헬스커뮤니케이션연구 제24권 제1호
Health Communication Research
2025, Vol. 24, No. 1, 61-88
DOI: 10.24172/hcr.2025.24.1.61.

Mapping the Landscape of Health Communication Technologies:

A Scientometric Analysis*

Sungbin Youk**

(Ewha Womans University, College of Social Science, Division of Communication and Media, Assistant Professor)

As digital technologies reshape health communication, numerous studies have examined the role of specific health communication technologies, yet a comprehensive, data-driven analysis of research trends in this field remains limited. This study employs a scientometric approach to systematically map the intellectual landscape of health communication technologies by analyzing 1,067 journal articles published between 2010 and 2024. Findings from co-word analysis and strategic mapping reveal that patient-centered digital tools, mobile health applications, and public engagement strategies are well-established research domains, whereas cybersecurity, blockchain, and speech communication technologies remain underexamined. Additionally, community detection analysis highlights the interdisciplinary nature of health communication technology research, with strong linkages among the social sciences, digital health, and information technology. These insights contribute to a deeper understanding of how technological advancements have shaped health communication and offer directions for future research in this rapidly evolving field.

Key words : Health communication technology, scientometric analysis, strategic mapping, network analysis

* This work was supported by the Ewha Womans University Research Grant of 2024

** sungbinyouk@ewha.ac.kr, Corresponding Author

1. Introduction

Health communication continues to evolve with the increasing integration of digital technologies in patient education, provider-patient interactions, health promotion, decision support, and service delivery (Suggs, 2006). The widespread adoption of these technologies is evident, with telemedicine utilization reaching 50.8% and electronic health records and social media platforms exceeding 90% in healthcare settings (Borges do Nascimento et al., 2023). The emergence of eHealth, which integrates digital communication technologies with healthcare delivery, and mHealth, which incorporates mobile applications into healthcare, also highlights the growing influence of technology in this field (Lewis et al., 2016).

Over the past decade, numerous studies have explored how technological innovations enhance clinical outcomes and improve communication between healthcare providers and patients. Digital health solutions, including telemedicine, electronic health records, and mobile health applications, have significantly improved access to care and strengthened health literacy (Fitzpatrick, 2023). The COVID-19 pandemic further accelerated the adoption of telemedicine and remote healthcare services, demonstrating both the immediate benefits during a global health crisis and the long-term potential of digital health technologies in transforming healthcare delivery (Barker et al., 2024).

Despite these advancements, there remains a need for a systematic examination of how different technologies have evolved and how research efforts are distributed across various domains within health communication. A scientometric analysis provides a structured approach to mapping research trends, identifying dominant themes, and assessing the extent of technological integration in the field. By systematically analyzing the existing literature, this study offers insights into the intellectual structure of health communication technologies, evaluates whether certain technological areas receive disproportionate scholarly attention, and highlights gaps that require further exploration. In doing so, this study contributes to a deeper understanding of how technological innovations have shaped the discipline and provides a foundation for guiding future research at the intersection of health communication and technology.

2. Literature Review

1) Health Communication Technologies

Health communication technologies encompass a diverse range of digital tools and systems designed to facilitate the dissemination of health-related information, enhance clinical and medical practices, and support public health initiatives (Yadav, 2024). These technologies include telemedicine, mobile health applications, wearable health devices, electronic health records, and artificial intelligence-driven health communication platforms (Fitzpatrick, 2023). As the healthcare industry continues to digitalize, the integration of these technologies has become increasingly vital in addressing contemporary healthcare challenges (Eysenbach, 2004).

The adoption of digital tools in health communication has evolved alongside advancements in information and communication technology. Initially, computers in healthcare settings were primarily used for administrative tasks, but their applications have since expanded to include patient-centered communication, diagnostic support, and remote care delivery (Suggs, 2006). The rise of the internet and mobile technology has further transformed health communication, enabling real-time data exchange, virtual consultations, and patient self-management tools. The emergence of Web 2.0 and social media platforms has also significantly changed how health messages are disseminated. Public health organizations and healthcare providers now leverage platforms such as TikTok and X (Twitter) to engage with audiences and share critical health information (Zhu et al., 2020). Additionally, patient portals and mobile applications facilitate personalized health communication and secure exchanges between patients and healthcare professionals (Neuhauser & Kreps, 2003).

More recently, emerging technologies have further expanded the scope of health communication. Wearable Internet of Things (WIoT) devices, such as fitness trackers and smartwatches, continuously monitor health metrics like heart rate, blood pressure, and sleep patterns, enabling early detection of anomalies and promoting healthier lifestyles (Dinh-Le et al., 2019; Mozumder et al., 2022). AI-powered chatbots and virtual assistants provide instant access to medical information, assist in symptom assessment, and support mental health

interventions through automated counseling services. Blockchain technology has also been introduced to ensure the secure storage and transfer of patient records, reducing data breach risks and strengthening patient trust in digital healthcare solutions (Singh et al., 2020). These advancements have improved accessibility and healthcare delivery by enabling remote consultations, continuous patient monitoring, and more personalized disease management (Aceto et al., 2020). Given that medication noncompliance remains a critical issue, particularly among elderly and chronically ill patients, digital communication technologies have been increasingly used to track medication intake and provide automated reminders (Silva et al., 2015).

Despite these advancements, several challenges persist in the adoption and implementation of health communication technologies, necessitating further research. The digital divide remains a significant concern, as socioeconomic disparities continue to limit access to digital health solutions, exacerbating existing healthcare inequities (Sieck et al., 2021). Additionally, data security and patient confidentiality present ongoing challenges, as the increased digitalization of health information raises concerns about privacy and unauthorized access (Singh et al., 2020). The widespread availability of health information also comes with the risk of misinformation dissemination, which can undermine public trust in science-based medical guidance and adherence to evidence-based treatments (Stockwell & Fiks, 2013).

2) Scientometric Analysis

Given the rapid evolution of health communication technologies and the complexities surrounding their adoption, a systematic approach is necessary to examine the thematic trends in academic research. The scientometric analysis provides a quantitative framework for assessing research trends, identifying dominant themes, and evaluating the broader impact of science and technology. As a broader field encompassing bibliometrics, scientometrics extends beyond analyzing publication counts and citation networks to examining research productivity, funding patterns, and innovation trends (Youk & Park, 2019).

Among the various methods within scientometric analysis, co-word analysis is particularly

useful for identifying keyword co-occurrence patterns in academic publications. Since keywords encapsulate the core themes and findings of a study, co-word analysis reveals structural connections within a research field and highlights dominant and emerging research themes (Van Raan & Tijssen, 1993). This method operates under the premise that recurring keyword relationships reflect thematic linkages, enabling scholars to better understand the intellectual structure of a field (Leydesdroff, 1989).

To visualize scientometric findings, researchers often employ co-word networks and strategic diagrams. Co-word networks map relationships between keywords, where nodes represent individual terms, and edges indicate their co-occurrence in literature. The strength of these connections signifies the frequency with which specific topics are studied together, highlighting conceptual relationships within the research landscape (Leydesdroff, 1989). Strategic diagrams, also known as strategic maps, classify research themes by organizing closely related words into research communities and evaluating them based on density and centrality (He, 1999). The density of a research community measures its internal cohesiveness, with higher density suggesting that a research area is well-established and mature (Leydesdroff, 1989). Centrality reflects the degree of interaction between a research community and other thematic areas, with higher centrality indicating a more influential and widely connected domain. By mapping research clusters based on these attributes, strategic diagrams provide a structured understanding of the thematic composition of health communication technologies.

While numerous systematic reviews have examined health communication and technology, many remain limited in scope. For instance, Colorafi (2016) analyzed 35 studies over five years, focusing on sample characteristics and operational definitions, while Mehdizadeh-Maraghi and Nemati-Anaraki (2024) reviewed 43 studies on health communication. Moorhead et al. (2013) conducted a systematic review of 98 studies on the role of social media in health communication. Although these reviews offer valuable insights, they are constrained by the number of studies that can be manually analyzed. Unlike traditional literature reviews, scientometric methods facilitate large-scale, data-driven assessments that uncover hidden patterns in research domains and provide a more comprehensive understanding of scholarly trends (Surulinathi et al., 2013).

Building on previous scientometric analyses related to health communication, this study extends beyond narrowly focused examination of studies related to health communication technologies. For example, Zulfikar and Setyonugroho (2023) examined telehealth by analyzing keyword trends, while Nti et al. (2023) focused specifically on sustainable healthcare research. Unlike these studies, which primarily relied on publication titles, this research advances the scientometric study of health communication technology by incorporating both author-generated keywords, abstracts, and titles, offering a more comprehensive view of the field. By integrating co-word analysis and strategic diagramming, this study systematically maps the intellectual structure of health communication technologies, identifies major research themes, and provides insights into how research efforts are distributed across different technological domains. Through this approach, the study contributes to a deeper understanding of the field's development and highlights areas requiring further scholarly attention.

3. Methods

1) Data Collection and Preprocessing

To examine the thematic landscape of research related to health communication technologies, data were collected from the Web of Science, a widely used multidisciplinary database. The search query included the term "health technology" appearing anywhere in the document (title, abstract, keywords, and full text, where available). To ensure relevance, the dataset was refined to include only research articles published in journals classified under communication studies between 2010 and 2024. A 15-year time frame (2010-2024) was selected to capture more than a decade of transformative technological innovation that significantly reshaped the field of health communication. The 2010s marked a turning point with the widespread emergence of wearable health trackers (e.g., Fitbit), voice-enabled virtual assistants (e.g., Siri, Alexa), and mobile health platforms, which collectively ushered in a new

era of personalized, real-time, and interactive health technologies. This period also builds upon and extends prior systematic reviews—such as Suggs' (2006) retrospective of technology and health communication research from 1996 to 2006, and Hu's (2015) review of digital health communication studies from 2008 to 2012—positioning this study to provide an updated and comprehensive scientometric perspective on the evolving research landscape. The term "health technology" was chosen because "technology" is a broad term encompassing various innovations utilized in healthcare settings (Colorafi, 2016). After removing duplicate records, the final dataset comprised 1,067 articles. The metadata retrieved from Web of Science included the list of authors, year of publication, title, author-generated keywords, abstract, journal name, citation count, and funding source.

The thematic structure was examined by conducting (a) a co-occurrence analysis of central words and (b) an identification and classification of technology-related terms. In the context of this research, central words refer to words found in the title, keywords, and abstract that summarize and represent the key themes of each research article. To conduct these analyses, a systematic text preprocessing approach was implemented. The text was first aggregated by combining the title, author-provided keywords, and abstract of each article into a single text corpus. Given the variability in spelling, phrasing, and terminology across studies (Cambrosio et al., 1993), a standardized text preprocessing approach was implemented to enhance analytical accuracy and reduce researcher subjectivity (Youk & Park, 2019). The preprocessing steps were as follows: all text was converted to lowercase for consistency, hyphens were removed to standardize compound words, and the WordSegment library in Python was used to split concatenated terms. Common stopwords such as "of," "the," "for," and "nor" were removed using the Natural Language Toolkit (NLTK), and frequently occurring generic research terms (e.g., "findings," "greater," "results," "literature," and "methods") were excluded to reduce noise in the dataset. The remaining words were lemmatized to their base form and further normalized using PorterStemmer in NLTK to consolidate similar terms (e.g., "theory" and "theoretical" were reduced to "theory"). The preprocessed text data were then subjected to co-occurrence analysis, wherein the frequency and patterns of word pairings were examined to identify key thematic relationships within the health communication technology

literature.

To extract and categorize technology-related terms, an automated natural language processing (NLP) approach was employed, integrating zero-shot prompting with ChatGPT-4o to systematically identify relevant technological terms from the preprocessed text. This method allowed for context-aware extraction of technology-related words without predefined keyword constraints. Extracted terms were manually verified for relevance and accuracy before being classified into nine distinct technology categories, including Artificial Intelligence & Machine Learning, Wearable & Assistive Technologies, Extended Reality & Immersive Media, Health & Medical Technologies, Smart & Digital Systems, Cybersecurity & Blockchain, Cloud & Edge Computing, Human-Computer Interaction & Robotics, and Speech & Communication Technologies. A word bank was created for each category to ensure comprehensive coverage of relevant terms (See Table 1). For instance, the category “Extended Reality & Immersive Media” included related terms such as “virtual reality,” “augmented reality,” and “mixed reality.”

Table 1. Technology Categories Related to Health Communication

Technology Category	Relevant Terms
Artificial Intelligence & Machine Learning	artificial intelligence, machine learning, deep learning, natural language, neural networks
Wearable & Assistive Technologies	wearable technology, wearables, assistive technology, biometric
Extended Reality & Immersive Media	virtual reality, augmented reality, mixed reality
Health & Medical Technologies	e-health, m-health, telemedicine, health informatics, genomics
Smart & Digital Systems	smart city, smart home, digital transformation
Cybersecurity & Blockchain	blockchain, cryptography
Cloud & Edge Computing	cloud computing, cloud storage
Human-Computer Interaction & Robotics	human-computer interaction, robotics, chatbot
Speech & Communication Technologies	speech recognition, chatbot

To determine the prevalence of each technology category within the dataset, a fuzzy string matching approach was applied using the FuzzyWuzzy library in Python. This method enabled the detection of variations in terminology, ensuring that near-identical words were correctly grouped (e.g., “machine-learning” and “machine learning” were treated as identical terms). The frequency of each technology-related term was then quantified across all articles in the dataset to examine patterns and trends in health communication technology research. The final classified dataset was subsequently used for network-based analyses to explore the landscape of certain health communication technologies.

2) Data Analysis

To provide an overview of the analyzed publications, this study provides a descriptive analysis of the metadata, including the total number of unique authors, institutional affiliations, and journals. For the 20 journals with the highest number of publications, additional indicators such as the average number of authors per publication, percentage of funded research, and average citation count are examined. Furthermore, the distribution of publications over time is analyzed to identify publication trends. The frequency of authorship and institutional affiliations is also examined to provide insights into collaboration patterns within the research articles analyzed in this study.

To investigate thematic relationships within the dataset, a co-occurrence analysis of central words was conducted. First, a co-occurrence matrix was generated, capturing the frequency with which pairs of words appeared together in the title, keywords, and abstracts. Using this matrix, a co-word network was constructed, where nodes represent words and edges represent co-occurrence relationships between words. The weight of each edge corresponds to the number of publications in which the word pair co-occurs, providing insights into the strength of conceptual associations. To further explore thematic structures, multiple centrality measures were calculated for each word, including degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality. These measures help identify the most influential terms in the field by assessing their importance within the co-word network. Additionally,

community detection was performed using the Louvain method, which identifies clusters of closely related terms that represent distinct research themes. For each community, the sum of inter-community edge weights (i.e., centrality) and the average of internal link weights (i.e., density) was computed.

To assess the significance of each research community within the field of health communication technology, a strategic diagram was created. In this diagram, the y-axis represents density, which measures the internal cohesiveness of a research theme, while the x-axis represents centrality, reflecting its integration and influence within the broader scholarly network. To systematically classify research themes, the median values of density and centrality were used to partition the diagram into four quadrants, following the methodological framework outlined by Hu et al. (2013). Clusters appearing in the upper-right quadrant (Q1) are characterized by high density and high centrality, indicating well-established and mature research areas that have been extensively studied and are central to the field. In contrast, the lower-right quadrant (Q2) consists of high-centrality but low-density topics, which are emerging yet conceptually significant—suggesting that while these areas are highly interconnected with other research themes, they have not yet developed internal cohesion. The upper-left quadrant (Q3) contains topics that exhibit high density but low centrality, implying that these themes were once more central but have evolved into specialized or niche areas over time. Lastly, the lower-left quadrant (Q4) represents both low-density and low-centrality communities, reflecting marginal research topics that have not yet gained widespread academic traction. By visualizing the distribution of research themes within this four-quadrant framework, the strategic diagram provides insights into the developmental trajectory of various topics in health communication technology. Themes may originate in peripheral and undeveloped areas (Q4), gain traction and become central and well-integrated (Q1) as they mature, or, conversely, decline in prominence over time and shift into peripheral but internally coherent categories (Q3) (Pourhatami et al., 2021).

For the analysis of technology-related terms, the study examined the proportion of each technology category mentioned over time by calculating the frequency of each technology-related term per publication and aggregating the occurrences by year to assess

longitudinal trends. The relative proportion of each technology in a given year was then analyzed to observe shifts in research focus across different time periods. To further explore conceptual relationships, a co-occurrence network of technology-related terms was constructed, illustrating how different technologies are studied in conjunction with one another. Additionally, to understand the contexts in which various technologies are discussed, the co-occurrence of technology-related terms with central words was examined. Specifically, the relationship between each technology and the research communities identified in the central word analysis was assessed by calculating the co-occurrence frequency of each technology term with words in each community.

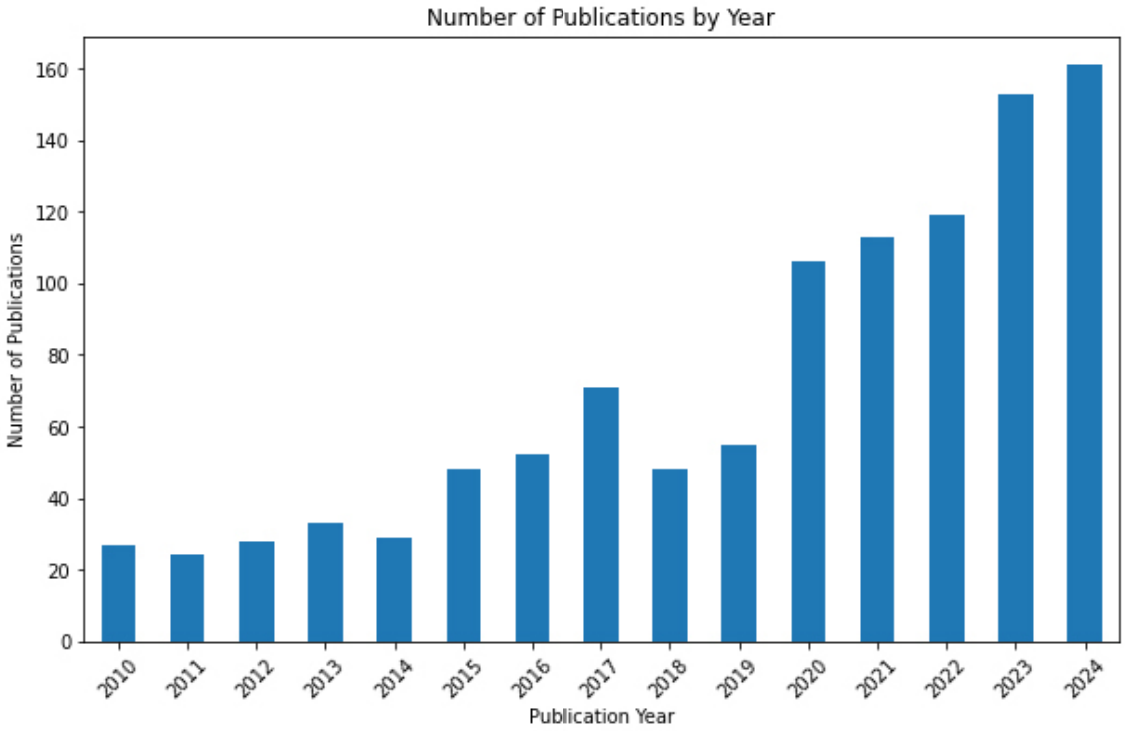
4. Results

1) Descriptive Analysis of the Data

The 1,067 research articles analyzed in this study are published across 152 academic journals. A total of 3,084 unique authors and 967 institutional affiliations were represented. The accumulated 47,520 citations across all publications and a total of 4,935 unique central words are analyzed in this study.

(1) Temporal trends in research output.

The annual distribution of publications from 2010 to 2024 indicates a steady increase in research activity on health communication technologies (See Figure 1). In the early years, fewer than 30 articles were published annually, with a gradual rise observed from 2015 onward. The number of publications exceeded 100 per year starting in 2020 and continued to grow, reaching 161 articles in 2024, marking the highest output within the analyzed period. This trend suggests a growing academic interest in the field, with a notable acceleration in research over the past five years.



<Figure 1> Number of Technology-Related Health Communication Research Studies over Time

(2) Journal distribution

Among the 152 journals, research was concentrated in a subset of high-output venues (See Table 2). The top three journals—Health Communication (n = 118, 11.06%), Journal of Health Communication (n = 100, 9.37%), and Information, Communication & Society (n = 63, 5.90%)—collectively accounted for 26.33% of all publications in the dataset. The remaining publications were distributed across a diverse range of interdisciplinary journals, reflecting the multifaceted nature of health communication technology research. A detailed examination of the 20 most prolific journals revealed variations in collaborative authorship, funding prevalence, and citation impact. The average number of authors per paper ranged from 1.94 (Media International Australia) to 4.49 (Journal of Health Communication), indicating differences in collaboration patterns across publication venues. The proportion of funded research was highest in the Journal of Social and Personal Relationships (100%) and Convergence: The International Journal of Research into New Media Technologies (78.57%),

Table 2. Descriptive Analysis of Top Journals

Journal Name	(1)	(2)	(3)	(4)	(5)	(6)
Health Communication	118.00	11.06	399.00	3.63	48.31	16.11
Journal of Health Communication	100.00	9.37	425.00	4.49	43.00	36.69
Information Communication & Society	63.00	5.90	185.00	3.02	60.32	83.25
New Media & Society	59.00	5.53	201.00	3.44	52.54	45.76
Public Understanding of Science	54.00	5.06	171.00	3.20	61.11	19.24
Journal of Science Communication	43.00	4.03	173.00	4.23	44.19	4.86
Frontiers in Communication	31.00	2.91	128.00	4.26	74.19	7.48
Social Media + Society	28.00	2.62	79.00	2.86	60.71	24.18
Telecommunications Policy	27.00	2.53	60.00	2.26	59.26	31.11
International Journal of Communication	23.00	2.16	64.00	2.83	60.87	24.57
Mobile Media & Communication	19.00	1.78	55.00	2.89	36.84	19.00
Media International Australia	17.00	1.59	32.00	1.94	47.06	23.12
Cyberpsychology-Journal of Psychosocial Research on Cyberpsychology	17.00	1.59	45.00	3.06	41.18	11.94
Journal of Computer-Mediated Communication	16.00	1.50	48.00	3.00	43.75	35.69
Convergence-The International Journal of Research into New Media Technologies	14.00	1.31	41.00	3.00	78.57	12.29
Information Society	14.00	1.31	29.00	2.07	0.00	21.64
Science Communication	14.00	1.31	32.00	2.50	64.29	32.57
Journal of Social and Personal Relationships	13.00	1.22	46.00	3.77	100.00	11.77
Feminist Media Studies	13.00	1.22	29.00	2.23	30.77	8.15
International Journal of Mobile Communications	12.00	1.12	31.00	2.67	25.00	11.58

Note. The table variables are defined as follows: (1) Number of Articles, (2) Percentage of Total Publications, (3) Number of Unique Authors, (4) Average Number of Authors per Publication, (5) Percentage of Funded Research, and (6) Average Citation Count.

while several journals, such as Information Society, had no reported funded research. Citation impact also varied, with Information, Communication & Society reporting the highest average citation count per paper (83.25), followed by Journal of Health Communication (36.69) and Science Communication (32.57). These findings suggest that certain journals attract more highly cited work, while others serve as key outlets for emerging research with lower citation impact.

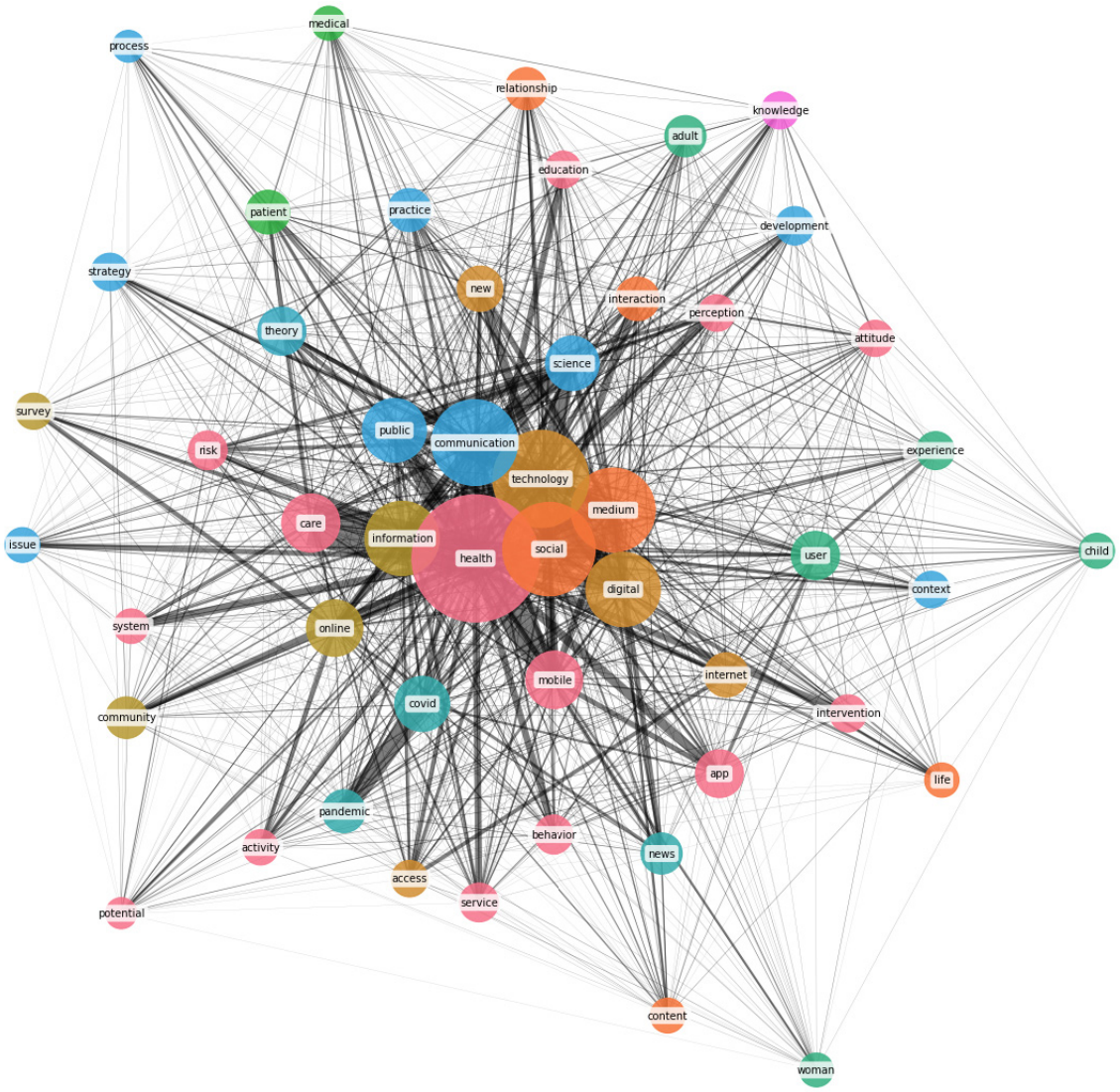
(3) Authorship patterns

A total of 3,084 authors contributed to the 1,067 papers, with an average of 1.11 publications per author (*SD* = 0.44). The 20 most prolific authors, who together produced 8.81% of all papers, had an average of 4.70 publications each (*SD* = 1.03). Citation analysis revealed that the average number of citations per author was 20.98 (SD = 102.06), while the most prolific authors received an average of 22.93 citations (*SD* = 13.39). Collaboration among researchers was evident, with the average number of co-authors per paper calculated at 3.23 (*SD* = 2.33). A considerable proportion of studies (47.61%) received external funding, highlighting the role of institutional and governmental support in advancing research on health communication technologies.

2) Co-occurrence Analysis of Central Words

To identify central themes in health communication technology research, a co-occurrence analysis of key terms was conducted (see Figure 2). The top 50 words with the highest degree centrality were extracted, indicating their importance within the overall network structure. Degree centrality measures the number of direct connections a word has, reflecting its prominence in the research landscape (for other centrality measures, see Table 2).

Excluding the terms “health” (degree centrality = 0.233), “technology” (degree centrality = 0.198), and “communication” (degree centrality = 0.153), which were used in the data collection process, other highly central terms included “social” (degree centrality = 0.169) and “medium” (degree centrality = 0.143). This is unsurprising given that communication



<Figure 2> Co-Occurrence Network of the Top 50 Central Words Related to Health Communication Technologies

research falls within the domain of social science and that media plays an integral role in the field. Additionally, terms such as “digital” (degree centrality = 0.125), “information” (degree centrality = 0.125), and “online” (degree centrality = 0.087) highlight the digital transformation in health communication technology, emphasizing the critical role of digital and online platforms as foundational infrastructures in this research area.

Beyond the core thematic structure, terms such as “care” (degree centrality = 0.082), “patient” (degree centrality = 0.064), “medical” (degree centrality = 0.044), and “service” (degree centrality = 0.048) suggest a substantial research focus on patient-centered applications of health technologies. The inclusion of “mobile” (degree centrality = 0.076) and “app” (degree centrality = 0.063) further underscores the prominence of mobile health applications as a key area of study. Moreover, the emergence of “COVID” (degree centrality = 0.078) and “pandemic” (degree centrality = 0.060), alongside terms such as “risk” (degree centrality = 0.051), “behavior” (degree centrality = 0.050), and “intervention” (degree centrality = 0.049), reflects the significant impact of the global pandemic on health communication research. These findings suggest that the pandemic has driven scholarly discussions on public health messaging, crisis communication, and digital interventions.

(1) Community Detection Analysis

To examine the thematic structure of health communication technology research, a community detection analysis was conducted using the Louvain method. The 17 identified communities represent distinct research areas, each characterized by a set of highly co-occurring keywords. The size of each community reflects the number of associated terms, while density indicates the internal cohesion of the community, and centrality measures its integration within the overall network (see Table 3 for details). Based on centrality and density, each community is plotted on a strategic map to assess its maturity and significance within academic discourse.

The largest communities include Community 0 (Health and Medical Applications), Community 1 (Social and Interactive Dimensions), and Community 2 (Digital and Technological Infrastructure). These communities encompass broad thematic areas, capturing key aspects of health interventions, social media, and digital health platforms. In contrast, smaller communities, such as Community 5 (School and Education) and Community 8 (Statistical and Measurement Methodologies), represent more specialized areas within health communication technology research. The relatively smaller size of these communities suggests that fewer studies utilize school and university students as research samples and that statistical

Table 3. Summary of Community Analysis

	Community Name	Size	Density	Centrality	Salient Central Words
0	Health and Medical Application	1329	2.88	2.24	health, care, mobile, app, behavior, service, risk, literacy, education, intervention
1	Social and Interactive Dimension	1312	1.50	1.16	social, medium, interaction, relationship, content, network, life, platform, wellbeing, usage
2	Digital and Technology Infrastructure	1337	0.83	0.89	technology, digital, new, internet, access, challenge, tool, concern, privacy, device
3	Information Sharing	886	0.23	1.09	information, online, community, source, cancer, trust, personal, sharing, seeking
4	Discourse and Critical Perspectives	525	-0.78	-1.01	discourse, critical, body, human, identity, virtual, voice, action, image, construction
5	School and Education	115	-0.68	-0.76	student, university, school, college, course, drinking, secondary, undergraduate, classroom
6	Patient-Centered Medical Treatment	655	-0.53	-0.10	patient, medical, family, video, website, text, member, active, treatment, physician
7	User Experience and Qualitative Research	806	0.15	0.48	user, adult, experience, older, child, woman, interview, young, qualitative, parent
8	Measurement and Methodologies	72	-0.43	-1.34	structural, reveals, equation, least, validity, simple, reliability, partial, model, invariance
9	COVID-19 and Pandemic Communication	1028	-0.03	-0.21	covid, pandemic, news, message, crisis, narrative, united, China, disease, global
10	Theoretical Frameworks	406	-0.67	-0.11	theory, framework, management, us, norm, practical, behavior, uncertainty, motivation, mechanism
11	Public Engagement and Health Communication Strategies	1613	1.07	0.83	communication, public, science, practice, development, strategy, context, issue, engagement, policy
12	Artificial Intelligence	152	-0.52	-1.03	artificial, intelligence, learning, robot, person, conversational, newsroom, another, agent, affordance
13	Cognition and Psychology	331	-0.76	-0.41	attention, language, cognitive, effort, game, computer, performance, function, genetic, therapy
14	Telecommunication Technologies	227	-0.80	-0.97	phone, traditional, mother, call, cell, possible, resistance, connected, blogger, household
15	Knowledge Gap and Facts	133	-0.67	0.59	knowledge, HIV, exposure, aid, gap, transition, regional, option, factual, misperception, PSA
16	Food and Agriculture	155	-0.79	-1.33	food, disclosure, modified, consensus, genetically, networked, agriculture, farmer

Note. The size of a community refers to the number of unique words it contains. Density and centrality scores are standardized for comparison

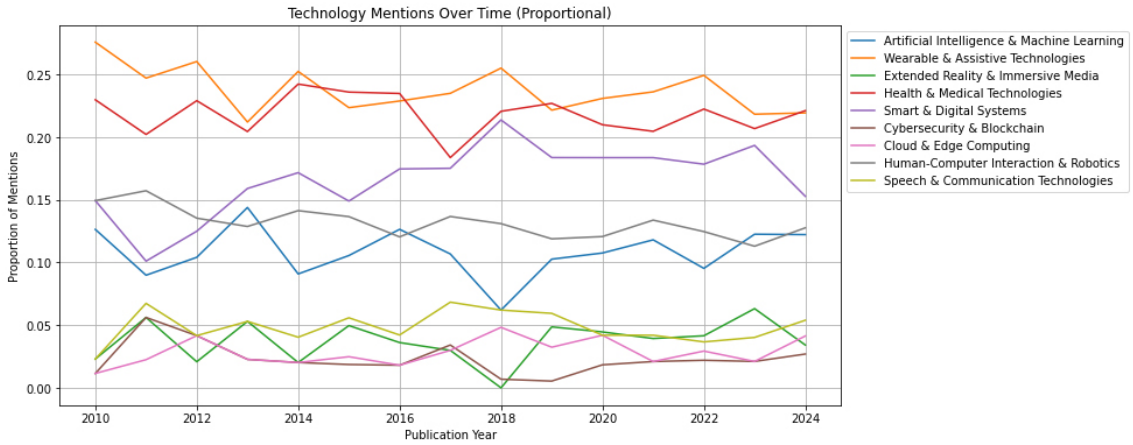
measurement methodologies play a less central role in health communication technology investigations.

To assess the relative prominence and maturity of these thematic communities, the identified communities were plotted on a strategic map, divided into four quadrants based on centrality and density. The results indicate that Community 0 (Health and Medical Applications), Community 1 (Social and Interactive Dimensions), and Community 11 (Public Engagement and Health Communication Strategies) represent well-established research areas that are both thematically cohesive and well-integrated within the broader health communication technology research network. This suggests that patient-centered health technologies, mobile applications, behavioral health interventions, health literacy programs, social networks, user engagement, digital health interactions, and public engagement strategies are foundational aspects of the research landscape.

On the other hand, some communities, while central, remain relatively underdeveloped. Community 15 (Knowledge Gap and Facts) is an emerging area that, despite being highly connected, remains conceptually fragmented, indicating the need for further consolidation. This community encompasses research on knowledge gaps, information dissemination, and health misinformation. Additionally, several communities—Community 16 (Food and Agriculture), Community 4 (Discourse and Critical Perspectives), Community 14 (Telecommunication Technologies), and Community 5 (School and Education)—are both peripheral and underdeveloped, suggesting that these areas may be overlooked in health communication research. The findings indicate that health communication research focused on technology tends to underexplore topics related to food and agriculture and would benefit from increased engagement with discourse analysis and critical perspectives. Furthermore, research utilizing student samples does not appear to play a central role in health communication technology studies. While mobile applications are well studied, traditional phone and voice-based communication technologies in health communication remain understudied, representing a potential gap in the existing literature.

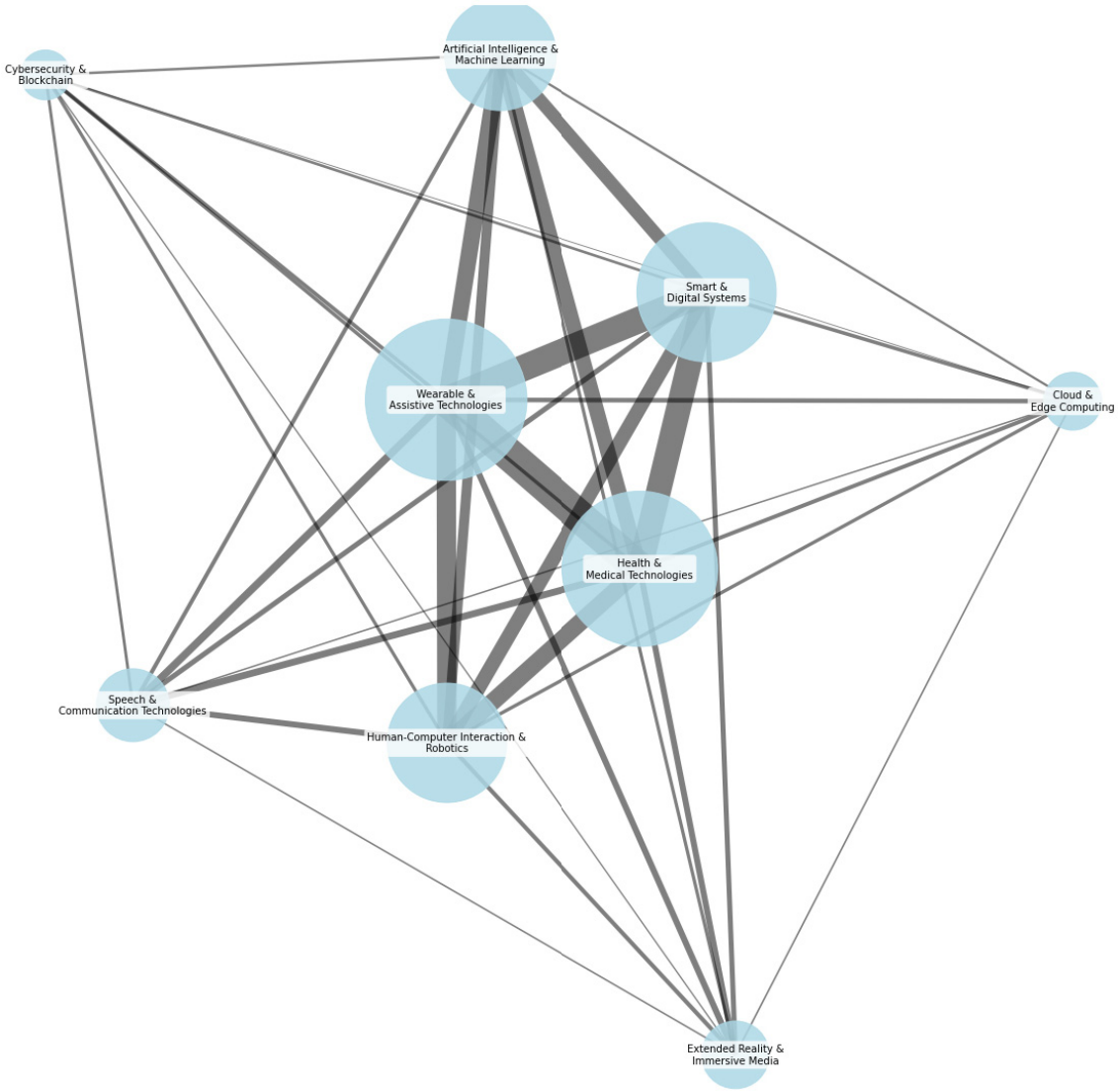
3) Technology-related Co-occurrence Analysis

To examine the role of different technologies in health communication research, a co-occurrence analysis of technology-related terms was conducted. When analyzing the proportion of different technologies mentioned over time from 2010 to 2024, the overall trend remains relatively stable (See Figure 3). Wearable and assistive technologies, as well as health and medical technologies, continue to be the most prevalent areas of research. In contrast, speech-focused technology, cloud computing, cybersecurity, blockchain, and extended reality remain less frequently studied. Additionally, human-computer interaction and robotics technologies have shown a slight decline, whereas smart and digital systems, such as smart homes, have exhibited an increasing trend.



<Figure 3> Proportion of Mentioned Technologies over Time

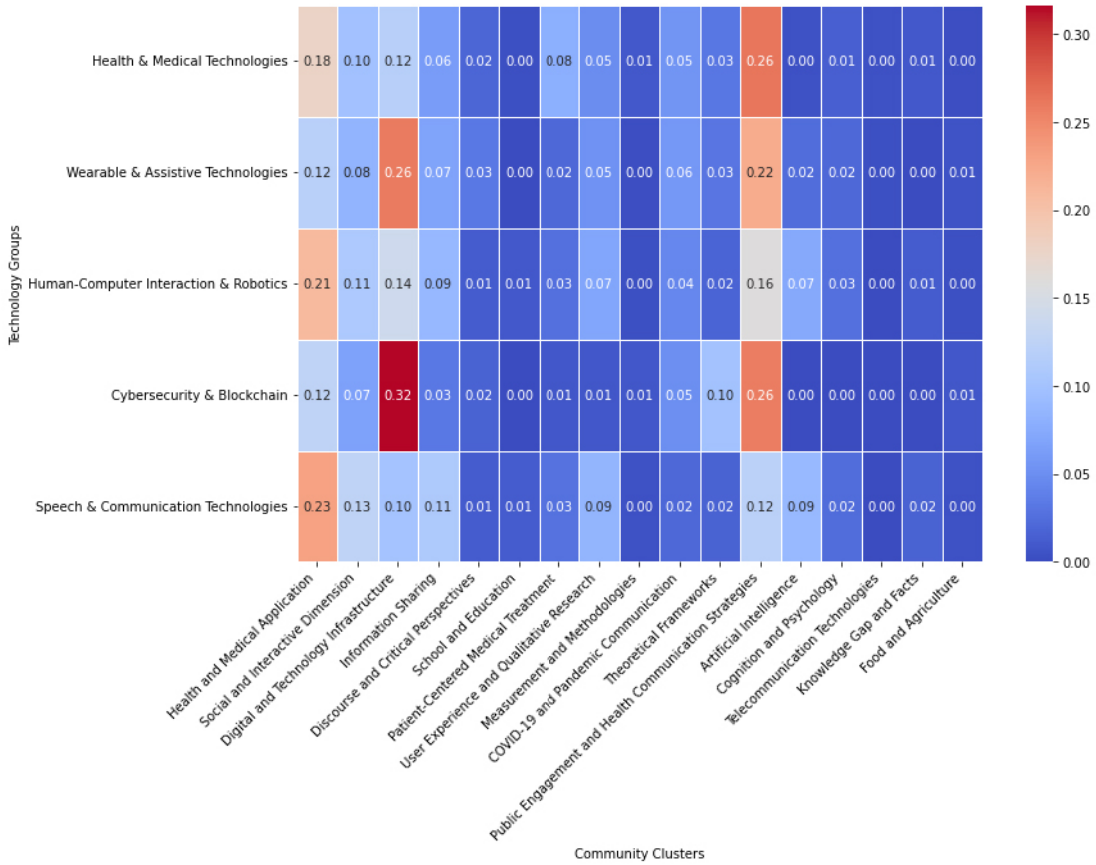
To explore the relationships between different health communication technologies, a co-occurrence analysis was conducted (See Figure 4). The results indicate that wearable technologies are closely studied alongside health and medical technologies, particularly mobile health applications, as well as with smart and digital systems, such as smart homes and the Internet of Things (IoT). However, cybersecurity, speech and communication technologies, extended reality and immersive media, and cloud computing appear to be relatively less studied in conjunction with other health communication technologies.



<Figure 4> Co-Occurrence Network of Health Communication-Related Technologies

To further investigate how different technologies are discussed within distinct thematic areas, a co-occurrence analysis was performed between technology-related terms and the identified research communities (See Figure 5). The proportion of mentions of each technology within a given community reflects the extent to which that technology is integrated into specific thematic research areas. The findings indicate that public engagement and eHealth communication strategies are most closely associated with various health communication

technologies. Health and medical technologies are most prominently mentioned in Community 11 (Public Engagement & Health Communication Strategies), suggesting that eHealth and mobile health technologies are primarily studied in the context of improving health communication strategies to enhance public engagement. Wearable and assistive technologies are most frequently associated with Community 2 (Digital & Technological Infrastructure) and Community 11 (Public Engagement & Health Communication Strategies), with proportions of 25.9% and 22.2%, respectively. Similarly, human-computer interaction and robotics are most frequently mentioned in Community 0 (Health & Medical Applications) and Community 11 (Public Engagement & Health Communication Strategies), accounting for 20.8% and 15.8% of mentions, respectively.



<Figure 5> Proportion of Technologies Mentioned in Relation to Identified Research Communities for Health Communication Technologies

5. Discussion

This study employed a scientometric approach to systematically examine research trends in health communication technologies over the past decade. The findings indicate a notable rise in publications since 2020, a trend that aligns with prior observations regarding the surge in digital health research following the COVID-19 pandemic (Khurana et al., 2023). A thematic analysis of the literature revealed three dominant research areas: health and medical applications, social and interactive dimensions, and digital and technological infrastructures. Patient-centered technologies, mobile health applications, and digital interventions emerged as central themes, while knowledge gaps, misinformation, and public engagement strategies were identified as developing yet increasingly significant areas.

The interdisciplinary nature of health communication technology research is evident in the strong connections between terms from multiple fields, including healthcare, social sciences, and information technology (Nti et al., 2023). The high connectivity of keywords related to digital health, social interaction, and public communication underscores the convergence of these disciplines. The prominence of mobile and digital platforms, along with pandemic-related themes, reflects both emerging research directions and long-standing priorities in the field (Silva et al., 2015). These findings provide a comprehensive mapping of the conceptual landscape of health communication technologies, illustrating how key research themes have evolved and identifying areas for future exploration.

The findings highlight several dominant research themes in the field, including patient-centered technologies, mobile health applications, and public engagement strategies. These findings align with longstanding priorities in digital health, such as increasing accessibility, enhancing health literacy, and empowering patients to manage their care (Neuhauser & Kreps, 2003). The prominence of mobile applications can also be interpreted in light of widespread smartphone adoption and their cost-effectiveness in delivering personalized interventions (Boulos et al., 2011). The emphasis on public engagement reflects growing concerns around health misinformation, vaccine hesitancy, and the role of social media in shaping public discourse, particularly during and after the COVID-19 pandemic (Betsch et al.,

2020).

Despite the field's rapid expansion, disparities remain in the technological focus of research. While wearable and assistive technologies and mobile health applications are widely studied, cybersecurity, blockchain, speech communication technologies, and extended reality remain underexplored, a gap also noted by other scholars (Sam et al., 2022; Talan et al., 2022). Although blockchain and extended reality technologies currently occupy peripheral positions in the research landscape, they represent critical frontiers for future inquiry. Blockchain has been explored in healthcare as a mechanism for enhancing security, interoperability, and trust in the management of electronic health records (Singh et al., 2020). These features are highly relevant to health communication contexts that require confidential and traceable message exchange. Similarly, virtual and augmented reality technologies offer immersive environments for training, health education, and behavioral interventions, often grounded in media richness theory and experiential learning models (Freeman et al., 2017). Additionally, health and medical technologies are most frequently associated with public engagement and eHealth communication strategies, underscoring their role in improving communication with patients and the broader public (Srivastava et al., 2015). However, eHealth should not be viewed merely as a matter of technology adoption but should also consider issues of engagement, empowerment, and ethical concerns for its successful implementation (Hardiker & Grant, 2011).

The methodological approach of this study contributes to advancing scientometric methodologies within health communication research. By integrating co-word analysis, strategic diagramming, and technology co-occurrence mapping, this study demonstrates how computational techniques can systematically assess research trends. The study extends previous bibliometric research (e.g., Nti et al., 2023; Khurana et al., 2023; Zulfikar & Setyonugroho, 2023) by incorporating both author-generated keywords and abstracts, whereas prior studies have often limited their analysis to titles. The results align with systematic reviews such as those by Mehdizadeh-Maraghi and Nemati-Anaraki (2024), and Moorhead et al. (2013), reinforcing the value of scientometric approaches in understanding the structure of health communication research.

Despite its contributions, this study has limitations that should be addressed in future research. First, the reliance on the Web of Science as the primary data source may have excluded relevant studies published in non-indexed or emerging academic outlets. Future research should integrate multiple databases, such as Scopus and PubMed, to construct a more comprehensive dataset. Second, while this study employed co-occurrence analysis and community detection methods to identify thematic clusters, these approaches do not capture the depth of theoretical and conceptual developments in health communication technologies. Future studies could complement scientometric analyses with qualitative content analysis to provide deeper insights into how digital health technologies are conceptualized. Last, this study adopts a scientometric approach, which is inherently descriptive in nature. The primary aim of such an approach is to document, map, and visualize the thematic and intellectual structure of a research field over time. Unlike causal or explanatory research methods, scientometric analysis does not attempt to determine underlying mechanisms or test theoretical relationships. Building on the empirical foundations provided in this study, future research should utilize other research methods to explain the observed trends in health communication.

The challenges of implementing digital health technologies remain a pressing issue, as Suggs (2006) noted, and continue to be relevant today. Barriers such as access disparities, variations in health and technology literacy, hardware and software compatibility issues, and concerns about information quality and privacy persist, even as digital solutions become more widely adopted. While advancements have been made, future research must continue addressing these structural challenges to ensure the effective and equitable integration of digital health communication technologies.

References

Aceto, G., Persico, V., & Pescapé, A. (2020). Industry 4.0 and health: Internet of things, big data, and cloud computing for healthcare 4.0. *Journal of Industrial Information Integration, 18*, 100129.

Barker, W., Chang, W., Everson, J., Gabriel, M., Patel, V., Richwine, C., & Strawley, C. (2024). The evolution of health information technology for enhanced patient-centric care in the United States: Data-driven descriptive study. *Journal of Medical Internet Research, 26*, e59791.

Betsch, C., Wieler, L. H., & Habersaat, K. (2020). Monitoring behavioural insights related to COVID-19. *The Lancet, 395*(10232), 1255-1256. https://doi.org/10.1016/S0140-6736(20)30729-7

Borges do Nascimento, I. J., Abdulazeem, H., Vasanthan, L. T., Martinez, E. Z., Zucoloto, M. L., Østengaard, L., ... & Novillo-Ortiz, D. (2023). Barriers and facilitators to utilizing digital health technologies by healthcare professionals. *NPJ Digital Medicine, 6*(1), 161.

Boulos, M. N. K., Wheeler, S., Tavares, C., & Jones, R. (2011). How smartphones are changing the face of mobile and participatory healthcare: An overview, with example from eCAALYX. *Biomedical Engineering Online, 10*, 24. https://doi.org/10.1186/1475-925X-10-24

Cambrosio, A., Limoges, C., Courtial, J., & Laville, F. (1993). Historical scientometrics? Mapping over 70 years of biological safety research with co-word analysis. *Scientometrics, 27*(2), 119-143.

Colorafi, K. (2016). Connected health: A review of the literature. *Mhealth, 2*, 13.

Dinh-Le, C., Chuang, R., Chokshi, S., & Mann, D. (2019). Wearable health technology and electronic health record integration: Scoping review and future directions. *JMIR mHealth and uHealth, 7*(9), e12861.

Eysenbach, G., Powell, J., Englesakis, M., Rizo, C., & Stern, A. (2004). Health-related virtual communities and electronic support groups: Systematic review of the effects of online peer-to-peer interactions. *BMJ, 328*(7449), 1166.

Fitzpatrick, P. J. (2023). Improving health literacy using the power of digital communications to achieve better health outcomes for patients and practitioners. *Frontiers in Digital Health, 5*, 1264780.

Freeman, D., Reeve, S., Robinson, A., Ehlers, A., Clark, D., Spanlang, B., & Slater, M. (2017). Virtual reality in the assessment, understanding, and treatment of mental health disorders. *Psychological Medicine, 47*(14), 2393-2400.

Hardiker, N. R., & Grant, M. J. (2011). Factors that influence public engagement with eHealth: A literature review. *International Journal of Medical Informatics, 80*(1), 1-12.

He, Q. (1999). Knowledge discovery through co-word analysis. *Library Trends, 48*, 133-159.

Hu, Y. (2015). Health communication research in the digital age: A systematic review. *Journal of Communication in Healthcare, 8*(4), 260-288.

Hu, C. P., Hu, J. M., Deng, S. L., & Liu, Y. (2013). A co-word analysis of library and information science in China. *Scientometrics, 97*(2), 369-382.

Kaliyaperumal, K. (2015). A scientometric analysis of mobile technology publications. *Scientometrics, 105*(2), 921-939.

Khurana, A., Ravikumar, V., & Kumar, V. (2023, July). A scientometric study of artificial intelligence in the health care sector. In *2023 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT)* (pp. 316-319). IEEE.

Lewis, J., Ray, P., & Liaw, S. T. (2016). Recent worldwide developments in eHealth and mHealth to more effectively manage cancer and other chronic diseases-A systematic review. *Yearbook of Medical Informatics, 25*(1), 93-108.

Leydesdorff, L. (1989). Words and co-words as indicators of intellectual organization. *Research Policy, 18*(4), 209-223.

Mehdizadeh-Maraghi, R., & Nemati-Anaraki, L. (2024). Application of problematic integration theory in health communication: A scoping review. *Health Communication, 39*(12), 2620-2646.

Moorhead, S. A., Hazlett, D. E., Harrison, L., Carroll, J. K., Irwin, A., & Hoving, C. (2013). A new dimension of health care: Systematic review of the uses, benefits, and limitations of social media for health communication. *Journal of Medical Internet Research, 15*(4), e1933.

Mozumder, M. A. I., Sheeraz, M. M., Athar, A., Aich, S., & Kim, H. C. (2022, February). Overview: Technology roadmap of the future trend of metaverse based on IoT, blockchain, AI technique, and medical domain metaverse activity. In *2022 24th International Conference on Advanced Communication Technology (ICACT)* (pp. 256-261). IEEE.

Neuhauser, L., & Kreps, G. L. (2003). Rethinking communication in the e-health era. *Journal of Health Psychology, 8*(1), 7-23.

Nti, I. K., Adekoya, A. F., Weyori, B. A., & Keyeremeh, F. (2023). A bibliometric analysis of technology in sustainable healthcare: Emerging trends and future directions. *Decision Analytics Journal, 8*, 100292.

Pourhatami, A., Kaviyani-Charati, M., Kargar, B., Baziyad, H., Kargar, M., & Olmeda-Gómez, C. (2021). Mapping the intellectual structure of the coronavirus field (2000-2020): A co-word analysis. *Scientometrics, 126*, 6625-6657.

Sam, M. F. M., Ismail, A. F. M. F., Bakar, K. A., Ahamat, A., & Qureshi, M. I. (2022). The effectiveness of IoT-based wearable devices and potential cybersecurity risks: A systematic literature review from the last decade. *International Journal of Online and Biomedical Engineering, 18*(9), 56-73.

Sieck, C. J., Sheon, A., Ancker, J. S., Castek, J., Callahan, B., & Siefer, A. (2021). Digital inclusion as a social determinant of health. *NPJ Digital Medicine, 4*(1), 52.

Silva, B. M., Rodrigues, J. J., de la Torre Díez, I., López-Coronado, M., & Saleem, K. (2015).

Mobile-health: A review of current state in 2015. *Journal of Biomedical Informatics, 56*, 265-272.

Singh, A. P., Pradhan, N. R., Luhach, A. K., Agnihotri, S., Jhanjhi, N. Z., Verma, S., ... & Roy, D. S. (2020). A novel patient-centric architectural framework for blockchain-enabled healthcare applications. *IEEE Transactions on Industrial Informatics, 17*(8), 5779-5789.

Srivastava, S., Pant, M., Abraham, A., & Agrawal, N. (2015). The technological growth in eHealth services. *Computational and Mathematical Methods in Medicine, 2015*(1), 894171.

Stockwell, M. S., & Fiks, A. G. (2013). Utilizing health information technology to improve vaccine communication and coverage. *Human Vaccines & Immunotherapeutics, 9*(8), 1802-1811.

Suggs, L. S. (2006). A 10-year retrospective of research in new technologies for health communication. *Journal of Health Communication, 11*(1), 61-74.

Surulinathi, M., Balasubramani, R., & Kalisdha, A. (2013). Continent-wise analysis of green computing research: A scientometric study. *Journal of Advances in Library and Information Science, 2*(1), 39-44.

Talan, T., Akturk, C., & Cubukcu-Cerasi, C. (2022). Investigation of scientific studies on wearable technologies in terms of security and privacy. *The Eurasia Proceedings of Educational and Social Sciences, 24*, 61-67.

Van Raan, A. F., & Tijssen, R. J. (1993). The neural net of neural network research: An exercise in bibliometric mapping. *Scientometrics, 26*, 169-192.

Wang, J., & Shahzad, F. (2022). A visualized and scientometric analysis of health literacy research. *Frontiers in Public Health, 9*, 811707.

Yadav, S. (2024). Transformative frontiers: A comprehensive review of emerging technologies in modern healthcare. *Cureus, 16*(3), e56538.

Yeung, A. W. K., Litvinova, O., Bragazzi, N. L., Khader, Y., Rahman, M. M., Said, Z., ... & Atanasov, A. G. (2024). Digital health and mobile health: A bibliometric analysis of the 100 most cited papers and their contributing authors. *Exploration of Digital Health Technologies, 2*, 86-100.

Youk, S., & Park, H. S. (2019). Where and what do they publish? Editors' and editorial board members' affiliated institutions and the citation counts of their endogenous publications in the field of communication. Scientometrics, 120(3), 1237-1260.

Zhu, C., Xu, X., Zhang, W., Chen, J., & Evans, R. (2020). How health communication via TikTok makes a difference: A content analysis of TikTok accounts run by Chinese provincial health committees. *International Journal of Environmental Research and Public Health, 17*(1), 192.

Zulfikar, A. R., & Setyonugroho, W. (2023). Bibliometric review of telemedicine using by patient and healthcare perspective. *World Journal of Advanced Research and Reviews, 17*(1), 1206-1213.

헬스 커뮤니케이션 기술 연구의 지형도 탐색

과학계량학적 분석을 중심으로*

육성빈** 이화여자대학교, 사회과학대학, 커뮤니케이션・미디어 학부, 조교수

최초 투고일: 2025년 02월 23일
논문 수정일: 2025년 04월 06일
게재 확정일: 2025년 04월 17일

본 연구는 개별 헬스 커뮤니케이션 기술 분석에 편중된 선행 연구를 보완하고자 포괄적 데이터 기반 분석을 수행하였다. 2010년부터 2024년까지 발표된 1,067편의 학술 논문을 대상으로 과학계량학적 접근법(scientometric analysis)을 활용해 헬스 커뮤니케이션 기술 연구의 지식 구조를 체계적으로 규명하였다. 동시출현단어 분석(co-word analysis) 및 전략 지형도(strategic mapping)를 통해, 환자 중심의 디지털 도구, 모바일 헬스 애플리케이션, 그리고 공중 참여 전략은 학문적 성숙도가 높은 핵심 영역으로 확인된 반면, 사이버 보안, 블록체인, 음성 커뮤니케이션 기술은 상대적으로 연구가 제한적인 것으로 분석되었다. 커뮤니티 탐지(community detection) 분석을 포함한 네트워크 분석에서는 사회과학, 디지털 헬스, 정보기술 간의 융복합적인 연구 특성이 두드러지게 나타났다. 이러한 연구 결과는 기술 발전이 헬스 커뮤니케이션 연구에 어떠한 방식으로 영향을 미쳐왔는지를 보다 심층적으로 이해할 수 있는 토대를 제공하며, 향후 학제 간 협력 연구의 방향성을 제시한다.

주제어 : 헬스 커뮤니케이션 기술, 과학계량학적 분석, 전략 지형도, 네트워크 분석

* 이 연구는 2024학년도 이화여자대학교 교내연구비 지원에 의한 연구임.
** sungbinyouk@ewha.ac.kr, 교신저자