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Research article

Computational analysis of a collaboration network on human-computer interaction in Korea

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Abstract: Since information and communication technology (ICT) has become one of the leading and essential fields for allowing developing countries to have the major growth engines, the majority of the countries have promoted collaboration in every ICT-related topics. In this study, we performed the trend and collaboration network analysis (CNA) in Korea for 2010–2019 among researchers who are related to human–computer interaction, one of the hottest research areas in ICT. Publication data were collected from SciVal, and the collaboration network was determined using *degree, closeness, betweenness centralities,* and *PageRank*. Hence, key researchers were identified based on their centrality metrics. The dataset contained 7,155 publications, thus reflecting the contributions of a total of 243 authors. The results of our data analysis demonstrated that key researchers can be identified via CNA; this aspect was not evident from the results of the most productive researchers. Additionally, on the basis of the results, the implications and limitations of this study were analyzed.

Keywords: collaboration; HCI Korea; research trend; network analysis

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1. Introduction

Human–computer interaction (HCI) is an interdisciplinary and integrated field of various areas such as service design, computer science, behavioral science, and artificial intelligence (AI). This implies that the focal point of HCI lies in examining and understanding the interaction between people and machines for more usable and reliable systems, as well as functionality of these interactions [1].

In the last two decades, the concept of HCI has been transformed through the sensational impact of data science and artificial intelligence [2]. In line with this trend, numerous researchers in AI, data science, humanities, and biology collaborate with each other. This is not surprising, given that scientific collaboration leverages the intellectual and material resources from different parts of the academic domain [3], which naturally improves the quality, efficiency, and visibility of scientific research outcomes [4].

As mentioned earlier HCI is a field which is interdisciplinary and integrated into various areas. In this sense, we can take an in-depth look into the HCI field and do more productive research using collaborative analysis. Moreover, unlike other single domain research analyzing collaboration within the domain, it is helpful to see core researchers using CNA as HCI has a wide range of applications and domains [5].

Thus, several researchers have attempted to explore collaboration networks of researchers in specific areas [6]. This is because collaboration network analysis (CNA) can be designated as one of the most efficient methods to reveal overall research trends, popular collaboration areas, and key researchers within different clusters [7] and to elucidate the evolution of the collaboration and the mechanisms underlying large-scale real-world networks among researchers [8]. Thus, collaboration networks have been studied extensively, in diverse approaches and from different perspectives, worldwide. Through this method, it is helpful for the development of research to look at core researchers that were not known before.

After the emergence of web and mobile environments in the mid-2000s, HCI such as ubiquitous, virtual reality and haptic became an important research topic also in Korea. Furthermore, HCI has grown with the development of many companies and industries. According to Lee [9], there were only five Korean researchers in the international HCI conference CHI '99. However, in 2014, there were 200 Korean participants ranked fifth among 47 countries. Like this, Korean HCI research is improving now. However, in Korea, few studies have analyzed current trends and collaboration networks of Korean HCI researchers [10]. Thus, this study aimed to analyze the collaboration networks of HCI researchers in Korea, in order to investigate the academic trends and cooperation structures among the HCI researchers. In addition, we suggest the potential future directions of HCI research. The research questions (RQs) considered are as follows:

- **RQ1.** What is the research trend in HCI publications in Korea?
- **RQ2.** How extensive is the structure of the collaboration network among HCI researchers in Korea?

By addressing the given RQs, we believe that our study will contribute to

- Administering the first comprehensive and focused study of the scientific collaboration network in the HCI field of Korea;

- Providing insights into the distinct collaboration patterns and the trends of HCI research, based on 243 researchers in 7,155 publications, collected from the SciVal* and *HCI Korea* Research Directory†; and
- Providing the dataset publicly available‡.

The remainder of the study is organized as follows. Section 1 provides an overview of the trends and history of HCI research, followed by an examination of previous research on CNA. Section 2 outlines the data collection and methodology used in our CNA. Section 3 discusses the results and limitations of the study. Finally, in Section 4, we present the implications of this study and the scope for future research.

2. Literature review

2.1. History and trend of global HCI research

The field of HCI originated from "*intertwined roots in computer science, cognitive computer graphics, operating systems, human factors, ergonomics, industrial engineering, cognitive psychology, and the systems part of computer science*" [11]. HCI has a relatively short history as compared to other areas within human factors; it was only in the late 1970s and the early 1980s that specialists began to consider a professional field of usability and HCI [12]. At the time, the popular topics of HCI research included interactive system development, interface building, user-centered design, and usability testing for computer applications [12]. In 1989, following the introduction of the internet, the main topic areas in HCI evolved into designing for web usability, cost-justifying usability, and computer-supported cooperative work [12]. With the advances in ubiquitous computing in 1999, the main HCI topic areas have been focused on designing for user control and context-sensitive transparency of systems anywhere, anytime model of computing, as well as addressing the challenges inherent in the design and evaluation of such systems [12].

2.2. History and trend of Korean HCI research

South Korea has a relatively short history of HCI research as compared with other advanced countries (e.g., the United States and European countries). However, with the development of information and communication technology, HCI research has developed significantly in both quantity and quality [9].

HCI research in Korea has been conducted mainly through a series of annual conferences held by *HCI Korea* [13]. *HCI Korea* is one of the special topic/research groups of the Korean Information Science Society (KISS). The HCI Research Group of the KISS commenced in 1990 as a research group affiliated with the Korea Advanced Institute of Science and Technology (KAIST) AI Research Center. At the time, scholars from various fields (e.g., computer science, cognitive psychology, design, linguistics, industrial engineering, and philosophy), who were interested in graphical user interface (GUI) and multimedia participated in the group. Since the HCI Research Group of the KISS held a symposium in 1991 and began its official activities, the significance of the group has gradually increased. In 2005,

*https://www.scival.com/
†http://labs.hcikorea.org/html/interview.html
‡`https://github.com/merry555/ProfNetwork`

the HCI Research Group was officially registered as a corporation and established as *HCI Korea* [14]. Since then, *HCI Korea* has held an annual academic conference to promote academic development and interaction among members in the HCI field. It has played the role of a venue to make joint research more active among researchers in various fields [10].

The trend of topics in the *HCI Korea* conference emerged and accelerated the development of ICT technologies [9]. In the early and the mid-1990s, with the growth of the computer industry, GUI was considered to be one of the most popular research areas, while visual programming, human factors, and information searching were ascertained to be the top research keywords. From the mid-1990s to the mid-2000s, web and mobile environments emerged as important research topics, while Internet-based content, multimedia interaction, and mobile/IPTV appeared as important research keywords. In the mid-2000s, user experience emerged as an important research topic, while major research keywords were ubiquitous, physiological/emotional interface, virtual reality/space, and haptic/touch [14]. In the 2010s, smartphones, augmented reality, and social network services appeared as prominent research keywords. However, in recent years, the Internet of Things, crowd computing, and human computation have emerged as leading research keywords [10].

Subsequently, HCI research has become remarkably and consistently associated with other domains. Comprehending the emergence and influence of HCI research through keywords and topics did not pose a challenge [10]. To this end, the importance of collaborations among researchers from different domains in HCI has been emphasized more than ever [15].

2.3. Collaboration network analysis (CNA)

CNA is a meaningful measurement for exploration of the status and emergence of research collaborations [4]. Hence, CNA was employed to understand the overall research trends, popular collaboration areas, and key researchers within different clusters [7]. Moreover, it was used to explain the evolution of collaboration, and the mechanisms underlying large-scale real-world networks among researchers [8]. Because of this advantage, collaboration networks have been extensively used in various ways for multiple purposes. For example, Lee [16] examined the network of research collaboration based on the resumes and survey results of 443 scholars from a university research center in the United States to examine the impact of collaboration on the outcomes. Cheng [4] examined the collaboration network of Library Hi Tech to identify key researchers and trends in collaboration publications. Larrosa [8] examined the structure of the collaboration network of Argentine economists during 1964 to 2014, to identify key researchers and universities of collaboration. Simultaneously, Higaki [17] explored a collaborative research network set during 2009–2019 in cardiovascular medicine using machine intelligence to identify key researchers.

As aforementioned, there are several studies that investigated collaboration networks with consideration of diverse countries and fields. However, few studies conducted network analyses on Korean HCI researchers. Thus, this study addressed the aforementioned research questions with a network analysis to efficiently examine the collaboration evolution among researchers and to determine the overall trend of Korean HCI research.

3. Data collection

To investigate the collaboration network among HCI researchers in Korea, we identified researchers who are members of *HCI Korea*. Further, we assimilated the publication information of each researcher in SciVal, a website that provides comprehensive access to the research performance of over 20,000 research institutions, and their associated researchers from 230 countries worldwide. Specifically, we listed the Korean representative HCI laboratories and professors and among them, we sampled the research lists from each researcher. To collect the data of researchers, we had to know the affiliation of each researcher. Also, by obtaining the affiliation information, we can analyze the main affiliation which actively conducts HCI research and its detailed information about the key researchers.

As a result, we obtained the information of a total of 243 *HCI Korea* members and their corresponding publications (7,155; Category: articles) in the set duration of 2010 to 2019.

When building our collaboration network, nodes represent researchers and the edges represent the number of co-associative relationships between two specific researchers. The example of data collection and network building is on Figure 1.

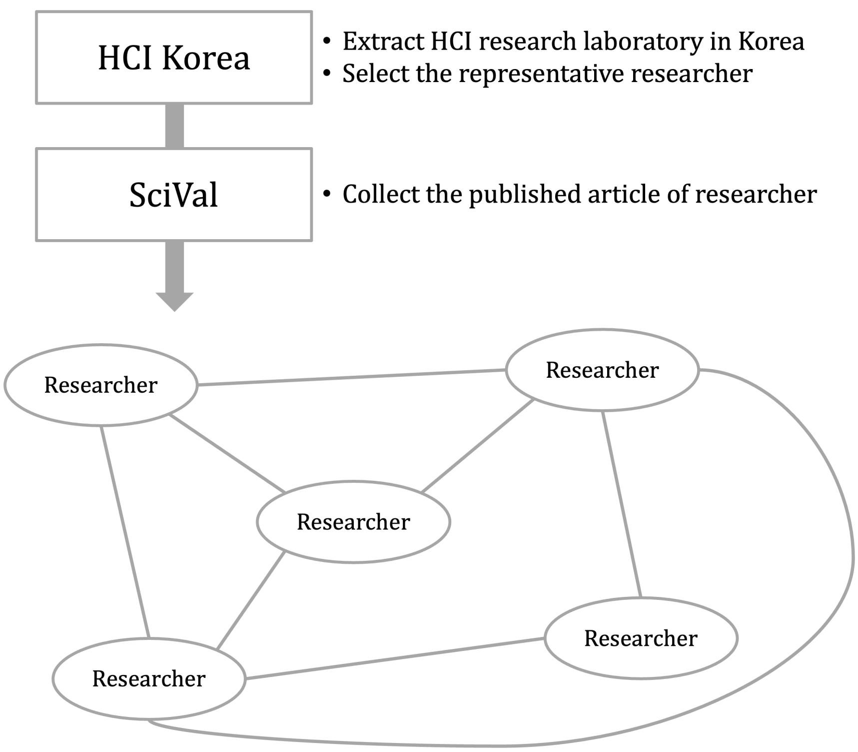


Figure 1. Example of data collection and network building.

4. Methods

Centrality analysis is one of the most important approaches for identifying key researchers in collaboration networks [4]. Centrality measures typically include *degree centrality, closeness centrality,* *betweenness centrality* and *PageRank*. Thus, we used the centrality approach to conduct an analysis of our collaboration network of *HCI Korea* researchers.

4.1. Degree centrality

Degree centrality is defined as "*the number of edges incident upon a node*" [18]. It is amongst the most rudimentary centrality measurements. It is evaluated using the number of edges connected to a node in a graph structure. In a weighted graph, *degree centrality* is calculated as the sum of the weights associated with the nodes. A node obtains a higher *degree centrality* when it has a greater number of edges connected to the other nodes in the network. Equation 4.1 is as follows:

$$C_D(i) = \sum_{j}^{n} a_{i,j} \tag{4.1}$$

where n is the number of nodes in the network, and i and j are nodes that are directly linked [19]. In collaboration networks, *degree centrality* indicates significant researchers who are connected with other researchers. The higher degree centrality indicates the greater productivity of researcher and higher connectivity with other researchers.

4.2. Closeness centrality

Closeness centrality, introduced by Bavelas [20], measures the importance of a node based on its proximity to other nodes in the network. *Closeness centrality* is calculated using the total length of the paths between a node and all other nodes in a network. A node obtains a higher *closeness centrality*, if the total length between itself and all other nodes in the network is shorter than the length of the other nodes. (Equation 4.2), $C_c(n_i)$ is the *closeness centrality* and $d(n_i, n_j)$ is the distance between two nodes in the network: (Equation 4.2):

$$C_c(n_i) = \frac{1}{\sum_{j=1}^{g} d(n_i, m_i)} \tag{4.2}$$

Distance d is defined as the shortest path which is the path with minimum number of edges. In social networks, *closeness centrality* is used to understand the importance of a specific researcher and to measure their influence on the entire collaboration network [21].

Thus, a specific researcher with a higher *closeness centrality* can be considered to have a broader range of influence over the entire collaboration network.

4.3. Betweenness centrality

Betweenness centrality measures the importance of a specific node, based on how much a given node is in-between other nodes in the network [22]. A node with a greater *betweenness centrality* has a considerable influence within a network as it controls the passing of information between other nodes. This metric is assessed by the number of shortest paths that pass through a node [8]. The metric is calculated as follows: (Equation 4.3):

$$C_B(n_i) = \sum_{j,k \neq i} \frac{g_{jik}}{g_{jk}} \tag{4.3}$$

where g_{jik} is all geodesics linking node j and node k, which passes through node i, and g_{jk} is the geodesic distance between nodes j and k. Here, geodesic distance indicates the number of edges between the two nodes.

In collaboration networks, the *betweenness centrality* of a specific researcher shows their impact in bridging two separate research groups in the network. This implies that researchers with a greater level of betweenness centrality can manage and initiate collaborations among researchers in different research fields [23]. Thus, the greater *betweenness centrality* was explained by greater interdisciplinary collaborations of researchers [4].

4.4. PageRank

The term *PageRank* was first introduced by Page and Brin, who attempted to explain the level of authority a particular page holds, through the topological structure of a web [24]. *PageRank* treated the web as a graph, with pages as vertices, and links between the pages as edges. The ranks of the pages were determined by the sum of the ranks of their backlinked pages. Hence, nodes with a higher total of significant (direct) neighbors had a higher *PageRank*. This metric is determined as follows: (Equation 4.4):

$$PR(p) = \frac{1-d}{N} + d\sum_{i=1}^{k} \frac{PR(p_i)}{C(p_i)} \tag{4.4}$$

Here, N is the total number of pages on the web, d is the damping factor, $C(p_i)$ is the out link of p_i, and p_i is the number of in-links of p. It is iterated until all vertices are assigned stable *PageRank* values.

In our collaboration network, researchers and the number of collaborations between two specific researchers were denoted by vertices and edges, respectively. A researcher was awarded a greater *PageRank* when they collaborated with a greater number of influential researchers. Through *PageRank*, the importance of a researcher can be calculated based on the number of their influential collaborators [4].

4.5. Interpretation of measures

We applied different types of network measure to find the main researchers from various points, while each measure indicates unique characteristics of researchers. Rather than simply comparing the number of documents, we can learn the academic characteristics of researchers through the network analysis measures. Among the 4 different measures, *degree centrality* and *closeness centrality* mainly indicates the individual researcher's academic productivity and influence in the HCI. *betweenness centrality* and *pagerank* mainly focus on the researcher's academic collaboration and significant relationship with other researchers.

4.6. Network analysis

We conducted two-stage analyses. First, the trends in HCI publications were observed. Specifically, we considered the number of annual publications of the members of *HCI Korea* across the years, based on affiliations and keywords. Second, a CNA using the employed centralities—*PageRank, degree, closeness, and betweenness centralities*—was performed.

5. Results

5.1. Overall trends of HCI in Korea

5.1.1. Distribution of publications

We conducted a descriptive analysis of 7,155 publications, retrieved from SciVal over the last decade (2010–2019). As shown in Figure 2, the highest number of publications (783) were published in 2015, while the annual average number of publications was 715.50 (SD = 57.60).

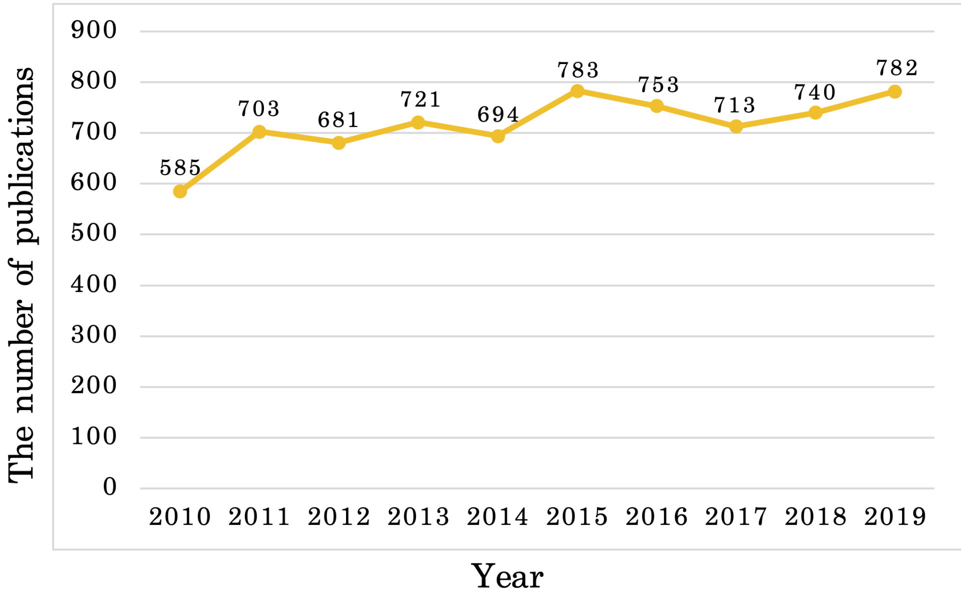


Figure 2. The number of publications each year.

We also analyzed the researchers' affiliations (Table 1). The results indicated that the KAIST was the most productive affiliation, with 1,189 publications (16.61%) in the decade considered, followed by Sungkyunkwan University (SKKU; 673, 9.40%) and Seoul National University (SNU; 526, 7.35%).

Table 1. Top 10 highly productive affiliations.

Rank	Affiliation	Counts	Percentage (%)
1	Korea Advanced Institute of Science and Technology (KAIST)	1,189	16.61
2	Sungkyunkwan University (SKKU)	673	9.40
3	Seoul National University (SNU)	526	7.35
4	Yonsei University (YU)	421	5.88
5	Hanyang University (HYU)	380	5.31
6	Korea University (KU)	363	5.07
7	Chung Ang university (CAU)	350	4.89
8	Ulsan National Institute of Science and Technology (UNIST)	313	4.37
9	Pohang University of Science and Technology (POSTECH)	290	4.05
10	Gwangju Institute of Science and Technology (GIST)	283	3.95

Table 2 shows the top 30 productive researchers, based on the number of publications. Professor Joonki Paik, who is affiliated with Chung-Ang University (CAU), ranked first (218 publications). His research area generally focuses on cultural content, graphics, game and human–robot interaction. Professor Sukhan Lee of robotics, affiliated with SKKU, ranked second (162 publications). His major research interests were user robotics, computer vision, human–robot interaction and AI. Professor Kyujin Cho of mechanical engineering at SNU, ranked third (152 publications). His research is focused on haptics, tangible display, and soft robotics.

Table 2. The most productive researchers in terms of researcher appearance; Details regarding affiliation full names in Table 8 in Supplement Material.

Rank	Researcher	Documents	Citations	Affiliation	Rank	Research	Documents	Citations	Affiliation
1	Joonki Paik	218	1,190	CAU	16	Hojung Cha	90	2,418	YU
2	Sukhan Lee	162	818	SKKU	17	Geehyuk Lee	87	755	KAIST
3	Kyujin Cho	152	3,382	SNU	18	Jongil Park	86	342	HYU
4	Woontack Woo	133	1,146	KAIST	19	Sangyoun Kim	85	458	KOREATECH
5	Taeho Woo	128	295	CUK	20	Sungchan Jun	82	1,179	GIST
6	Jundong Cho	125	499	SKKU	21	Nakhoon Baek	80	86	KNU
6	Seungmoon Choi	125	1,303	POSTECH	22	Ian Oakley	78	955	UNIST
8	Hangsik Shin	124	3,722	CNU	23	Myunghwan Yun	75	340	SNU
9	Jungwon Yoon	116	1,158	GIST	24	Byoungho Choi	73	285	KU
10	Jaeboong Choi	112	1,538	SKKU	25	Euichul Lee	73	997	SMU
11	Eunil Park	105	1,898	SKKU	26	Dongman Lee	71	712	KAIST
11	Uichin Lee	105	2,883	KAIST	26	Sungeui Yoon	71	1,002	KAIST
13	Ilhong Suh	98	858	HYU	26	Jinwoo Jung	71	3,023	DGU
14	Jounghyung Kim	97	395	KU	29	Seokjoo Koh	68	311	KNU
14	Sungphil Kim	97	1,182	UNIST	30	Tackdon Han	66	332	YU

5.1.2. Trend of keywords

Table 3 displays the major keywords and their frequencies. The results show the keywords with high frequencies including ‘haptics’, ‘augmented reality’, and ‘touch’. Early researchers in *HCI Korea* leaned towards ‘multi-touch’ interaction in diverse environments. After 2015, other emerging topics, such as ‘gesture’, ‘text entry’, or ‘object detection’, were considered. Moreover, several studies on ‘augmented reality’, ‘object detection’, and ‘convolutional neural network’ (CNN) were recently conducted.

5.2. Network of collaboration

Table 4 lists the top 30 researchers as per the results of *degree centrality* (DC) analysis. The results indicated that Professor Jeein Kim and Professor HyungSeok Kim (DC: 36), who are with Konkuk University (KKU), have the highest *degree centrality*. The main areas of their research were wearable device/cognitive computing/communication, and augmented reality/virtual reality/3D modeling, respectively. Professor Seungmoon Choi of computer science (DC: 27), who is affiliated with Pohang University of Science and Technology (POSTECH), ranked third. His research interests were haptics, virtual reality, and tactile perceptions.

Table 5 presents the summary of the *closeness centrality* (CC) analysis. Professor Ian Oakley of human factors and ergonomics at Ulsan National Institute of Science and Technology (UNIST; CC: $282.416 * 10^{-3}$) has the highest *closeness centrality*. It indicates that he can be largely influential to

Table 3. Summary of topic keywords.

Year	Keywords	Frequency	Year	Keywords	Frequency
2010	Haptics	22	2015	Haptics	40
	Augmented reality	19		Tactile Display	27
	Deformable objects	13		Touch	21
	Mobile Robots	12		Touch screens	17
	Multi-Touch	11		Augmented Reality	12
	Collision Detection	11		Gestures	12
2011	Haptics	24	2016	Haptics	21
	Augmented reality	18		Tactile Display	15
	Multi-Touch	15		Augmented Reality	14
	Touch screens	14		Text Entry	12
	Rendering	12		Gestures	12
	Touch	12		Depth Estimation	12
2012	Haptics	32	2017	Haptics	28
	Touch	21		Touch screens	23
	Tactile Display	20		Text Entry	22
	Mobile Robots	11		Augmented Reality	21
	Simultaneous localization and mapping	10		Gestures	19
	Internet of Things	10		Tactile Display	19
2013	Haptics	26	2018	Haptics	42
	Touch screens	22		Tactile Display	26
	Multi-Touch	18		Touch	21
	Tactile Display	18		Touch screens	18
	Touch	18		Text Entry	17
	Augmented reality	16		Gestures	14
2014	Haptics	36	2019	Haptics	27
	Augmented reality	18		Augmented reality	22
	Touch screens	16		Tactile Display	20
	Touch	16		Touch	18
	Tactile Display	14		Object Detection	16
	User Studies	13		CNN	16

other researchers and his research areas are wearable, haptics, and tangible user interfaces [25, 26]. Professor Andrea Bianchi ($279.674 * 10^{-3}$), who is affiliated with KAIST, ranked second. His major research interests were wearable, haptics, and augmented reality [27, 28]. Professor Sungphil Kim ($259.573 * 10^{-3}$), who is affiliated with UNIST ranked third. His research focuses on haptics, cognitive engineering, and voice.

In the case of *betweenness centrality* (BC), as shown in Table 6, Professor Woontack Woo (BC: $17.82 * 10^{-2}$), affiliated with KAIST, has the highest *betweenness centrality*. He is academically co-operative researcher and his main research interests include augmented reality, interaction design, and wearables [29]. Professor Uichin Lee at KAIST ranks second ($13.60 * 10^{-2}$). His research focuses on user experience and interactive computing. Professor Seungmoon Choi at POSTECH whose main research interests include haptics [30], ranks third ($12.48 * 10^{-2}$).

Table 4. Results of *degree centrality*; Details about affiliation full names in Table 8 in Supplement Material.

Rank	Researcher	Index	Affiliation	Rank	Researcher	Index	Affiliation
1	Jee-In Kim	36	KKU	15	Uichin Lee	17	KAIST
1	HyungSeok Kim	36	KKU	17	Youn-kyung Lim	15	KAIST
3	Seungmoon Choi	27	POSTECH	18	Sangsu Lee	14	KAIST
4	Andrea Bianchi	25	KAIST	19	Shinjin Kang	13	HIU
5	Ian Oakley	23	UNIST	19	Seokhee Jeon	13	KHU
6	Kunpyo Lee	23	KAIST	21	Sejung Choi	12	KU
7	Sungchan Jun	22	GIST	21	Yongjun Sung	12	KU
7	Minkyu Ahn	22	HGU	23	Nakhoon Baek	11	KNU
9	Hokyoung Ryu	21	HYU	23	Jounghyung Kim	11	KU
10	Woontack Woo	19	KAIST	25	Byungchull Bae	10	HYU
11	Hyuntaek Kim	18	KU	25	Sungphil Kim	10	UNIST
11	Heecheon You	18	POSTECH	25	Hwanyong Lee	10	AJOU
11	Jundong Cho	18	SKKU	28	Mincheol Whang	9	SMU
11	Kihyo Jung	18	UOU	28	Mingyu Lim	9	KU
15	Kwanguk Kim	17	HYU	28	Hyeonjeong Suk	9	KAIST

Table 5. Results of *closeness centrality*; Details about affiliation full names in Table 8 in Supplement Material.

Rank	Researcher	Index	Affiliation	Rank	Researcher	Index	Affiliation
1	Ian Oakley	$282.416{*}10^{-3}$	UNIST	16	Kunpyo Lee	$229.054{*}10^{-3}$	KAIST
2	Andrea Bianchi	$279.674{*}10^{-3}$	KAIST	17	Seokhee Jeon	$227.062{*}10^{-3}$	KHU
3	Sungphil Kim	$259.573{*}10^{-3}$	UNIST	18	Minsam Ko	$226.672{*}10^{-3}$	HYU
4	Jundong Cho	$257.397{*}10^{-3}$	SKKU	19	Byungjoo Lee	$225.468{*}10^{-3}$	KAIST
5	Woontack Woo	$255.318{*}10^{-3}$	KAIST	20	Youn-kyung Lim	$223.194{*}10^{-3}$	KAIST
6	Hwajung Hong	$247.585{*}10^{-3}$	SNU	21	Sangsu Lee	$221.137{*}10^{-3}$	KAIST
7	Uichin Lee	$247.467{*}10^{-3}$	KAIST	22	Youngyim Doh	$219.921{*}10^{-3}$	KAIST
8	Byungchull Bae	$246.489{*}10^{-3}$	HIU	23	Sungkil Lee	$217.171{*}10^{-3}$	SKKU
9	Daniel Saakes	$244.582{*}10^{-3}$	KAIST	24	Sangyoun Kim	$215.163{*}10^{-3}$	KOREATECH
10	Seyoung Chun	$242.652{*}10^{-3}$	UNIST	25	Geehyuk Lee	$210.355{*}10^{-3}$	KAIST
11	Yoosoo Oh	$237.912{*}10^{-3}$	DU	26	Gahgene Gweon	$204.627{*}10^{-3}$	SNU
12	Seungmoon Choi	$234.697{*}10^{-3}$	POSTECH	27	Jounghyung Kim	$200.917{*}10^{-3}$	KU
13	Jeha Ryu	$233.745{*}10^{-3}$	GIST	28	Jungwon Yoon	$194.636{*}10^{-3}$	GIST
14	Hyeonjeong Suk	$231.730{*}10^{-3}$	KAIST	29	Youngho Lee	$192.878{*}10^{-3}$	MNU
15	Tekjin Nam	$230.012{*}10^{-3}$	KAIST	30	Kyungsik Han	$191.070{*}10^{-3}$	AJOU

In the case of *PageRank* (Table 7), Professor Seungmoon Choi ($2.728{*}10^{-2}$) shows the highest values, while Professors Andrea Bianchi ($2.253{*}10^{-2}$) and Ian Oakley ($2.178{*}10^{-2}$) are also considered. It can be said that Professor Seungmoon Choi was collaborative with influential researchers.

Table 6. Results of *betweenness centrality*; Details about affiliation full names in Table 8 in Supplement Material.

Rank	Researcher	Index	Affiliation	Rank	Researcher	Index	Affiliation
1	Woontack Woo	$17.82*10^{-2}$	KAIST	16	Hyunjhin Lee	$2.02*10^{-2}$	HIU
2	Uichin Lee	$13.60*10^{-2}$	KAIST	17	Sangwon Lee	$1.61*10^{-2}$	SKKU
3	Seungmoon Choi	$12.48*10^{-2}$	POSTECH	18	Byeongseok Shin	$1.60*10^{-2}$	INHA
4	Jeha Ryu	$11.21*10^{-2}$	GIST	18	Seungyong Lee	$1.60*10^{-2}$	POSTECH
5	Ian Oakley	$9.39*10^{-2}$	UNIST	18	Mincheol Whang	$1.60*10^{-2}$	SMU
6	Gahgene Gweon	$5.47*10^{-2}$	SNU	21	Hwajung Hong	$1.50*10^{-2}$	SNU
7	Sungphil Kim	$4.78*10^{-2}$	UNIST	22	Kyungsik Han	$1.34*10^{-2}$	AJOU
8	Jounghyun Kim	$4.68*10^{-2}$	KU	23	Sunghee Lee	$1.29*10^{-2}$	KAIST
9	Hyeonjeong Suk	$4.50*10^{-2}$	KAIST	24	Juho Kim	$1.09*10^{-2}$	KAIST
10	Andrea Bianchi	$4.41*10^{-2}$	KAIST	25	Dongman Lee	$0.86*10^{-2}$	KAIST
11	Joonhwan Lee	$3.17*10^{-2}$	SNU	26	Youn-kyung Lim	$0.83*10^{-2}$	KAIST
12	Jinwoo Kim	$3.16*10^{-2}$	YU	27	Bongwon Suh	$0.81*10^{-2}$	SNU
13	Sangyoun Kim	$3.15*10^{-2}$	KOREATECH	27	Gyerae Tack	$0.81*10^{-2}$	KKU
13	Jundong Cho	$3.15*10^{-2}$	SKKU	27	Hyuntaek Kim	$0.81*10^{-2}$	KU
15	Sungkil Lee	$2.37*10^{-2}$	SKKU	27	Eunil Park	$0.81*10^{-2}$	SKKU

Table 7. Results of *PageRank*; Details about affiliation full names in Table 8 in Supplement Material.

Rank	Researcher	Index	Affiliation	Rank	Researcher	Index	Affiliation
1	Seungmoon Choi	$2.728*10^{-2}$	POSTECH	16	Youn-kyung Lim	$1.154*10^{-2}$	KAIST
2	Andrea Bianchi	$2.253*10^{-2}$	KAIST	17	HyungSeok Kim	$1.142*10^{-2}$	KAIST
3	Ian Oakley	$2.178*10^{-2}$	KAIST	18	Sang-wook Lee	$1.071*10^{-2}$	SGU
4	Woontack Woo	$2.053*10^{-2}$	UNIST	19	Changgeun Song	$1.061*10^{-2}$	SNU
5	Uichin Lee	$1.928*10^{-2}$	KAIST	20	Juhyun Eune	$1.029*10^{-2}$	SNU
6	Kunpyo Lee	$1.636*10^{-2}$	KAIST	21	Jieun Kim	$0.990*10^{-2}$	HIU
7	Jundong Cho	$1.511*10^{-2}$	SKKU	22	Mincheol Whang	$0.973*10^{-2}$	KAIST
8	Sungphil Kim	$1.404*10^{-2}$	YU	23	Sangsu Lee	$0.967*10^{-2}$	HYU
9	Joonhwan Lee	$1.359*10^{-2}$	KU	24	Nakhoon Baek	$0.955*10^{-2}$	HYU
10	Jinwoo Kim	$1.299*10^{-2}$	UNIST	25	Byeong-seok Shin	$0.936*10^{-2}$	HLU
11	Jounghyun Kim	$1.236*10^{-2}$	SNU	26	Shinjin Kang	$0.897*10^{-2}$	KOREATECH
12	Seokhee Jeon	$1.231*10^{-2}$	KU	27	Sungkil Lee	$0.885*10^{-2}$	SKKU
13	Hokyoung Ryu	$1.220*10^{-2}$	KKU	28	Bongwon Suh	$0.884*10^{-2}$	SMU
14	Jeein Kim	$1.188*10^{-2}$	HYU	29	Eui Chul Lee	$0.872*10^{-2}$	KNU
15	Changhun Kim	$1.158*10^{-2}$	KHU	30	Minsam Ko	$0.870*10^{-2}$	KAIST

6. Discussion and conclusion

The current study aimed to analyze the collaboration networks of HCI researchers in Korea from 2010 to 2019, to gain an insight into the academic trends and structure of cooperation in South Korean HCI society. First, we determined the trends of research topics in HCI through an analysis of the distribution of HCI publications in the last ten years (2010–2019). Second, we studied the network structure of researchers in *HCI Korea* by identifying key researchers through a network analysis. We employed a dataset extracted using SciVal for this purpose. The dataset included 243 researchers and

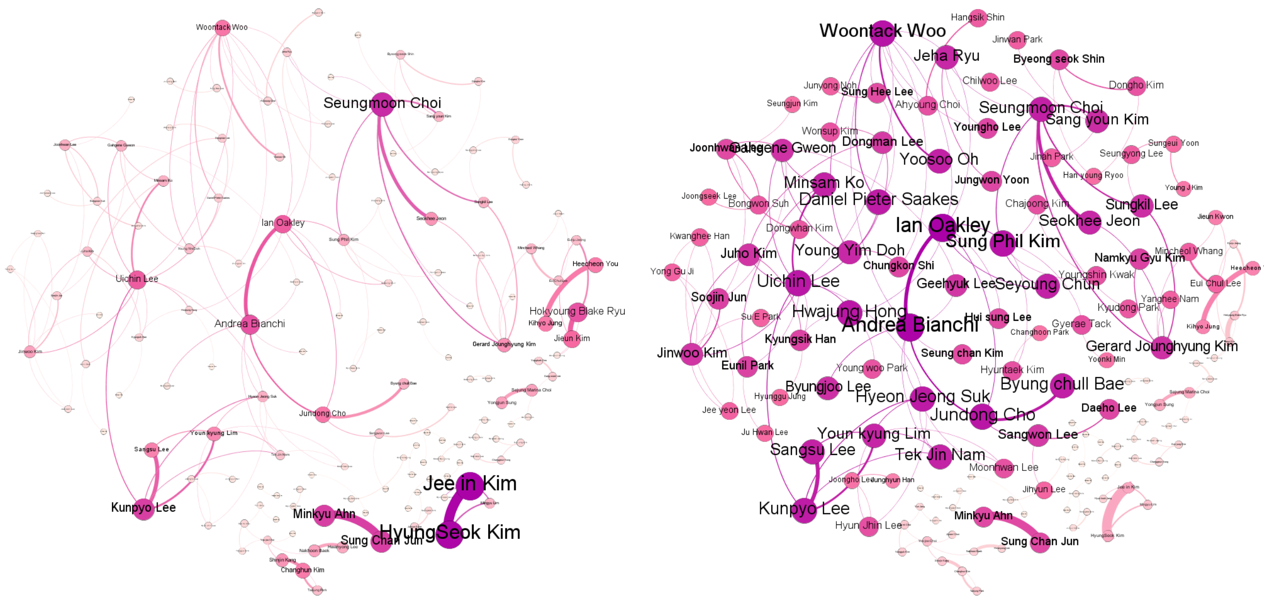
7,155 publications from 2010 to 2019.

We organized the dataset into a collaboration network comprising 163 edges and 143 nodes. Further, we computed the *degree centrality*, *closeness centrality, betweenness centrality*, and *PageRank*, using this network, and identified the top 30 researchers.

With regards to the first research question, we discovered that the number of HCI publications has increased over the past 10 years. In terms of numbers, KAIST was the most productive affiliation, while Professor Joonki Park from CAU, was the most productive researcher.

In addition, as a result of the keyword analysis, we identified keywords related to 'haptic', and 'touch', such as 'touch', 'tactile display', 'touch screens', and 'multi-touch', to be the popular research topics over the years. Starting from 2019, 'CNN' and 'object detection' emerged as new major topics.

Similarly, with regards to the second research question (Figure 3 and Figure 4), we discovered that Professors Jeein Kim and HyungSeok Kim (CAU) ranked first in terms of *degree centrality*, followed by Professor Seungmoon Choi (POSTECH, Figure 3a). In the case of *closeness centrality*, Professor Ian Oakley (UNIST) ranked first, followed by Professors Andrea Bianchi (KAIST) and Sungphil Kim (UNIST, Figure 3b). In terms of *betweenness centrality*, Professor Woontack Woo (KAIST) ranked first, followed by Professors Uichin Lee (KAIST) and Seungmoon Choi (POSTECH, Figure 4a). In the case of *PageRank*, Professor Seungmoon Choi (POSTECH) ranked the first, followed by Professor Andrea Bianchi (KAIST) and Ian Oakley (UNIST, Figure 4b).



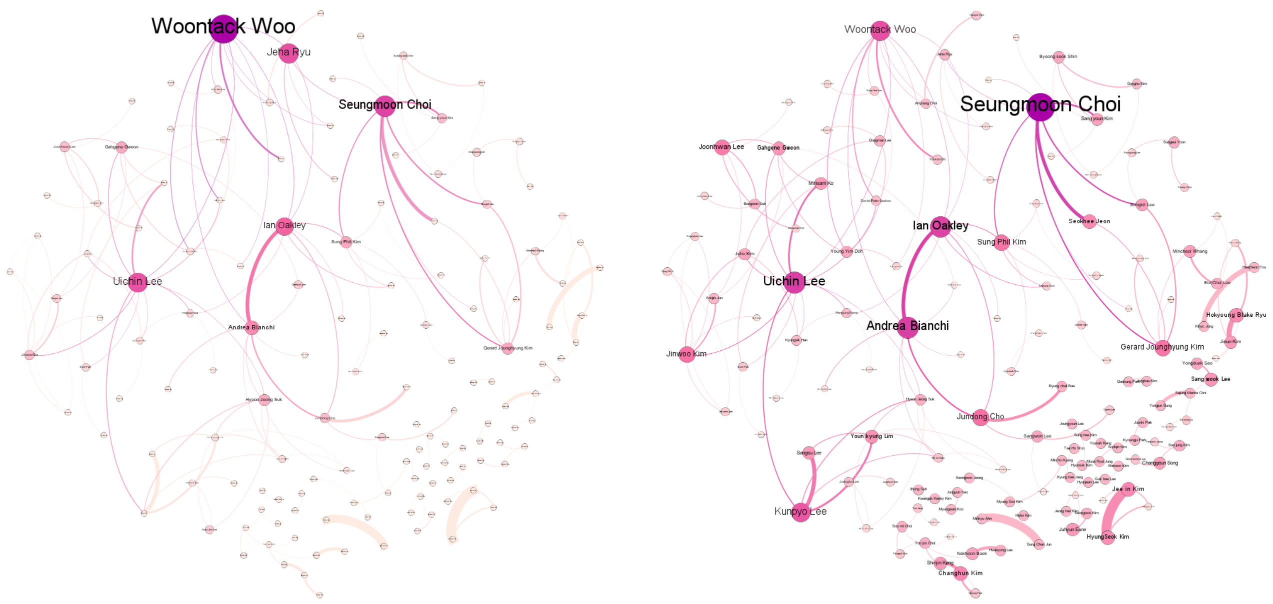
(a) *Degree centrality*.

(b) *Closeness centrality*.

Figure 3. Overview of *degree centrality* and *closeness centrality*.

Although several researchers were not listed among the most productive researchers (Table 2), such as Professors Andrea Bianchi, Jeein Kim, and HyungSeok Kim (KKU), they were included in the lists of other network analyses.

The findings of this study have several implications. First, as previously stated in the introduction, only a few studies have analyzed the current trends and collaboration networks of Korean HCI



(a) *Betweenness centrality*. **(b)** *PageRank*.

Figure 4. Overview of *betweenness centrality* and *PageRank*
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researchers with domestic publications [10]. In contrast, this study contributes to the trends and collaborations with *HCI Korea* researchers by considering their international publications. Second, one of the notable findings of this study was the identification of key researchers made possible using the CNA, which were otherwise not evident from the results of the most productive researchers.

One of the main findings is that we identified the latest trends in South Korean HCI research. Through our findings, future researchers will be able to conduct follow-up HCI research that reflects trends by referring to our research results. This could eventually contribute to the latest HCI technology advancements. According to our research results, HCI research has undergone the following evolutionary process: In research that encompasses one-dimensional simple device operation including keywords such as haptic and touch, the scope of human interaction has been expanded including keywords such as gesture. In recent years, application of machine learning and deep learning technologies have been shown in the field of HCI.

Although the current study afforded several pertinent findings, several limitations remain. Primarily, we only considered researchers who were registered as members of *HCI Korea* for our CNA. There may be other researchers who have conducted active research in the field of HCI but were not registered as members of *HCI Korea*. Thus, future studies should consider these limitations to extend the findings of the current study. Despite these limitations, it is obvious that our study has made a methodological contribution to domain-specific regional collaboration network analysis. Our data analysis approach can be used in other domains or regions that our analysis framework would become an interesting contribution that can help researchers gain insights in different research areas.

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Conflict of interest

The authors declare there is no conflict of interest.

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Appendices

Table 8. A list of affiliations' full name.

Affiliation	Abbreviation	Affiliation	Abbreviation
Ajou University	AJOU	Korea University of Technology and Education	KOREATECH
Chonnam National University	CNU	Kyung Hee University	KHU
Chung-Ang university	CAU	Kyungpook National University	KNU
Cyber University of Korea	CUK	Mokpo National University	MNU
Daegu University	DU	Pohang University of Science and Technology	POSTECH
Dongguk University	DGU	Samgmyung University	SMU
Gwangju Institute of Science and Technology	GIST	Seoul National University	SNU
Hallym University	HLU	Sogang University	SGU
Hanyang University	HYU	Sungkyunkwan University	SKKU
Hongik University	HIU	Ulsan National Institute of Science and Technology	UNIST
Inha University	INHA	Yonsei University	YU
Konkuk University	KKU	University of Ulsan	UOU
Korea Advanced Institute of Science and Technology	KAIST	Handong University	HDU
Korea University	KU		