co-authors' countries / regions and research institutes to elucidate partnerships between different countries / regions or research institutes, for co-occurrence analysis to identify research hotspots. Keyword extraction, keyword clustering analysis to identify the direction of major research in a field. In this way, Bibliometrics plays an important role both in providing an overview of the past and in predicting the future.

5.2. Data Collection

The first step in data collection in Bibliometrics analysis is to collect primary source metadata. This metadata may include the title of the article, abstracts, author keywords, author information, country, and references. In this study, we collected data from mHealth-related papers published between 2000 and 2020 from the Web of Science database (Agarwal et al. 2016). The Web of Science database was chosen because it covers a wide range of research, including 21,000 peer-reviewed high-quality journals. In addition, the Web of Science includes six high-impact citation databases in its core collection, including the Science Citation Index extension, the Social Science Citation Index, and many regional databases. In this way, the reliability of the database was guaranteed.

As with most studies, using mHealth and its synonyms as search topic keywords (search by title, abstract, author keyword) to find potential publications related to mHealth, we conducted publication searches. However, this simple approach has major limitations. As Sweileh suggested, for reasons such as personal understanding and habits, many researchers might not recognize that their treatises focus on mHealth when introducing mHealth-related treatises (Sweileh et al. 2017). Therefore, the second search strategy was also used in this study. Because mHealth depends on a variety of mobile devices, we searched for author keywords related to both mobile devices and mHealth (smartphones, mobile phones, etc.), and general health (health, healthcare, etc.). Prioritizing author keyword search over topic search, the latter may include articles that do not focus on mobile device and health research. The former, on the other hand, is a keyword that the author presents to emphasize the content of the treatise. Therefore, if the author keywords include both "mobile device" and "health", the author can be considered to emphasize the treatises on these keywords. In this way, we decided that it would be more appropriate to search by author keyword to ensure the reliability of the data.

In addition, all search strategies set the search year range from 2000 to 2020, and searched only articles published in English. Documents were collected on March 2, 2021. The first search strategy yielded 6,604 search results, and the second search strategy yielded 7,037 search results. Of these, 1,048 documents were duplicated in the search results of the two search strategies, and the duplicated parts were deleted to finally collect 12,593 documents. The specific search process is shown below (Fig. 1.3).

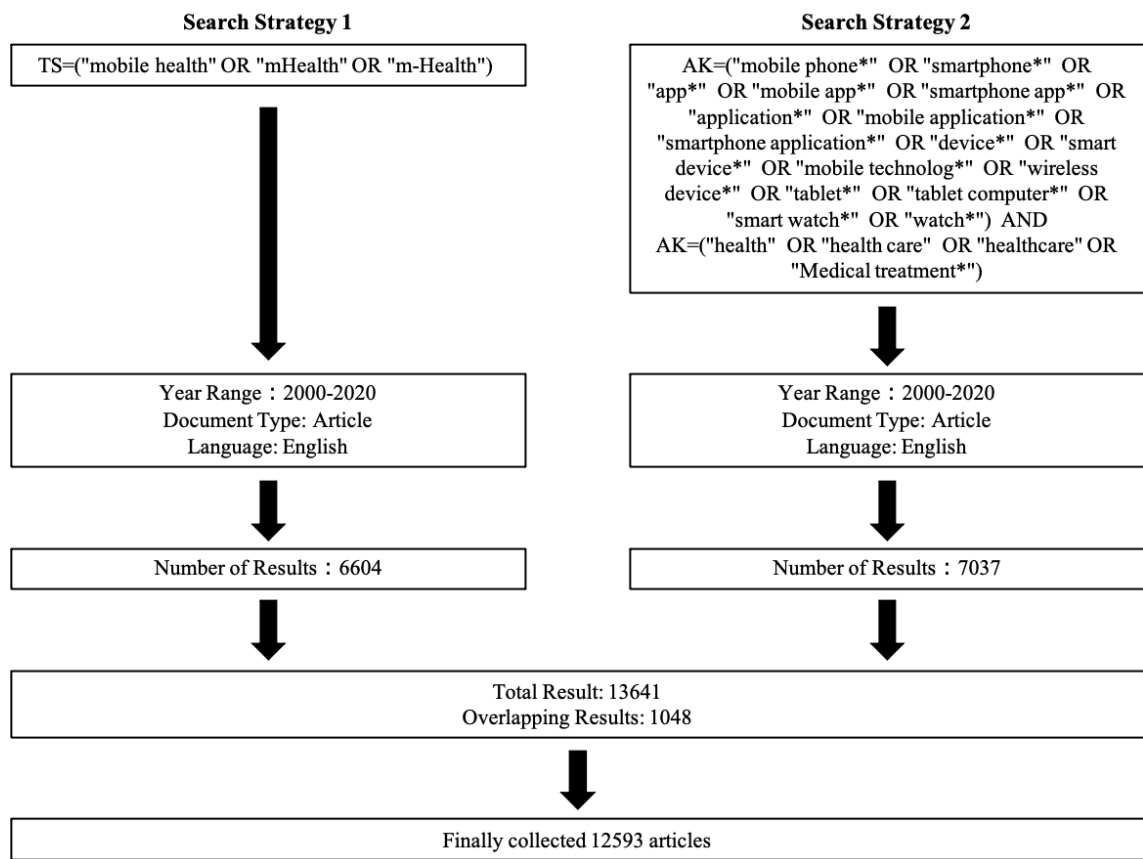


Fig. 1.5 Data collection strategy for the bibliometric analysis of mHealth research. Replicated by the author from web of science.

Source (WOS)

5.3. Data Analysis

In this study, we used VOSviewer version 1.6.15 as a data analysis tool. Of the many tools applied to Bibliometric analysis, mapping and clustering techniques that provide insight into network structure are usually used together as the most common combination (He and Hui 2002), (Uribe-Toril et al. 2021). However, these two technologies are usually developed independently of each other and rely on different ideas and assumptions. Waltman combined the two and proposed a unified mapping approach and clustering that applies to VOSviewer. With powerful data processing and data visualization capabilities, this analytical tool has been applied to many disciplines of bibliometric analysis (Waltman et al. 2010b).

In this study, we first calculated the annual number of papers and the annual growth rate and observed the publishing tendency of mHealth-related literature. Furthermore, we analyzed the tendency of treatises by country / region and the distribution of treatises by journal based on the number of papers. We created various bibliometric maps using VOSviewer. In addition, to clarify the hot spots of research in the field of mHealth, we visualized this network based on co-

occurrence keywords created from author keywords, classified research topics by clustering analysis of author keywords. Finally, we analyzed research trends by visualizing the average year of publication of keywords.

6. Results

6.1. Number of Publications in the mHealth Field

We analyzed the annual growth trends of the treatises according to the search strategy described above (Table 1.1, Fig. 1.6). As a result, it was found that the number of papers related to mHealth has increased since 2004 and shows a similar exponential growth trend. Applying this to the exponential formula, the growth curve of the literature is $y = 37e^{0.3062x}$, $R^2 = 0.9935$, where x is the number of years of growth since 2000 and y is the cumulative number of treatises. Specifically, 2015 was a turning point. The number of documents published in 2015 increased by 366 compared to 2014, and the annual growth rate reached 61%, the highest annual growth rate in the last 20 years. Overall, the mHealth literature has a compound annual growth rate (CARG) of 25%, indicating that the mHealth field is drawing the attention of scholars.

Table 1.1 Descriptive statistics of the collected mHealth literature. Replicated by the author. *Source* (WOS)

Year	NP ^a	AG ^b	AGR ^c	CNP ^d
2000	37	-	-	37
2001	29	-8	-22%	66
2002	41	12	41%	107
2003	37	-4	-10%	144
2004	50	13	35%	194
2005	77	27	54%	271
2006	86	9	12%	357
2007	96	10	12%	453
2008	123	27	28%	576
2009	158	35	28%	734
2010	184	26	16%	918
2011	236	52	28%	1,154
2012	302	66	28%	1,456
2013	437	135	45%	1,893
2014	603	166	38%	2,496

2015	970	367	61%	3,466
2016	1,206	236	24%	4,672
2017	1,383	177	15%	6,055
2018	1,725	342	25%	7,780
2019	2,132	407	24%	9,912
2020	2,681	549	26%	12,593

^aNP = number of publications

^bAG = annual growth

^cAGR = annual growth rate

^dCNP = cumulative number of publications

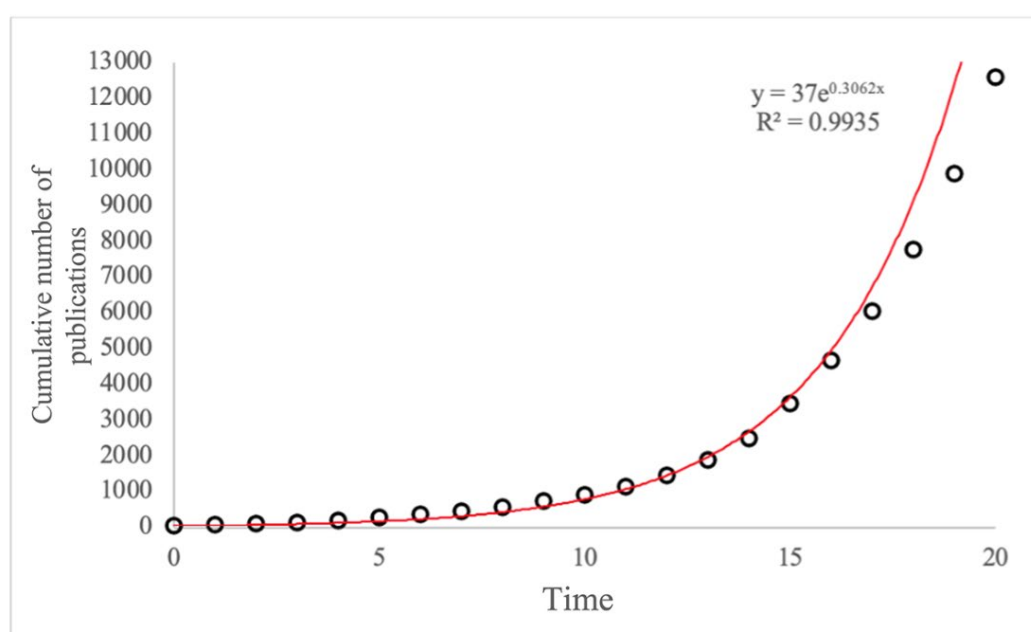


Fig. 1.6 Growth curve of the cumulative number of publications in mHealth literature. Source (WOS)

6.2. Number of Publications in Countries and Regions

As a result, it was found that researchers in 166 countries / regions contributed to publications on mHealth. Compared with the previous bibliometric analysis, the United States remains the country with the most publications, accounting for 42% of the total (5,294 / 12,593). The United Kingdom came in second with 1,372 cases, accounting for 11% of the total (1,372 / 12,593 cases). Australia (979 / 12,593, 8%), China (842 / 12,593, 7%) and Canada (828 / 12,593, 7%) are closely followed. It also shows the changes in the annual number of papers in the top 10 countries / regions since 2000 (Fig. 1.7). As can be seen from the change curve in Fig. 1.7, the growth curve

of the United States shows explosive growth compared to other countries. This reflects the early focus of American researchers on mHealth and is still of increasing interest. The annual number of treatises in other countries / regions is increasing, though not as much as in the United States.

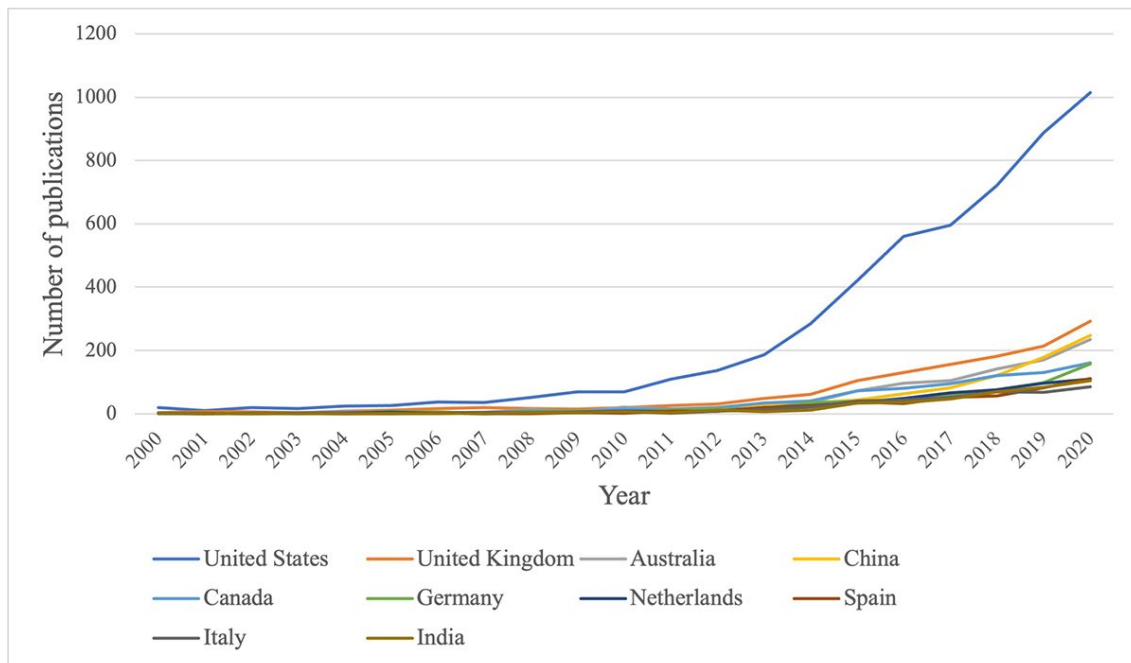


Fig. 1.7 Comparison of the growth trends of mHealth-related research publications in various countries between 2000 and 2020. *Note* Due to research cooperation between scholars of different nationalities, some papers have been counted more than once.

Replicated by the author. Source (WOS)

6.3. Partnering Networks of Countries and Regions

A visual network diagram showing partnerships between countries / regions is shown in Fig. 1.8. This shows the partnerships of the top 50 countries in terms of publication volume. The size of the circle indicates the number of publications. The larger the circle, the greater the number of publications. The length and thickness of the link between circles indicates the strength of partnership between countries. In general, the closer the two circles are to each other, the thicker the link and the stronger the relationship between the countries / regions. Different colors indicate different clusters, and circles belonging to the same cluster usually have similar properties and characteristics. All countries in the figure are linked to the United States, which means that all countries are in partnership with the United States. From Fig. 1.8, we can see that the network diagram has a triangular shape, with the four countries occupying the center of it: the United States, the United Kingdom, Canada, and Australia. In other words, of the top five countries with the largest number of treatises, these four countries were located in the center of the network

diagram, and the distances between the nodes are almost the same. This suggests that these four highly productive countries have strong cooperation. Furthermore, from the position of the country node, the cooperative relationship between countries / regions is clear, such as the Asian countries / regions represented by red clusters and the European countries / regions represented by green clusters.

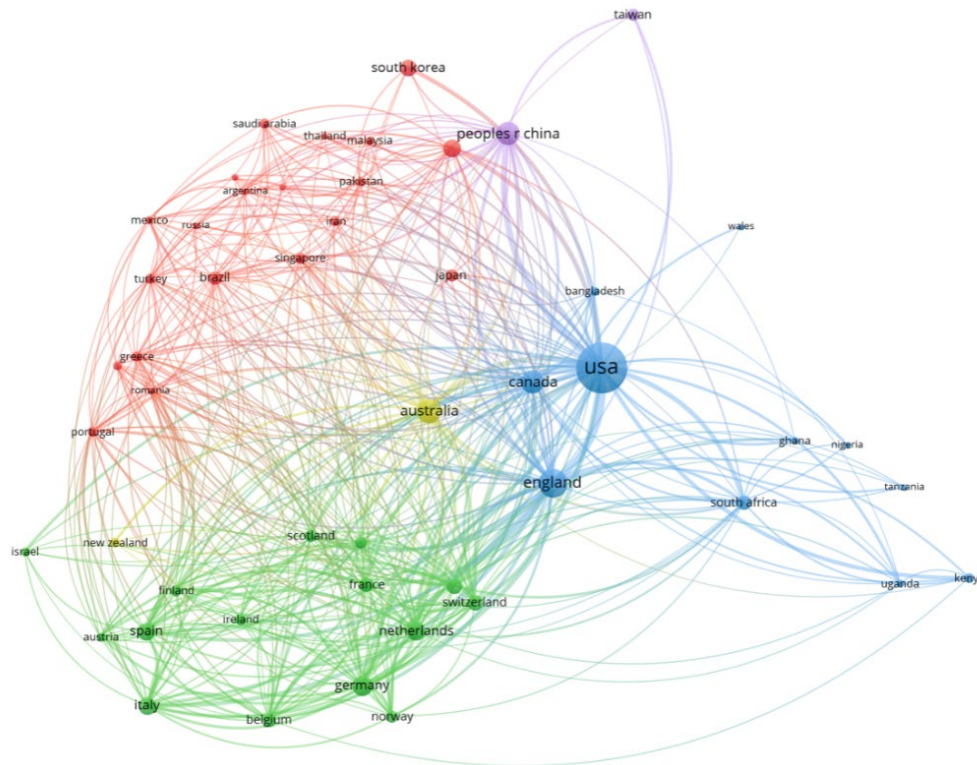


Fig.1.8 Visual network diagram of cooperation between countries/regions. Replicated by the author. Source (WOS)

6.4. Top Journals in the mHealth Field

According to the search results, the literature related to mHealth was distributed in 3,268 journals. Table 1.2 shows information on the top 10 journals by number of publications. Of the top 10 journals, the Canadian Journal of Medical Internet Research and its sister journals, JMIR mHealth and uHealth, JMIR Research Protocols, and JMIR Mental Health, fall under this category. The number of joint publications is 1,763, accounting for 14% of all publications. In addition, the impact factor of the top 10 journals excluding JMIR Research Protocols exceeds impact factors of 2.

Table 1.2 Top 10 journals in terms of the number of publications of mHealth literature between 2000 and 2020.

Replicated by the author. Source (WOS)

Rank	Journal	Country	Two-year impact factor (2019)	NP ^a	% of 12,593, i.e., total number of articles
1	JMIR mHealth and uHealth	Canada	4.31	956	7.59
2	Journal of Medical Internet Research	Canada	5.03	463	3.676
3	JMIR Research Protocols	Canada	-	235	1.866
4	Telemedicine and Health	The United States	2.841	202	1.604
5	International Journal of Environmental Research and Public Health	Switzerland	2.849	145	1.151
6	BMC Public Health	The United Kingdom	2.69	139	1.104
7	JMIR Mental Health	Canada	3.54	109	0.865
8	International Journal of Medical Informatics	Ireland	3.025	106	0.842
9	BMC Medical Informatics and Decision Making	The United Kingdom	2.317	101	0.802
10	Sensors	Switzerland	3.275	99	0.786

^aNP = number of publications

Author keywords are commonly thought of as abbreviations for the topic of a treatise written by the author. Author keyword co-occurrence analysis can accurately provide hotspots for current research in the field. In this study, we used VOSviewer's author keyword co-occurrence analysis and set the minimum number of co-occurrences to 50. Keywords with mHealth and smartphones, and keywords with similar meanings to mHealth and smartphones, appeared frequently in search strategies and occupy a large weight in the co-occurrence network graph. We've removed the keywords used in the search strategy displayed in the search results because such keywords are likely to affect the distribution of the remaining keywords. In addition, we intended to pinpoint the buzzwords of more valuable research topics. Then, we extracted the top 100 keywords and mapped them to the keyword co-occurrence network. The result of the keyword contribution network graph is shown in Fig. 1.9.

The top 100 keywords were classified into 5 clusters by keyword clustering analysis, and the top 10 keywords with co-occurrence frequency are shown in Table 1.4. The average year of publication of the keywords shown in Table 1.4 was 2015.26 to 2017.90, and the average number of citations was 10.75 to 17.98. The most frequent keyword was "mental health", with 449 co-occurrences, followed by "physical activity" with 285 co-occurrences.

6.5. Top Keywords and Networks of mHealth publications

Table 1.3 Top 10 author keywords of mHealth research between 2000 and 2020. Replicated by the author. Source (WOS)

Rank	Keyword	Cluster	Occurrences	Average year of publication	Average number of citations
1	mental health	Purple	449	2017.30	12.48
2	physical activity	Blue	285	2017.46	14.00
3	health promotion	Green	243	2015.26	14.97
4	self-management	Red	234	2017.90	10.75
5	public health	Red	232	2016.29	13.41
6	depression	Purple	227	2017.51	17.98
7	HIV	Yellow	208	2017.57	11.37
8	text messaging	Yellow	207	2016.90	13.22
9	obesity	Blue	173	2016.65	13.81
10	adherence	Yellow	157	2017.48	13.85

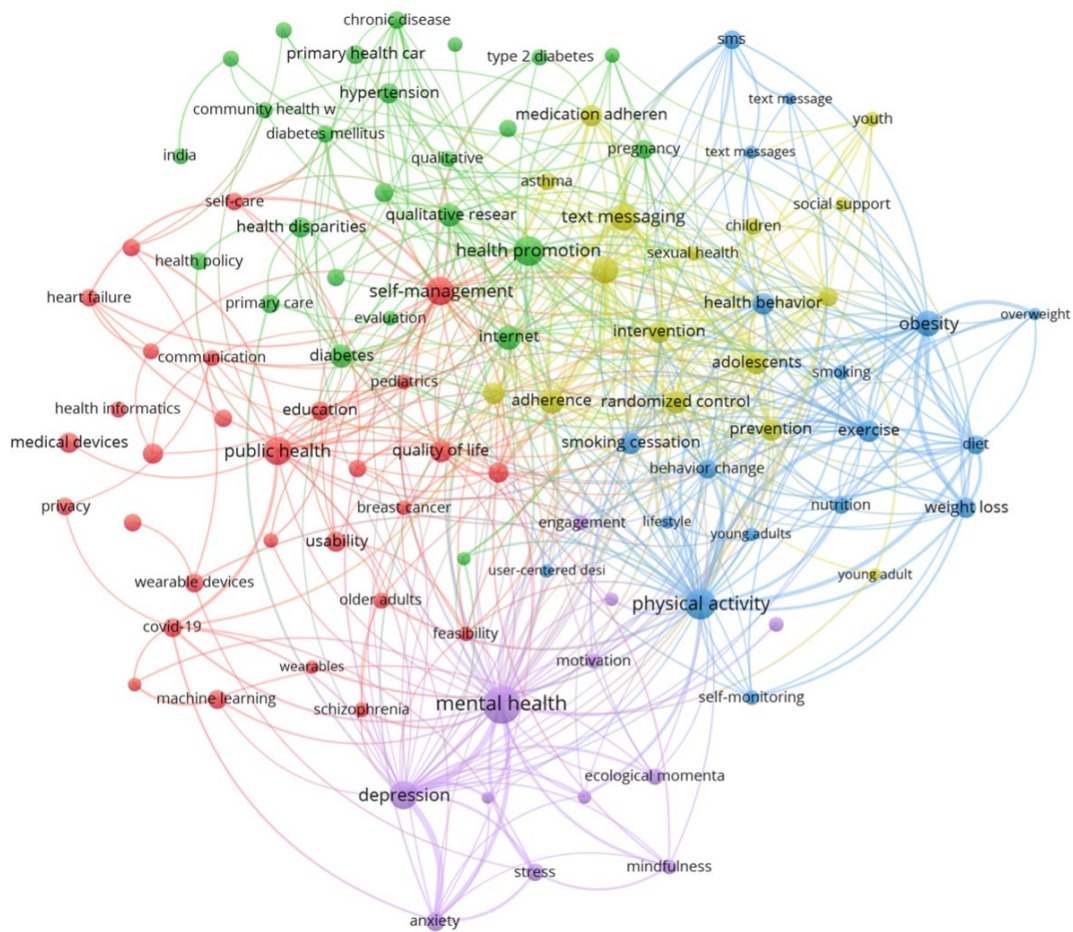


Fig. 1.9 Co-occurrence network diagram of the top 100 author keywords in mHealth research between 2000 and 2020. Replicated by the author. Source (WOS)

From the average year of appearance of keywords, it is possible to infer the secular change of mHealth research hotspots. The top 100 author keywords appearing in Fig. 1.8 are visualized in Fig. 1.9 according to the average publication year. The size of the node indicates the number of times the author's keyword has appeared, and the color of the node is gradually distinguished according to the average year of publication. As shown in Fig. 1.9, the more node displayed in yellow gradient, the higher the average publication year of the keyword. Table 1.5 shows the top 15 and bottom 15 author keywords. The average publication year range for the top 15 author keywords are 2017.98 to 2020.05, and the frequency range is 41 to 135 times. Of the top 15 keywords, 8 belong to cluster red, 5 belong to cluster purple, 1 belongs to cluster yellow, and 1 belongs to cluster green. The average publication year range of the bottom 15 author keywords is 2015.26 to 2016.19, and the appearance range is 46-243. Of the bottom 15 keywords, 10 belong to Cluster Green, 2 to Cluster Red, 2 to Cluster Yellow, and 1 to Cluster Purple.

Table 1.4 Comparison of the top 15 and bottom 15 author keywords. Replicated by the author. Source (WOS)

Top 15 author keywords				Bottom 15 author keywords			
Cluster	OC ^a	APY ^b	Keyword	Keyword	APY ^a	OC ^b	Cluster
Red	86	2020.05	covid-19	health promotion	2015.26	243	Green
Red	41	2019.05	artificial intelligence	primary healthcare	2015.35	95	Green
Red	43	2018.79	wearables	health policy	2015.40	81	Green
Red	85	2018.55	machine learning	evaluation	2015.45	55	Green
Purple	42	2018.54	gamification	children	2015.53	80	Yellow
Red	47	2018.48	feasibility	medical devices	2015.58	103	Red
Red	87	2018.31	wearable devices	prevention	2015.79	117	Yellow
Purple	67	2018.26	ecological momentary assessment	health disparities	2015.82	97	Green
Yellow	135	2018.24	randomized controlled trial	internet	2015.84	152	Green
Red	69	2018.22	internet of things	focus groups	2015.94	50	Green
Purple	54	2018.16	mindfulness	primary care	2015.97	87	Green
Purple	45	2018.09	sleep	developing countries	2016.00	67	Green
Purple	93	2018.05	anxiety	well-being	2016.07	46	Purple
Green	59	2018.04	qualitative	health informatics	2016.15	59	Red
Red	55	2017.98	schizophrenia	health education	2016.19	84	Green

^aOC = occurrences^bAPY = average publication year

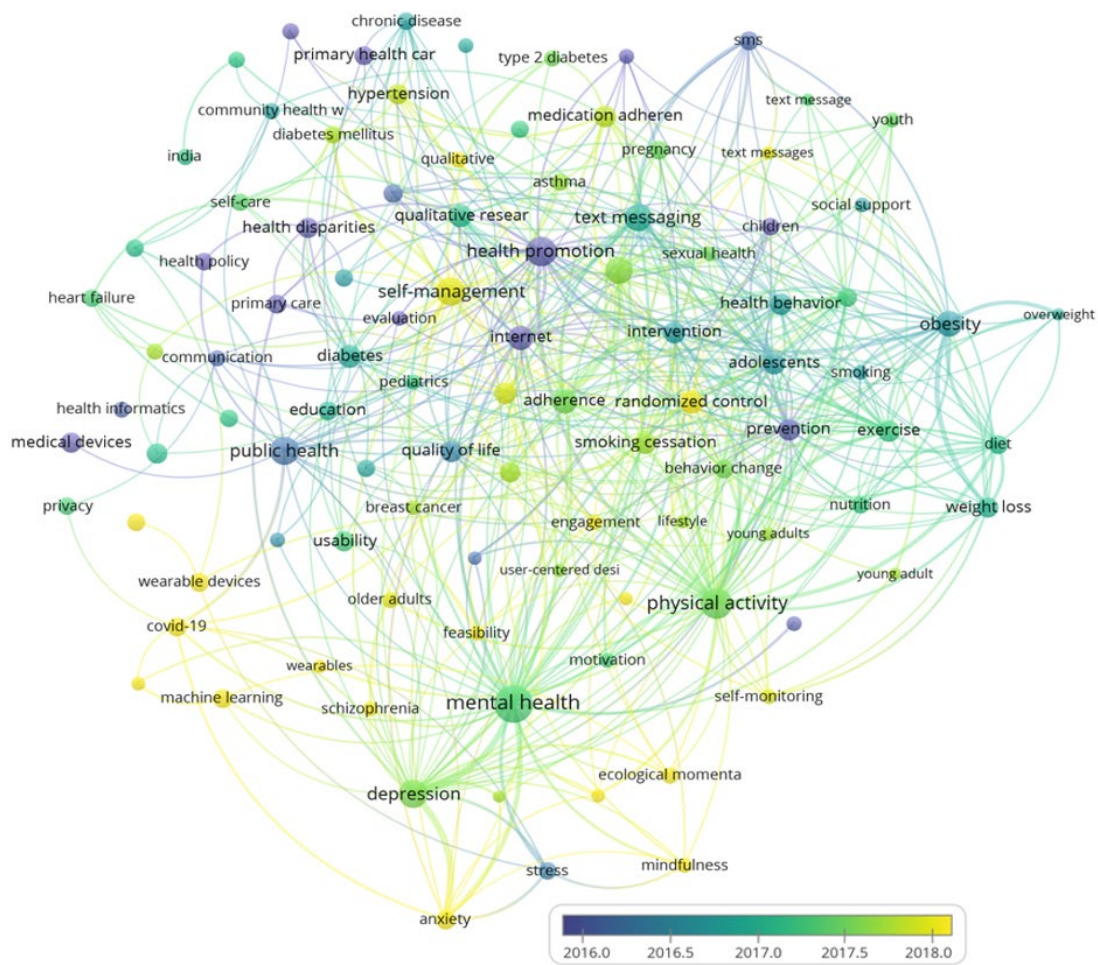


Fig 1.10 Overlay visualization maps of the average publication year of the top 100 author keywords. Replicated by the author.

Source (WOS)

In addition, to better understand the direction of AI-related research in the mobile health field, we focused on AI and narrowed down the research targets from the above research results using the procedure shown in Fig. 1.8. After manual checking, we finally came up with 555 related articles.

Looking at Fig. 1.11, we can see that machine learning is the most frequently used related keyword in AI-related articles in the field of mobile health. In addition, Fig. 1.11 and 1.12 show that the overall average of high-frequency author keywords appearing in AI-related articles is after 2017. The author keywords are divided into eight clusters, with machine learning and deep learning at the center. In addition, the new keyword covid-19 has appeared and belongs to a high frequency vocabulary. In addition to covid-19, the newest average keywords are monitoring, digital phenotype, and digital health.

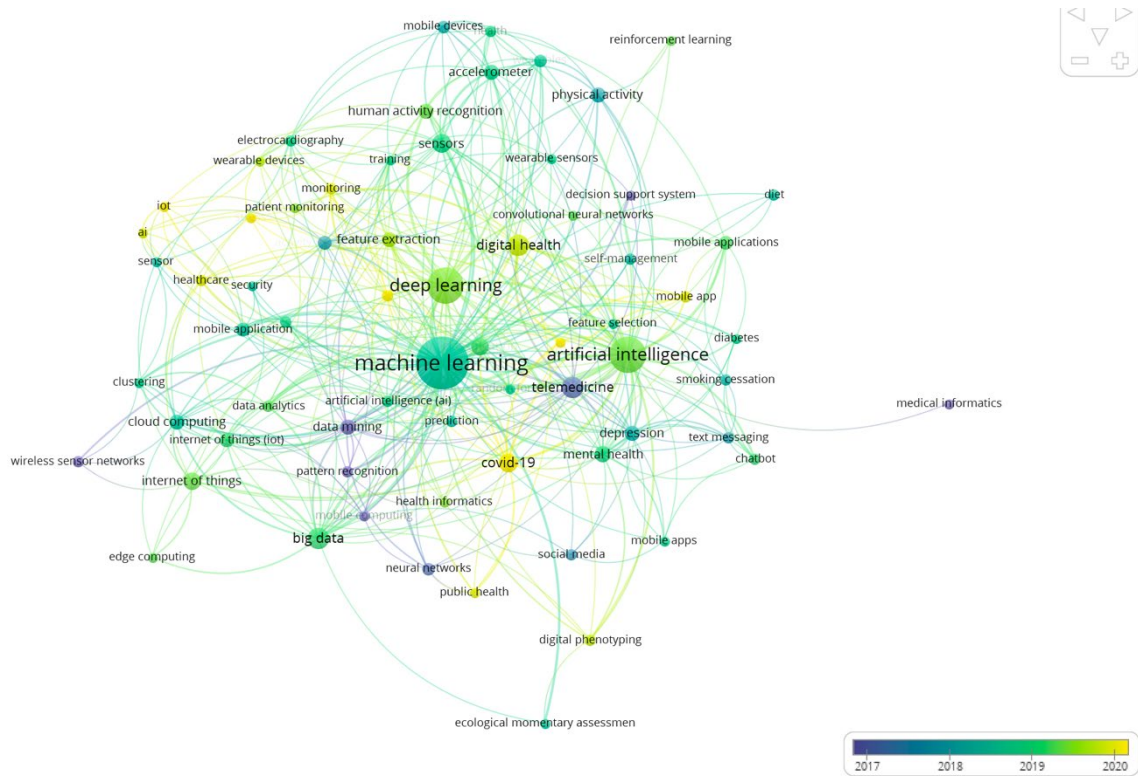


Fig. 1.13 Keyword co-occurrence network appeared according to Average year 2000-2020. Replicated by the author. Source (WOS)

6.6. Chronological Trends of mHealth Publication in Countries and Regions

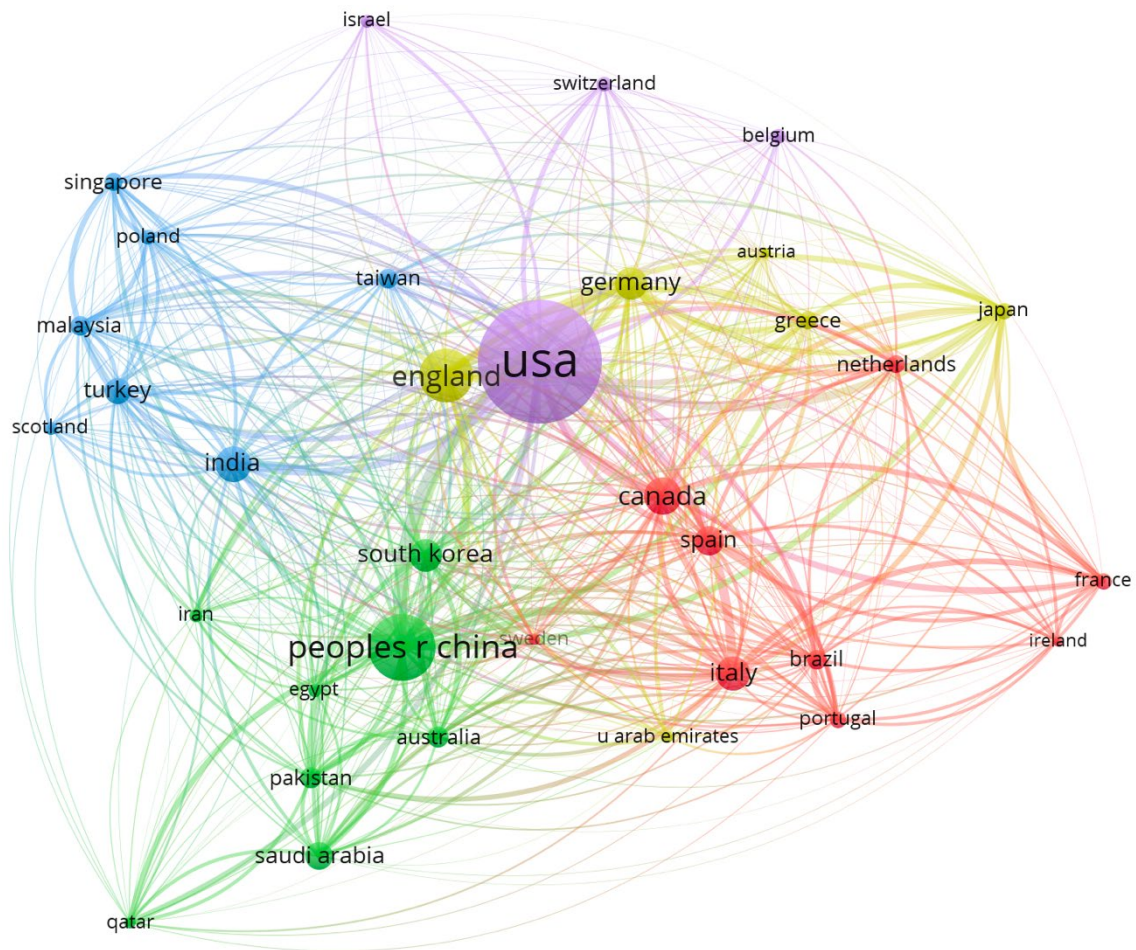


Fig. 1.14 The co-occurrence network of related of country

In European countries such as the United Kingdom, Spain and Italy, the annual number of papers has not been increasing, and the average number of papers per year is relatively small. Conversely, Asian countries such as Singapore, India, and South Korea are growing more than before as emerging countries. Perhaps development will be more active in countries that are trying to make effective use of such information than in countries that have regulations that take personal information and security into consideration.

AI technology, which has the characteristic of black boxing the personal information, which has the unpleasant feeling that the content of it has not fully understood, however the advantage is that personal information is mixed into as a main information and individuals' information cannot be identified.

According to the results, it is suggested that the development of mobile health and AI is mainly based on the development of machine learning. In the cooperation between mobile health and AI countries, there is a good tendency for countries on different continents to work closely together, which will undoubtedly promote the rapid development of this industry.

Asian countries such as China are gradually paying attention to this field and are becoming emerging forces in the development of mobile health and AI. This phenomenon is very exciting as Asia has a huge population base and continues to suffer from medical and health problems. This trend is expected to accelerate the rapid development of mobile health to the stage where commonly used in the daily life. And it is thought to bring new solutions to medical and health problems.

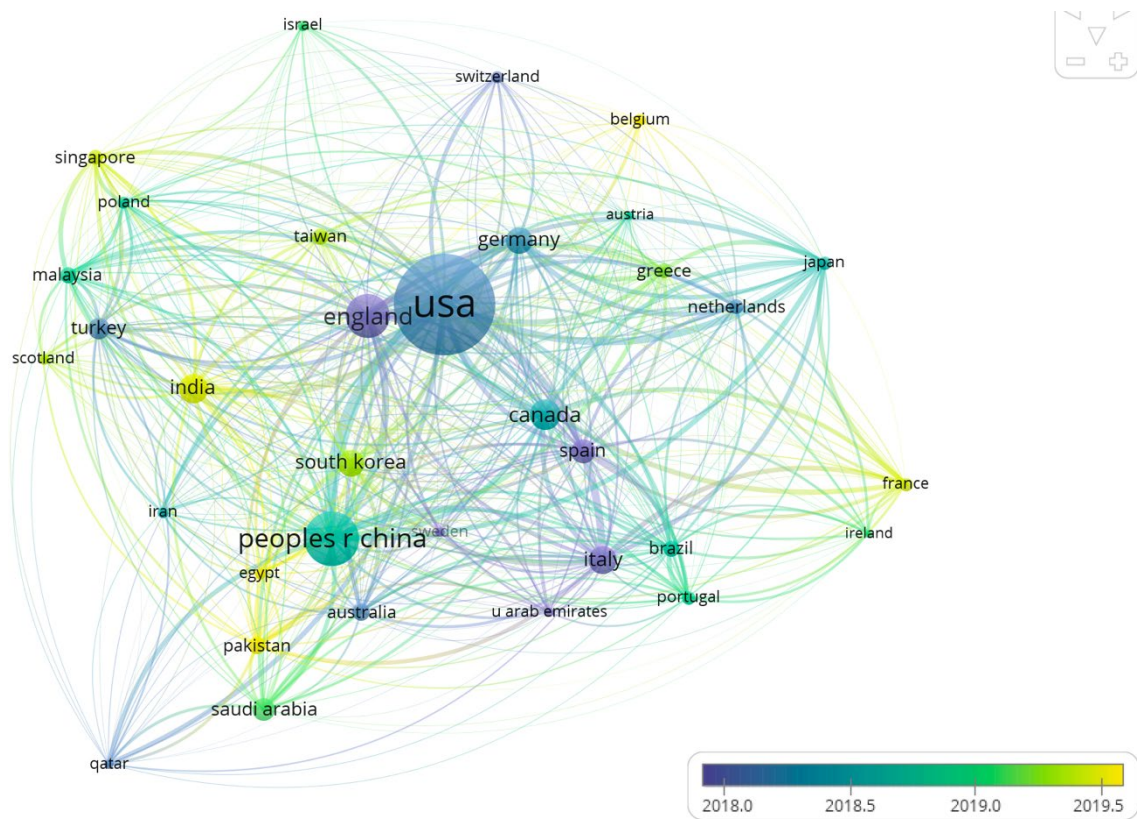


Fig. 1.15 The co-occurrence network of related of country, average year from 2000-2020. Replicated by the author. *Source* (WOS)

7. Discussion

This provides a bird's-eye view of trends in the development of mHealth and related AI technologies by conducting a bibliometric analysis of literature published in the field of mHealth research. As a result, the tendency of publication of mHealth research papers, cooperation between countries, research hotspots, research trends in this field, etc. were clarified.

The advent of mHealth is a major innovation in the rapid development of information technology. mHealth has avoided location issues and disruptions to medical resources in traditional health care, giving more people access to health care. According to the logical curve of literature growth published between 2000 and 2020, the trend of cumulative publications is similar to the exponential curve. Based on Rogers' theory of innovation dissemination, it can be inferred that the development of mHealth technology is currently in the early stages of rapid growth. It is also expected that mHealth technology will continue to attract academic attention and make great progress in the healthcare field.

7.1. Key take-aways from each of the analysis

The following section will depict each analysis take-aways. First is the number of the publications in the mHealth literature. There is an exponential growth trends in the mHealth research since 2004 with the annual growth rate of 35%. The compound annual growth rate is 25% therefore, it is clear that research in the mHealth field is drawing its attention of scholars in recent years.

The analysis of the number of publications in each country and region. Following the United States with United Kingdom is the country with large number of publications in the fields of mHealth. Subsequent countries are Australia, China and Canada. Comparing this result with a bibliometric analysis of mHealth studies up to 2016, we found that the United States remains the most productive country in this area (Shen et al. 2018). Compared the American researchers, there are experiencing gradual growth with the rest of the countries.

Regarding the tendency of cooperation between countries / regions, the four highly productive countries (US, UK, Canada, and Australia) are in close cooperation with each other. On the other hand, clear geographical patterns were seen in other countries / regions. As shown in Fig. 1.6, the red and green clusters represent the regions of Asia and Europe, respectively. Therefore, it is speculated that international partnerships may be influenced by geographical conditions, regional characteristics, language, international relations, political and economic alliances, and so on. In addition to this, it is clear that all the countries are connected to the United States in the network mapping. Therefore, it signifies that the partnering with United States is conducted with the top

50 countries in terms of volume of the mHealth field research. The triangular shaped diagram consists of four countries as United States placed in the center. Shaping the triangle with United Kingdom, Canada and Australia. The whole diagram consists of three main clusters, red cluster contain Asian countries, green cluster entailed with the European countries.

Considering the top journals in the mHealth field, the journal with the most publication of mHealth related was JMIR mHealth and uHealth. In the range of top mHealth related Journals, 14% of all the publication were published on the Canadian Journal of Medical Internet Research and its sister journals JMIR mHealth and uHealth, JMIR Research Protocols, and JMIR Mental Health. There are widespread of journals which publish mHealth related publications. Since the top 10 most publishing mHealth related journal's publications in sum consists of 20.4% in the publication period from 2000 to 2020.

Approaching the author keywords co-occurrence analysis of mHealth publication. While conducting co-occurrence analysis as well as keywords clustering analysis with author keywords have revealed 5 clusters. Within the period of 2000 to 2020, the co-occurring keywords average year range from 2015.26 to 2017.90. Within this period, the mHealth research field could have been formulated its knowledge structure and foundation. The most frequently occurring keyword was mental Health with the number of 449 publications. In addition to this, top keyword in each cluster is mental health (Purple), physical activity (Blue), health promotion (Green), Self-management (Red), HIV (Yellow).

The top 15 keywords and the bottom 15 keywords form co-occurrence author keywords of author provided keywords. The top 15 author keywords average publication year range is relatively novel compared to the bottom 15 author keywords. On the other hand, the bottom 15 author keywords used more frequently than the top 15 author keywords with the occurrence number with both maximum and minimum amount. From the top 15 author provided keywords, the most keywords were consisted in the red cluster with 8 keywords. On contrary, there were 9 author provided keywords with green cluster. Therefore, red cluster contains relatively higher co-occurrence keywords and on the other hand, green cluster contains relatively lower co-occurrence keywords.

From the overlay visualization maps of the average publication year of the top 100 author keywords in the mHealth related publication. From the diagram, there is a shift in the topic of mHealth related publication from the top of the diagram to the bottom of the diagram while the color changes gradually towards 2018.

The co-occurrence network of the top 100 author provided keywords in the AI related publications from 2000 to 2020. The top co-occurrence keywords is machine learning, and it is in the center of the co-occurrence network which imply that the concept of machine learning is holding the significance of the AI related research. The network diagram consists of eight clusters

consisting of machine learning and deep learning in the center of the diagram.

Chronological trends of Author provided keyword co-occurrence network appeared according to Average year 2000-2020. The majority nodes in the network diagram consists in the period before 2019 while centering machine learning and followed with deep learning and artificial intelligence in the center of the diagram. This could imply that since there is a transformation shift in the AI related journals from the chronological trends with network diagram of author provided keywords co-occurrence.

Chronological Trends of mHealth Publication in countries and Regions. The center of the diagram is United States, there diagram consists of five clusters. The greatest number of countries consisting of is the red cluster with Canada, Italy, Spain, Netherlands, Brazil, Portugal, Ireland, France, Sweden. The second largest number contained cluster is the green with Asian countries such as China, South Korea, Australia, Pakistan, Saudi Arabia, Qatar and Iran. Therefore, the two main research area of AI related field are conducted in the main two cluster consisting of regions.

The co-occurrence network of related of country, average year from 2000-2020. There is a transformation shift in the period of 2018 to 2019. United States and England were mainly publishing publications in the year of 2018. From the chronological trends with network diagram, it revealed that there is a new trend of country and regional shift towards Asian countries. India, Pakistan, Singapore and Taiwan.

7.2. Challenges and Possibilities Faced by Implementation of mHealth

Interest in applications of machine learning and deep learning technologies, known as artificial intelligence (AI), continues to grow worldwide, especially in the healthcare field. With the increasing ease of collecting consumer and patient data from smartphones and other devices, there is growing interest in using these technologies to evaluate the effects and side effects of pharmaceuticals and to improve the accuracy and adaptability of medical devices. However, products in the medical field have traditionally been developed under very strict regulations because of their direct impact on human health and life.

As introduced in this paper, mHealth, which is a medical system that utilizes mobile wireless devices, enables a form of approaching patients without the intervention of a medical professional, and the AI algorithm used for that judgment is due to its nature, algorithms are continually updated based on the existence of new datasets, and many countries have not yet determined a regulatory method to deal with the fact that old management methods cannot handle it. This is making it difficult for newcomers to adapt to the regulations. At present, we believe that this situation is the main factor hindering innovation in this field.

To overcome this challenge, governments have already started working on special legislative systems for AI-based medicine. The intention is to clarify the distinction between types that should truly be treated as medical devices and those that do not require regulation, and to eliminate the inhibition of innovation caused by unclearness.

7.3. Implication of this Discussion Paper

The healthcare industry, not just mHealth, is a knowledge-intensive industry based on science. In addition, the direct customers of these related products are not patients who benefit from medical care and medical treatment under medical insurance, but medical professionals, mainly doctors, who perform these services, and thus have different market principles from general consumer goods. As a result, end consumers, who are the patients who benefit from medical treatment and medical care, consume products without knowing the price, value, and problems of the products they use and consume in detail. The mHealth technology has the characteristic of shifting the direct customers from medical professionals, who are the direct customers in the healthcare business at the moment, to the end consumers, and thus it will promote a paradigm shift in the entire healthcare system and the system behind which supports it. As this was discussed in the first part of this paper, the speed of acceptance by the people with the use of mHealth is likely to be influenced by the existing health care system and its systems which support in each region. However, there is no doubt that the increase in medical expenses will continue in the future, coupled with the aging of developed countries. For this reason, to make the healthcare system sustainable, technologies that promote automation such as mHealth will be implemented in society as a result of market-wide pressure, whether fast or slow, as shown by the examples of driverless cars and unmanned stores in other industries.

At this time, the question then becomes how to deepen the literacy of end consumers about these products without involving professional medical personnel. While consumer goods in other fields, such as automobiles and home appliances, are easy for consumers to understand in terms of their external appearance and functions, the differences in products and services in the healthcare field are very difficult to understand without specialized knowledge. In addition, there is a large gap between the price consciousness of consumers and the market price because consumers are basically covered by medical insurance for most of their costs. This is a major barrier to entry for non-Medicare health care products and services. We think it will be necessary especially in the mHealth sector to foster literacy, including price awareness, in the healthcare industry among end consumers, as well as to build a medical insurance system that adapts to the automation of the healthcare sector.

Finally, a more detailed analysis and discussion related to this paper will be published in "mHealth industry from the perspective of innovation management," edited by Kota Kodama and Shintaro Sengoku, to be published by Springer in 2022. (edited by Kota Kodama and Shintaro Sengoku) to be published by Springer in 2022. We hope you will pick up this paper and read it.

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DP 22-01 (Mars 2022)

“Potentials and Challenges of The Connected Autonomous Shared Electric Vehicle (CASE) from Urban Geography Perspective in Southeast Asia Mega-Urban Regions”, Kulacha Sirikhan (The University of Tokyo), 2021 FFJ/Valeo Fellow

DP 21-05 (December 2021)

“East Asian and European Firms: Comrades or Competitors”, Willem Thorbecke (Research Institute of Economy, Trade and Industry), 2020 FFJ/Banque de France Fellow

DP 21-04 (December 2021)

“The Mobility of Paris Residents and Retailers: Their Viewpoints on the Effects of the City’s Pedestrianization”, Meriç Kirmizi (Ondokuz Mayıs University), 2020 FFJ/Michelin Foundation Fellow

DP 21-03 (August 2021)

“City logistics for sustainable and liveable cities”, Eiichi Taniguchi (Kyoto University), 2020 FFJ/Michelin Foundation Fellow

DP 21-02 (May 2021)

“The impact of Paris 2024 on the construction of the Grand Paris Express: a hidden extra cost of the Olympic”, Alexandre Faure (Fondation France-Japon de l’EHESS, EHESS)

DP 21-01 (March 2021)

“Local Government and Innovation for Sustainable mobility”, Soichiro Minami (Policy Research Institute for Land, Infrastructure, Transport and Tourism), 2018 FFJ/Valeo Fellow

DP 20-05 (Septembre 2020)

“International Spillover Effects of Unconventional

Monetary Policies of Major Central Banks”, Tomoo Inoue (Seikei University), Tatsuyoshi Okimoto (Australian National University), 2019 FFJ/Banque de France Fellow

DP 20-04 (July 2020)

“Characteristics of Bike taxis in African rural society: A case study of Dschang, West Cameroon”, Makiko Sakai (Tokyo University of Foreign Studies), FFJ Visiting Researcher

DP 20-03 (June 2020)

“Decomposing Preference for Redistribution Beyond the Trans-Atlantic Perspective”, Ryo Kambayashi (Hitotsubashi University), Sébastien Lechevalier (EHESS, CCJ-FFJ), Thanasak Jenmana (PSE)

DP 20-02 (April 2020)

“A Comparative Analysis of Autonomous Vehicle Policies among Korea, Japan, and France”, Jeehoon Ki (KISTEP), 2018 FFJ/Renault Fellow

DP 20-01 (March 2020)

“Comparing the Development and Commercialization of Care Robots in the European Union and Japan”, James Wright (Sheffield University), 2019 FFJ/Michelin Fellow

DP 19-05 (November 2019)

“Credit Guarantees and Zombie Firms: A Case Study of Small and Medium-Sized Enterprises in Japan”, Scott Wilbur (Yale University), 2018 FFJ/Banque de France Fellow

DP 19-04 (October 2019)

“Impact of R&D Activities on Pricing Behaviors with Product Turnover”, Yasushi Hara (Hitotsubashi University), 2018 FFJ/Michelin Fellow, Akiyuki Tonogi (Toyo University) & Konomi Tonogi (Rissho University)

DP 19-03 (September 2019)

“From Agribusiness to Food Democracy. Comparative Study on Agricultural Policy and

Organic Farming in France and in Japan”, Shoichiro Takezawa (National Museum of Ethnology, Japan); 2018 FFJ/Air Liquide Fellow

DP 19-02 (June 2019)

“Legitimation of Income Inequality in Japan: A Comparison with South Korea and the United States”, Shin Arita (The University of Tokyo), Kikuko Nagayoshi (Tohoku University), Hirofumi Taki (Hosei University), Hiroshi Kanbayashi (Tohoku Gakuin University), Hirohisa Takenoshita (Keio University) and Takashi Yoshida (Shizuoka University); Prizewinners of the 2019 FFJ/SASE Best Paper Award.

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