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Mapping Human–Computer Interaction Research Themes and Trends from Its Existence to Today: A Topic Modeling-Based Review of past 60 Years

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ABSTRACT

As it covers a wide spectrum, the research literature of human-computer interaction (HCI) studies has a rich and multi-disciplinary content where there are limited studies demonstrating the big picture of the field. Such an analysis provides researchers with a better understanding of the field, revealing current issues, challenges, and potential research gaps. This study aims to explore the research trends in the developmental stages of the HCI studies over the past 60 years. Automated text mining with probabilistic topic modeling has been used to analyze 41,720 journal articles that are indexed by the SCOPUS database between 1957 and 2018. The results of this study reveal 21 major topics mapping the research landscape of HCI. By extending the discovered topics beyond a snapshot, the topics were analyzed considering their developmental stages, volume, and accelerations to provide a panoramic view that shows the increase and decrease of trends over time. In this context, the transition of HCI studies from machine-oriented systems to human-oriented systems indicates its future direction toward context-aware adaptive systems.

1. Introduction

Human-computer interaction (HCI) is an interdisciplinary field of research and practice that focuses on both the interaction between computers and users (human) and the design of interfaces that enable the interaction between them to be more effective (Dix, 2009; Kim & Group, 2015). More specifically, HCI is a dynamic discipline that studies how to design, build, implement and evaluate human-centric interactive computer systems and to maximize the usability, effectiveness, efficiency and satisfaction of the interfaces between users, computers, and other phenomena surrounding these elements (Çağıltay, 2018; Dix, 2017; Hewett et al., 1992; Shneiderman & Plaisant, 2010). In general, the letter "I" in HCI denotes both the interaction and the interface that illustrates an abstract model and technical methodology. In a more explicit sense, interaction is an abstract model that expresses human behavior and communication with a computer to perform a task, and an interface is the process of evaluating and selecting systems, platforms, or applications that technically enable such an interaction model (Hewett et al., 1992; Karray et al., 2008; Kim & Group, 2015; Shneiderman & Plaisant, 2010). The HCI system has four main components consisting of user, task, tool, and context. HCI studies generally evaluate the results of experimental observations obtained by users while performing specific tasks using related tools together with behavioral processes. The findings and experiences from this experimental process are used in the design and development of interactive systems (Çağıltay, 2018; Kim & Group, 2015; Shneiderman & Plaisant, 2010).

As HCI considers the interaction between human beings and the computers, those fields that study the human behaviors, psychology, sociology, cognitive science, anthropology, and education, as well as those related to computer science, software engineering, ergonomics, industrial design, and graphical design have been involved in HCI studies (Dix, 2017; Shneiderman & Plaisant, 2010). Besides its interdisciplinary feature, HCI is also a rapidly developing field which has been affected by technological developments (Dix, 2009; Hornbæk & Hertzum, 2017). Although HCI initially focused mostly on mainframe computers, after the emergence of personal computers in the late 1970s, it expanded into an interdisciplinary field covering almost all information technology design and applications (Dix, 2009; Kim & Group, 2015). From desktop computers to mobile devices, smart systems and the Internet of things, all innovative technologies that require human interaction at the highest level have made HCI a lively discipline (Kim & Group, 2015). Accordingly, there is an increased interest in HCI studies. Scientific literature is a rich source of information covering a wide range of disciplines, especially in dynamic areas, such as HCI, in which ever-changing research and practice are indexed (Dix, 2017; Karray et al., 2008; Kim & Group, 2015). It is important understand the trends and main topics studied in the field of HCI to better comprehend the scope of the field, and its development and future. However, as there are a large number of studies considered to be under the field of HCI, it is not very easy to analyze all of these studies and create a big picture of the

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field (Hinze-Hoare, 2007; Karray et al., 2008). However, such an analytical data-driven view can help researchers engage in new areas by informing them about the current popular topics and how focusing on different topics can change over time (Blei & Lafferty, 2007; Griffiths & Steyvers, 2004).

In today's technology-driven research environments, developments in digital publishing and open access facilities have led to greater access to scientific content, which makes it difficult and sometimes impossible for researchers to analyze the literature in order to identify the trends and evolution of research areas (Blei, 2012; Blei & Lafferty, 2007; Debortoli et al., 2016; Griffiths & Steyvers, 2004). The analysis of scientific literature using automated text-mining procedures offers a valuable insight into how research trends and themes evolve over time (Aggarwal & Zhai, 2013; Blei, 2012; Blei & Lafferty, 2007; Griffiths & Steyvers, 2004). In this context, using the automated text-mining technique to discover the hidden semantic structures (topics) in a collection of documents allows large amounts of text documents to be efficiently summarized (Blei, 2012; Blei & Lafferty, 2007; Griffiths & Steyvers, 2004; Gurcan, 2019; Gurcan & Cagiltay, 2019). In parallel to this background, the main aim of this study was to discover the topics and developmental trends in HCI studies from the beginning to date using a probabilistic topic-modeling technique. Since the studies found in the literature either concentrate on specific sub-topics of HCI or were conducted on a limited time period, this study aims to contribute to this field by filling the gaps in the history of HCI.

2. Background

The background for this study is based on HCI studies and the topic-modeling approach used for the data analysis of the study.

2.1. Human-computer interaction

Practical and theoretical studies in the field of HCI aim to produce information and communication technologies for people and their needs. Vannevar Bush's article, "As we may think", can be considered the first conceptual paper on HCI (Bush, 1945). The first study in this field was conducted by Shackel in 1959 (Shackel, 1959), after which the "International Journal of Man-Machine Studies" began publishing articles in the field. In the 1970s, the concept of "user-friendliness" was introduced, and in 1976, NATO sponsored a workshop on "man–computer interaction". In following years, improvements in the information and communication technologies directly affected HCI studies, and since the late 1970s, the field of HCI has taken its place in the scientific literature as a young and dynamic discipline (Grudin, 2012). In the early years, the interaction between one or more humans and machines were mainly addressed in HCI studies. More recently, the main consideration of the field has become to create systems with increased functionality and usability via state-of-the-art paradigms of interaction (Te'eni et al., 2007). In order to achieve this aim, HCI studies need to build systems having higher usability by considering all aspects of the interaction between human behaviors and technologies.

With the development of many technologies, the level and scope of the interactions are becoming very complicated. Earlier research results show that web interactivity significantly correlates with user enjoyment, positive attitudes, and desirable behavioral intentions (Yang & Shen, 2018), and usable website development should follow a model (Cunliffe, 2000). Due to the limitations in the design and use of the mobile platforms (Kjeldskov & Graham, 2003), there is a need for studies into mobile HCI (Coursaris & Kim, 2011; Harrison et al., 2013; Ocak & Cagiltay, 2017). Additionally, understanding human performance efficiency in virtual worlds influenced by task characteristics, user characteristics, human sensory and motor physiology, multimodal interaction, and the potential need for new design metaphors (Karacan & Cagiltay, 2009; Stanney et al., 1998) are also important for HCI studies. Player and video game interaction (Caroux et al., 2015) and game research in HCI (Carter et al., 2014) are also significant factors considering the aim of the interaction. Individual human differences also need to be considered in HCI studies (Dillon & Watson, 1996), such as age (Kaya et al., 2017), culture (Aryana & Øritsland, 2010; Clemmensen & Roese, 2009; Kyriakoullis & Zaphiris, 2016), cognition (Gordon, 2005; Hurtienne, 2009), emotion (Perez-Gaspar et al., 2016; Peter et al., 2007), affect (Akgun et al., 2010), and social engagement (Hochheiser & Lazar, 2007).

An increased degree of human involvement during human-machine interaction also escalates the complexity (Karray et al., 2008). This derives from the activities of the human during this interaction which can be physical (Chapanis, 1965), cognitive (Norman & Draper, 1986), and affective (Picard, 2003), and the devices being developed involve human senses like vision, audition, and touch (Te'eni et al., 2007). These technologies create a multimodal HCI perspective for the traditional uni-model communication (Turk, 2014). These advances in computer technologies also bring with them the considerations of new HCI options. Another important issue for HCI is its universal design (Akoumianakis & Stephanidis, 1989; Cagiltay, 1999), architectural design characteristics (Anshuman & Kumar, 2004), pattern languages (Dearden & Finlay, 2006), and user experience (Hornbæk & Hertzum, 2017). The improvements in sensor technologies also allow us to obtain information directly from the human brain, which enables users to control their brain activity or an application (Tan & Nijholt, 2010). Thus, direction brain–computer interface applications are becoming an important research area in the field (Atkinson & Campos, 2016; Tan & Nijholt, 2010). Improvements in the electroencephalogram (EEG) technology create opportunities for better understanding the brain–computer interaction (BCI). Recent research refers to the integration of BCI in the daily life of human beings through wireless, mobile, dry, wearable, and low-cost EEG headsets (Atkinson & Campos, 2016; Minguillon et al., 2017).

Accordingly, the challenge is to understand the level of these interactions and improve them, and the majority of the contributions to the HCI field mainly come from engineering and social sciences (Harrison et al., 2007). In the earlier days of HCI studies, computer science, psychology, ergonomics, and media were the involved disciplines;

however, today these subjects have been joined by various other disciplines, such as ergonomics, mathematics, biology, and artificial intelligence (Dix, 2017). Thus, HCI is a highly inter- and multi-disciplinary field. Based on the three foundations of principles, practice, and people (Dix, 2017). The three main waves of HCI are now defined as human factors and ergonomics, cognitive science, and culture (Duarte & Baranauskas, 2016). As the field of HCI matures, there is a lack of studies reflecting the knowledge it produces and their forms. Defining this knowledge will create a map to help navigate the field of HCI, which will increase the process of discovery and push toward further developments in the field (Wobbrock & Kientz, 2016). Currently, there are very limited studies in the literature that attempt to review the literature to better understand the developmental stages and paradigm shifts of HCI. Such reviews are very important in identifying the gaps in the research, determine the directions, and guide future studies. In that context, Clemmensen and Roese (2009) reviewed publications between 1998 and 2008 considering the culture dimension and suggested that there should be more research on qualitative and empirical work in HCI (Clemmensen & Roese, 2009).

Li et al. (2005) conducted a study considering 337 HCI studies published between 1990 and 2002 in seven journals (Li et al., 2005). Additionally, Zhang et al. (2009) reviewed HCI studies published between 1990 and 2008 and analyzed 758 articles using a similar approach used by Li et al. (2005) but enlarging their scope. They classified the main HCI topics as information technology (IT) development, IT use & impact, and generic research topics and designated the methods used as non-empirical and empirical studies (Zhang et al., 2009). The research fields are also identified as broad research fields, disciplines for Information, computing and Communication Sciences and Subjects for the Information systems (Zhang et al., 2009). According to Zhang et al. (2009), HCI studies surged significantly after establishment of the Association for Information Systems (AIS) Special Interest Group on HCI (SIGHCI) in 2001 (Zhang et al., 2009). Later, another review study was conducted by Agrawal et al. (2010), reporting a dearth in the literature with respect to dyadic communication, focus on cultural issues, involvement of enterprise systems, and "levels of analysis" issues (Agrawal et al., 2010). Another review study has considered mobile HCI methods and included 144 studies (Kjeldskov & Paay, 2012). The authors concluded that the mobile HCI research is being empirically driven which is later developed through a more multi-methodological direction combining and diversifying methods from different disciplines (Kjeldskov & Paay, 2012). Coursaris and Kim (2006) presented a review concerning mobile empirical studies concerning usability dimensions measured by 45 empirical mobile usability studies (Coursaris & Kim, 2006). Hinze-Hoare (2007) also reviewed HCI principles by analyzing the most frequently cited 10 studies and reported the fundamental principles as recoverability, familiarity, consistency, sustainability, task migratability, synthesizability, predictability, and perceptual ergonomics (Hinze-Hoare, 2007). Another meta-review conducted by Coursaris and Bontis (2012) on papers published by three main journals concluded that the research productivity in this field was exploding. Gurcan and Sevik (2019) performed an analysis on journal articles published in the last 20 years using automated text-mining techniques, and as a result they revealed the most focused research themes of the HCI (Gurcan & Sevik, 2019). Their study included a preliminary analysis process in which only the first implications in the field of the HCI are investigated and only the domain-specific research themes are roughly examined without temporal trends and developmental stages (Gurcan & Sevik, 2019). Hornbæk et al. (2019) were also studied the word "Interaction" among 4,604 studies and have reported the effect of changing technologies on characteristics of interaction which are becoming more of topic than specific devices (Hornbæk et al., 2019).

As these review studies were conducted by considering limited periods and considers only specific publication sources, there is still a big gap in the literature in revealing the big picture of the trends in HCI studies. In order to fill this gap, all studies conducted during the period from its first occurrence until 2019 have been analyzed in the current study using text-mining techniques. The main aim of this study is to better understand the developmental stages of HCI studies and provide a map to assist in achieving a better navigation in the field, which, in turn, aims to improve and guide future HCI studies.

2.2. Topic-modeling approach

Topic modeling is a text-mining technique, which provides probabilistic models to discover hidden semantic structures, referred to as topics, from a collection of textual documents. In this context, latent Dirichlet allocation (LDA) (Blei, 2012; Blei et al., 2003) is a powerful topic-modeling algorithm widely used for the semantic analysis of document collections in text mining and nature language processing (Griffiths & Steyvers, 2004). The LDA algorithm makes available a "generative probabilistic model" for fitting a topic model. The term "latent" in this algorithm points out the unobserved (hidden) semantic structures (topics) in the observed documents (Blei, 2012; Blei & Lafferty, 2007). The generative model denotes the representation of the words in the documents as observed variables in an iterative probabilistic process based on the Dirichlet distribution (Blei et al., 2003; Karl et al., 2015). The LDA topic-modeling approach is established on the assumption that each document is represented by multiple topics, and each topic is represented by a distribution of words in the corpus (Blei, 2012; Wallach, 2006). It builds the topics per document and the words per topic using iterations of the Dirichlet distribution. More specifically, LDA-based topic-modeling aims to automatically reveal the hidden semantic topic structures from observed document collections (in the current study, these are peer-reviewed journal articles) by calculating per-document topic distributions, and the per-document per-word topic assignments. The probabilistic topic-modeling approach provides advanced analysis capabilities in many more ways than traditional text-mining techniques. Since the LDA model has an unsupervised machine learning procedure, it can effectively analyze the large collections of text documents to identify semantic topics without the need for any training set, predefined tags, or metadata (Griffiths et al., 2007; Gurcan & Cagiltay, 2019). It can also be applied on data sets with different types and characteristics, such as texts, scientific articles, genetic data, images, videos, forums, blogs, and social networks (Blei, 2012; Gurcan, 2018a, 2019; Gurcan & Cagiltay, 2019; Gurcan & Kose, 2017; Moro et al., 2015; Wallach, 2006). Due to these features, the LDA model is considered as a robust tool for semantic content analysis that automates the discovery of latent topics within documents in a large-scale textual corpus.

In this context, the LDA topic-modeling algorithm was used to investigate dimensions of interdisciplinary research supported by science foundations (Nichols, 2014), reveal research topics and trends in scientific articles published between 1990 and 1999 (Blei & Lafferty, 2007), extract main themes in the literature of business intelligence in the banking industry (Moro et al., 2015), investigate temporal trends of topics in the field of computational linguistics from 1978 to 2006 (Hall et al., 2008), analyze research trends on big data in marketing from 2010 to 2015 (Amado et al., 2018), examine themes and trends in academic research on personal information privacy from 1972 to 2015 (Choi et al., 2017), identify the knowledge structure of bioinformatics from 2000 to 2010 (Song & Kim, 2013), and undertake a bibliometric analysis of text mining in medical research between 2008 and 2017 (Hao et al., 2018). This type of analysis may provide important insights into understanding the dynamics of domain-specific research and development to support academic and industrial communities' future research, plans, and investments (Blei & Lafferty, 2007; Griffiths & Steyvers, 2004; Gurcan & Cagiltay, 2019). However, although the LDA topic-modeling algorithm is a continually developing paradigm, it has received little attention from HCI scholars. To the best of our knowledge, topic modeling based on LDA has not been used for the identification of themes and trends in research on HCI; therefore, we applied the LDA model for the first time on the scientific articles related to HCI published between 1956 and 2018 to analyze the themes and trends reflecting the research landscape of the HCI discipline and reveal the methodological gains of topic modeling.

3. Research design

In keeping with the purpose of the study, the research methodology was designed considering the generative topic-modeling processes comprising five main stages: (1) peer-reviewed journal articles were collected to generate the experimental HCI corpus, (2) the preprocessing steps were implemented on the unstructured textual corpus, (3) the document-term matrix (DTM) was created to perform the quantitative analysis, (4) the data defined as DTM were analyzed using LDA-based topic modeling, and (5) the discovered topics were interpreted and their temporal trends were investigated. Each stage of the methodology is described below in more detail.

In this study, it is expected to discover trends in HCI and also confirm previously stated arguments such as human centeredness and interdisciplinary nature. Therefore, analysis of results methodology will be based on descriptive statistics to explore and confirm the trends in HCI for 60 years of research.

3.1. Data collection

Domain-specific literature provides a rich source of information for studies conducted to identify research themes and trends in a scientific field. Through online access facilities, the literature allows information communities to benefit from a wide range of document types, such as journal articles, conference proceedings, reviews, technical reports, book chapters, books, and white papers. Among these literature sources, journal articles consist of studies that have been subjected to a specific referee evaluation and have reached a certain scientific maturity. Besides, peer-reviewed journal articles reveal the research landscape of a particular discipline in time-dependent settings more consistently than other sources. For this reason, only peer-reviewed journal articles were included in this study. At this point, we should especially point out that the current literature includes numerous HCI-specific conferences with high respectability and quality criteria (Hornbæk et al., 2019). On the other hand, in order to avoid any conflict in terms of the objectivity of the study, we considered that it would be more appropriate to analyze HCI-specific conference papers in a separate study apart from journal articles.

In terms of data source, Web of Science and Elsevier's Scopus are the two main bibliographic electronic databases commonly used in such analysis (Mongeon & Paul-Hus, 2016; Sahoo & Kumar, 2018). In the beginning, we searched both databases using the same search-query. Consequently, Elsevier's Scopus was selected, as it covers more journals than Web of Science and provides access to more articles with effective search options (Mongeon & Paul-Hus, 2016; Sahoo & Kumar, 2018).

The choice of search terms used to obtain articles appropriate for the purpose of the study is a very critical process that directly affects the search results. From this perspective, an iterative process was implemented in this study to decide on effective search terms. First of all, the search process was started by searching the phrase "Human-Computer Interaction", the most common term in the field of HCI. In the next step, the phrase "Human-Computer Interface", which has a high frequency among the results obtained after the first search, was included in the list of search terms. The search results were reevaluated and very general phrases such as "Robots", "Artificial Intelligence", "Automation", "Design", "Speech Recognition" and "Feature Extraction" were excluded from the search to capture more specific phrases for HCI discipline. Similarly, common keywords such as "Study", "Article", "Human", "Article", "Male", "Female", and "Adult" were also filtered out. By excluding such keywords that are not directly relevant, the search query was updated in each iteration; thus, the iterative search process was repeated until a satisfactory level is reached. This iterative search process is conducted to better define the HCI-specific terms for the search query in a systematical manner. The concluding context of the search query achieved at the end of this iterative process is as follows:

TITLE-ABS-KEY ((“human computer “ OR “computer human “ OR “machine human” OR “human machine” OR “human robot” OR “robot human “ OR “brain computer” OR “computer brain” OR “man machine” OR “machine man”) AND (interact* OR interface* OR system*)) AND (PUBYEAR > 1955) AND (PUBYEAR < 2019) AND (LIMIT-TO (DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “re”)) AND (LIMIT-TO (LANGUAGE, “English”))

This search query was implemented on the Scopus bibliometric database on June 25, 2019. As a result, an experimental data set was created containing 41,720 journal articles published in English only in the last 60 years between 1957 and 2018 of which, 39,100 were research articles and 2,620 were review articles. The data set contained the title, abstract, author keywords, and index keywords for each article. This information offers a comprehensive but short-term summary for each article, thus minimizing the influence of data noise.

3.2. Data preprocessing

Data preprocessing is a data-mining technique used to transform raw data into a clean data set (Aggarwal & Zhai, 2013; Gurcan, 2018b; Srivastava & Sahami, 2009). Real-world data are often inconsistent, has missing elements, and/or is in an unstructured format; thus, it is likely to contain many errors, which requires the conversion of raw data to an appropriate format for analysis (Aggarwal & Zhai, 2013). To remedy this situation, data preprocessing consists of sequential steps, such as data cleanup, data integration, data transformation, and data reduction (Kantardzic, 2011). In this study, to prepare the HCI corpus for LDA-based topic modeling, we sequentially implemented a number of necessary preprocessing steps. Initially, the word tokenization was implemented on the dataset in order to split the texts into simple tokens (words). All words were then converted to lowercase, and misleading words, special characters, punctuation, and links were eliminated. Stop words (is, and, a, the, of, for, etc.) which do not make sense alone have a high frequency in English texts and considerably increase the dimensionality of the word space (Aggarwal & Zhai, 2013; Gurcan & Cagiltay, 2019); therefore, all stop words were deleted. Also, generic words (e.g., research, article, paper, and study) that are frequently found in scientific articles and do not represent a specific theme were also excluded. Finally, we implemented the Snowball stemming algorithm (Porter, 2001) to reduce the words to their stems and thereby represent the derivations of same word with a unique word for LDA. For example, for ‘develop’, ‘developed’, ‘developing’, and ‘development’, the stem ‘develop’ was used. After the preprocessing steps were completed, DTM necessary for the implementation of LDA was created with the remaining words (Blei, 2012).

3.3. LDA implementation and model fitting

In this study, the LDA topic-modeling algorithm was used as it was the most suitable method for the purpose of our research, which was the discovery of emerging trends and topics in HCI articles. With the aim of fitting and implementing the LDA model to our experimental data set which consisted of HCI articles, we used the R package “topicmodels” (Grün & Hornik, 2011) that provides a basic infrastructure for fitting topic models using the Gibbs sampling algorithm (Geman & Geman, 1984). The fitting of the LDA model requires the estimation of three parameters (α, β and K) used for the optimization of the model. The parameter of α regulates the per-document topic distribution, and increasing the value of α makes it possible for the documents to contain a combination of more topics (Blei et al., 2003). The parameter of β regulates the per-topic word distribution, and increasing the value of β allows the topics to contain a combination of more words (Blei et al., 2003). To measure the fit of the model, the α and β parameters of Dirichlet prior were tested with a wide spectrum of values within a reasonable range (i.e., $0.01 < \alpha, \beta < 1$), and it was observed that there were only minor changes in the topic and word distributions, which could be ignored (Wallach, 2006). Therefore, as recommended in the literature for the topic modeling of short texts, the predefined values were $\alpha = 0.1$ and $\beta = 0.01$ (Li et al., 2016; Nguyen & Caplier, 2015; Zuo et al., 2016). The other parameter used in the model fitting was the K parameter that indicates the number of topics. Increasing the value of K parameter allows the creation of finer-grained topics while decreasing this value results in the creation of coarser-grained topics (Grün & Hornik, 2011; Wallach, 2006). In this context, the LDA model was implemented with varied K-values in the range $K \in \{15, 16, 17, \ldots, 65\}$ in order to choose the ideal number of topics. As a result, the topic-word distributions at a desired level were achieved when the number of topics was equal to 21. Following the analysis, the labeling of the topics was undertaking with the aid of the frequencies of the top descriptive words for each topic (Nguyen & Caplier, 2015). The majority of the topic names were assigned by using the first five words belonging to that subject. A few of the topic names were chosen considering the general meanings of all topics.

4. Results

The results of this study are presented under six subheadings. Firstly, descriptive statistics demonstrating the distribution of the articles by years, subject areas, and publication sources (journals) are given. In the second section, the topics generated by LDA are demonstrated and analyzed. In the following sections, the developmental analysis and temporal trends of the discovered topics are presented.

4.1. Preliminary analysis

Before applying LDA-based topic modeling to the articles that create the empirical data set, descriptive statistics were initially analyzed based on the distribution of the articles by years, subject areas, and publication sources (journals). Table 1 shows the number of publications according to ten-year periods. As seen in Table 1, initial studies indexed by the SCOPUS database were published in 1957. After this year, the field evolved, and there were an increasing number of

Table 1. Distribution of studies in ten-year periods.

Yearly Periods	n	%
1957–1958	5	0.01
1959–1968	223	0.53
1969–1978	616	1.48
1979–1988	2,088	5.00
1989–1998	4,958	11.88
1999–2008	10,858	26.03
2009–2018	22,972	55.06
Total	41,720	100

publications. It is interesting that every 10 years, the number of publications doubled that of the previous period, with 55% of the studies having been published within the last decade (2009–2018).

Table 2 shows the top 15 publication sources of the analyzed studies, revealing that 2.95% of the studies (n = 1,232) were published in the "Computers in Human Behavior" journal, followed by the "International Journal of Human Computer Studies" with 609 studies (1.46%).

The top 15 subject areas of the studies are listed in Table 3, demonstrating that 50.77% of the studies (n = 21,181) were considered under the topics of "Computer Science", followed by "Engineering" (16,228 study, 38.90%), "Social Sciences" (6,471 study, 15.51%), "Medicine" (6,183 study, 14.82%), and "Neuroscience" (3,799 study, 9.11%). According to Table 2, the HCI field is an interdisciplinary area mainly comprising the fields of "Computer Science", "Engineering", "Social Sciences", "Medicine", "Neuroscience", "Psychology", and "Arts & Humanities".

Table 2. Publication sources.

The Publication Source Name	n	%
Computers In Human Behavior	1,232	2.95
International Journal Of Human Computer Studies	609	1.46
Ergonomics	549	1.32
Journal Of Neural Engineering	482	1.16
Interacting With Computers	468	1.12
Lecture Notes In Computer Science	434	1.04
IEEE Transactions On Neural Systems And Rehabilitation Engineering	401	0.96
International Journal Of Human Computer Interaction	377	0.90
Plos One	350	0.84
Interactions	348	0.83
Human Factors	314	0.75
International Journal Of Man Machine Studies	280	0.67
Applied Ergonomics	277	0.66
Computers And Education	270	0.65
IEEE Transactions On Biomedical Engineering	257	0.62

Table 3. Subject areas of the studies.

Subject Areas	n	%
Computer Science	21,181	50.77
Engineering	16,228	38.90
Social Sciences	6,471	15.51
Medicine	6,183	14.82
Neuroscience	3,799	9.11
Psychology	3,584	8.59
Arts & Humanities	2,603	6.24
Biochemistry, Genetics & Molecular Biology	2,194	5.26
Physics & Astronomy	1,738	4.17
Health Professions	1,677	4.02
Materials Science	1,309	3.14
Nursing	972	2.33
Business, Management & Accounting	924	2.21
Decision Sciences	913	2.19
Agricultural & Biological Sciences	714	1.71

4.2. Topic-modeling analysis

The LDA-based topic-modeling analysis found 21 topics from the empirical corpus containing 41,720 HCI articles. Table 4 shows these topics with the keywords of each topic. The topic names are assigned by considering the top-ranked keywords demonstrating each topic. In most cases, the first five keywords were combined in a meaningful manner to name each topic. As seen in Table 4, the top-rated topics were "User Interface Design" (10.17%), "Intelligent Decision Systems" (7.90%), "Machine Control Systems" (7.06%), "Online Social Communication" (6.81%), "Feature Recognition" (6.47%), and "Task Efficiency/Effectiveness" (6.23%). The topics, such as "Brain–Computer Interface" (5.48%) and "Medical" (5.37%) are also highly rated while the lowest-rated topics were "Assistive Technologies" (2.41%), "Virtual Reality" (2.67%), "Neural Interface" (2.75%), and "Sensors" (2.76%).

4.3. Analysis of the trend-lines on each topic for ten-year periods

In this stage of the analysis, the discovered topics are expanded from a snapshot view into a panoramic perspective of the increase and decrease of the topics over time. Table 5 shows the mean (M), acceleration (A) and trend-line of each discovered topic in ten-year periods. The trend-line graphics for the mean (M) values were drawn using the mean of number of publications conducted in each decade. The accelerations in each topic were calculated for each decade by subtracting the sum of previous decade's values from the sum of current decade's values and dividing the result by 10. As seen from the figure in some of the topics like "Machine Control System", "Medical", "Education" and "Information Retrieval" the acceleration values show a decrease. Topics like "Brain–Computer Interface", "Online Social Communication ", "Task Efficiency/Effectiveness", "Human–Machine Systems", "Musculoskeletal Control", "Sensors"," Neural Interface", "Assistive Technologies", and "Feature Recognition" show an acceleration after 2008.

The topics, such as "User Interface Design", "Intelligent Decision Systems", "Machine Control Systems", "Medical", "Human-Machine Systems", "Speech Recognition", "Task Efficiency/Effectiveness", "Visual Display Interface", and "Education" have been studied for a longer period of time, and thus can be labeled as older topics. Other topics, namely "Human-Robot Interaction", "Mobile", "Musculoskeletal Control", "Information Retrieval", "User", "Virtual Reality", and "Assistive Technologies" that have been studied more after 1998 can be considered as middle-aged.

4.4. Developmental analysis of the topics

In Table 6, based on their developments in each decade, the top five topics are summarized. In this table, it can be seen that the order of the topics has changed over the decades; for example, the top five topics during the first three decades (1959–1988) were "Human-Machine Systems", "Machine Control Systems", "Task Efficiency/Effectiveness", "Intelligent Decision Systems", and "User Interface Design", and this trend continued for the last four topics "from 1989 to 2008. However, from 1999 to 2008,

Table 4. Discovered topics and keywords of the studies.

Topic Name	Keywords	Rate %
User Interface Design	design*; user*; interfac*; system*; comput*; develop*; interact*; softwar*; evalu*; usabl*; engin*; applic*; tool*; process*; approach*	10.17
Intelligent Decision Systems	model*; system*; comput*; human*; decis*; intellig*; machin*; knowledg*; process*; simul*; interact*; cognit*; agent*; approach*; fuzzi*	7.90
Machine Control Systems	system*; control*; machin*; oper*; comput*; process*; interfac*; power*; product*; industri*; softwar*; manufactur*; design*; data*; plant*	7.06
Online Social Communication	social*; commun*; behavior*; onlin*; person*; interact*; media*; inform*; effect*; experi*; self*; peopl*; particip*; relationship*; human*	6.81
Feature Recognition	recognit*; featur*; algorithm*; method*; imag*; gestur*; network*; detect*; model*; data*; classif*; analysi*; extract*; learn*; neural*	6.47
Task Efficiency/ Effectiveness	perform*; task*; time*; human*; measur*; experi*; effect*; cognit*; subject*; test*; error*; particip*; rate*; evalu*; respons*	6.23
Brain-Computer Interface	brain*; comput*; interfac*; bci*; signal*; eeg*; classif*; electroencephalographi*; potenti*; motor*; analysi*; imageri*; human*; accuraci*; evok*;	5.48
Medical	health*; comput*; inform*; medic*; nurs*; care*; system*; human*; patient*; educ*; manag*; clinic*; hospit*; record*; attitud*	5.37
Visual Display Interface	visual*; displai*; interfac*; comput*; ey*; track*; user*; imag*; system*; devic*; interact*; touch*; movement*; vision*; human*	4.53
Human-Robot Interaction	robot*; human*; interact*; control*; system*; task*; manipul*; motion*; environ*; machin*; behavior*; humanoid*; intellig*; assist*; autonom*	4.46
Human-Machine Systems	human*; system*; machin*; autom*; safeti*; oper*; vehicl*; control*; drive*; driver*; simul*; factor*; accid*; ergonom*; risk*	4.29
Mobile	mobil*; servic*; network*; user*; system*; comput*; devic*; applic*; commun*; data*; inform*; smart*; secur*; environ*; context*	4.08
Speech Recognition	speech*; emot*; languag*; recognit*; system*; commun*; human*; express*; natur*; dialogu*; comput*; interact*; affect*; facial*; machin*	3.54
Musculoskeletal Control	control*; forc*; human*; muscl*; hand*; motion*; system*; movement*; machin*; joint*; arm*; mechan*; design*; actuat*; bodi*	3.54
Information Retrieval	inform*; data*; web*; search*; databas*; user*; retriev*; comput*; analysi*; sequenc*; semant*; structur*; visual*; protein*; queri*	3.42
Education	learn*; student*; educ*; comput*; train*; teach*; skill*; instruct*; program*; surgeri*; cours*; surgic*; develop*; assist*; school*	3.04
User	ag*; comput*; adult*; femal*; male*; internet*; risk*; factor*; human*; adolesc*; questionnair*; health*; middl*; associ*; self*	3.01
Sensors	sensor*; devic*; pressur*; electron*; human*; skin*; materi*; electrod*; machin*; mechan*; flexibl*; sens*; surfac*; measur*; tissu*	2.76
Neural Interface	brain*; interfac*; neural*; motor*; comput*; cortex*; activ*; stimul*; function*; movement*; decod*; neuron*; anim*; control*; signal*	2.75
Virtual Reality	virtual*; game*; realiti*; video*; interact*; environ*; comput*; plai*; real*; experi*; player*; augment*; simul*; graphic*; world*	2.67
Assistive Technologies	patient*; rehabilit*; assist*; disabl*; comput*; control*; stroke*; therapi*; clinic*; function*; ag*; wheelchair*; motor*; devic*; diseas*	2.41

the number of the studies on the topic "Brain–Computer Interface" was the lowest, and in the last decade the topics "Feature Recognition", "Brain–Computer Interface", and "Online Social Communication" had higher ratios. Hence, it can be concluded that until 2009, the baseline topics for the HCI studies mainly studied were "Human-Machine Systems", "Machine Control Systems", "Task Efficiency/Effectiveness", "Intelligent Decision Systems", and "User Interface Design".

After 2008, the trend of studied topics changed toward "Feature Recognition", "Brain–Computer Interface", and "Online Social Communication". Furthermore, from an analysis of the accelerations given in Table 5, it can be concluded that there are some signs that the trends in next decade will be toward studies on "Human-Robot Interaction", "Sensors", "Online Social Communication", "Brain–Computer Interface", and "Feature Recognition". As shown in Figure 1, each of three main developmental stages of HCI developed over time with the "Legacy Systems Age" taking 30 years, "Internet Age" 20 years, and the "Pervasive Age" in the last 10 years, and in each age, new topics evolved.

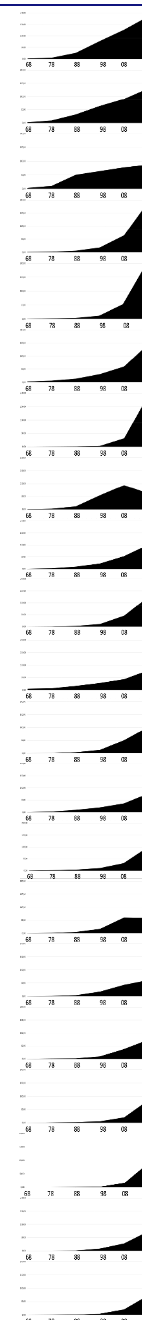
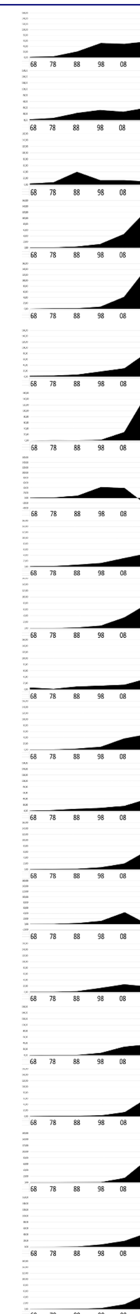
4.5. Volume analysis of each topics

Table 5 shows that all the discovered topics are being continuously studied; however, the number of studies for each topic shows an increase during the last ten-year period (2009–2018). The trend-line of each topic and their acceleration values differs during the 10-year periods. Additionally, the number of publications shows the volume of each topic is also different in relation to the time periods. Figure 2 shows the volume of each topic considering the number of publications and their overall percentages relating to all the publications printed during the period from 1957 to 2018. Figure 2 shows that the topics "User Interface Design", Intelligent Decision Systems", Machine Control Systems", Online Social Communication", Feature Recognition", and "Task Efficiency/ Effectiveness" can be considered as high-volume with percentages of publications higher than 6%. Similarly, the topics "Brain Computer Interface", "Medical", "Visual Display Interface", Human-Robot Interaction", and "Mobile" can be considered as middle-volume with percentages of publications higher than 4% and lower than 6%. Finally, the topics "Speech Recognition", "Musculoskeletal Control", "Information Retrieval", "Education", "User", "Sensors", "Neural Interface", "Virtual Reality", and "Assistive Technologies" are considered as low-volume with percentages of publications less than 4%.

4.6. Acceleration analysis of each topic

In order to better understand the developmental speed of each topic, the acceleration values for each topic are given in Figure 3.

Table 5. Trend-lines of each discovered topic.

Topic Name		1959-1968	1969-1978	1979-1988	1989-1998	1999 - 2008	2009-2018	Trend-line M	Trend-line A
User Interface Design	M	1.64	5.52	26.61	78.28	127.24	185.14		
	A	1.69	3.83	21.09	51.67	48.96	57.90		
Intelligent Decision Systems	M	2.48	9.15	31.84	64.08	90.88	130.96		
	A	2.50	6.65	22.69	32.24	26.80	40.08		
Machine Control Systems	M	3.39	10.47	50.64	64.34	77.94	87.53		
	A	3.50	6.97	40.17	13.69	13.61	9.59		
Online Social Communication	M	0.89	1.90	5.92	18.38	64.50	192.50		
	A	0.91	0.99	4.02	12.46	46.12	128.00		
Feature Recognition	M	0.21	1.54	3.20	10.75	52.87	201.35		
	A	0.21	1.33	1.65	7.56	42.11	148.49		
Task Efficiency/Effectiveness	M	2.91	6.48	13.50	31.14	60.02	145.94		
	A	3.00	3.48	7.02	17.64	28.88	85.92		
Brain-Computer Interface	M	0.11	0.61	1.06	2.92	31.23	192.79		
	A	0.11	0.49	0.45	1.87	28.31	161.55		
Medical	M	0.70	2.68	11.29	54.32	93.70	61.53		
	A	0.72	1.96	8.61	43.03	39.38	−32.18		
Visual Display Interface	M	1.01	2.94	9.61	22.50	52.89	100.13		
	A	1.03	1.91	6.67	12.89	30.39	47.24		
Human-Robot Interaction	M	0.16	0.54	2.85	11.00	45.86	125.55		
	A	0.16	0.37	2.31	8.14	34.86	79.69		
Human-Machine Systems	M	5.50	7.10	16.29	28.22	43.22	78.59		
	A	5.63	1.48	9.19	11.93	15.00	35.37		
Mobile	M	0.13	0.57	3.94	13.38	50.41	101.66		
	A	0.13	0.45	3.36	9.44	37.03	51.26		
Speech Recognition	M	0.72	3.35	9.99	19.92	36.56	77.00		
	A	0.72	2.63	6.64	9.93	16.64	40.44		
Musculoskeletal Control	M	0.62	2.25	4.35	11.25	31.44	97.60		
	A	0.63	1.62	2.10	6.90	20.18	66.16		
Information Retrieval	M	0.44	1.41	5.12	16.83	60.60	58.36		
	A	0.44	0.97	3.71	11.71	43.76	−2.23		
Education	M	0.45	0.94	3.93	17.54	42.88	61.21		
	A	0.47	0.47	2.99	13.61	25.34	18.33		
User	M	0.37	1.41	2.30	9.85	37.89	73.70		
	A	0.37	1.04	0.89	7.54	28.05	35.81		
Sensors	M	0.26	1.50	2.62	5.81	20.23	84.93		
	A	0.26	1.24	1.12	3.19	14.42	64.70		
Neural Interface	M	0.15	0.52	1.18	2.13	16.77	94.11		
	A	0.15	0.37	0.66	0.95	14.63	77.34		
Virtual Reality	M	0.06	0.20	0.97	8.49	27.88	73.73		
	A	0.06	0.14	0.77	7.52	19.39	45.85		
Assistive Technologies	M	0.10	0.49	1.57	4.66	20.79	72.89		
	A	0.10	0.39	1.08	3.09	16.13	52.10		

M: Mean, A: Acceleration

Accordingly, the speed considering the number of publications for the topics “Feature Recognition”, “Brain–Computer Interface”, “Online Social Communication”, and “User Interface Design” can be considered as very fast (higher than 8%). The speed of the topics, namely, “Medical”, “Education” and “Information Retrieval” can be considered as slow (lower than 3%). The other topics can be considered as fast ones (between 3.00% and 6.50%).

5. Discussion

The results of this study have important implications for HCI communities mainly by confirming the previous studies in distilled manner. These findings and implications are discussed under five sub-headings in this section.

5.1. Interdisciplinary background of HCI

The findings of this study, as emphasized in previous studies, confirmed the interdisciplinary background and wide application areas of HCI. As reported in Table 3, researchers from Engineering, Social science, Medical, Education, Humanities and many other fields conduct research in HCI. Chakraborty et al. (2017) reported nine related research fields of the HCI studies as “Computer science”, “Ergonomics & Human Factors”,

Table 6. Summary of topic trends.

Decade	Top Five Highest Mean Topics
1959–1968	Human-Machine Systems, Machine Control Systems, Task Efficiency/Effectiveness, Intelligent Decision Systems, User Interface Design
1969–1978	Machine Control Systems, Intelligent Decision Systems, Human-Machine Systems, Task Efficiency/Effectiveness, User Interface Design
1979–1988	Machine Control Systems, Intelligent Decision Systems, User Interface Design, Human-Machine Systems, Task Efficiency/Effectiveness
1989–1998	User Interface Design, Machine Control Systems, Intelligent Decision Systems, Medical, Task Efficiency/Effectiveness
1999–2008	User Interface Design, Medical, Intelligent Decision Systems, Machine Control Systems, Online Social Communication
2009–2018	Feature Recognition, Brain-Computer Interface, Online Social Communication, User Interface Design, Task Efficiency/Effectiveness

"Engineering", "Design", "Sociology & Social Psychology", "Ethnography", "Cognitive Science", "Psychology", "Information Security", and "Speech-language pathology" (Chakraborty et al., 2017). From the findings of this current study (see Table 3), fields such as "Business, Management & Accounting", "Neuroscience", "Biochemistry, Genetics & Molecular Biology", "Health Professions", "Physics & Astronomy", and "Nursing" are some of the disciplines that can be added to this list. Additionally, even the earlier studies have been listed the related fields of the HCI studies, their power to influence the field of HCI have not yet been well defined. The current study similarly showed that (see Table 3), the related research fields defined by Chakraborty et al. (2017), "Computer Science", "Engineering", "Social Sciences", "Medicine", Neuroscience", "Psychology", and "Arts & Humanities" had higher influencing power compared to the others. As a result, this study not only confirmed the interdisciplinary nature of the HCI field, but also extend the list of contributing fields.

5.2. The wide spectrum of research and application areas

In addition to its interdisciplinary nature, HCI studies also cover a wide range of research spectrum and application areas. However, there is lack of longitudinal studies analyzing changes in research and application areas in HCI. Surprisingly even though it is a new emerging area, the number of publications and the acceleration value that "Brain–Computer Interface" area is one of those disciplines that will deeply influence HCI studies. Another unexpected result is about the topic area "Medical" which shows a negative acceleration in the last decade (see Table 5). Because of the recent Corona Pandemic, we expect to see significant amount of new research studies in medical area, impacting the medical-related HCI studies. "Education" is another application area for HCI where its importance for educational systems has been also discussed by earlier studies (Berg, 2000; Inkpen, 1997). One of the major contributions of this study is to shed light on a wide range of the spectrum of the HCI field. As it can also be derived from the results of the current study (see Table 5), resent research focus on better understanding of the human cognition, face behaviors, eye movements, and brain functions, as well as the emergence of the new technologies, including robotics, virtual worlds and games.

5.3. Evolution of HCI in line with the progression of computer systems

The developmental stages of HCI are closely related with the developments in computer systems (see Figure 1). For instance, the accessibility, multi-application and decentralized nature of the Internet started to display rapid growth during the 1990s (Luppicini, 2013). Parallel to this development, HCI topics are differentiated across specific topics, such as medical studies and the influence of the online communication. Here, it should be noted that as medical systems are directly related to human health, there is a large number of research studies that evaluate medical systems from the HCI perspective.

As seen from Figure 1, Legacy Systems Age took around 30 years. Since developments in computer systems were slow and only limited number of experts had access to computers, topic trends were limited to scientific areas. Internet Age speeded up the changes and added new topics to the HCI

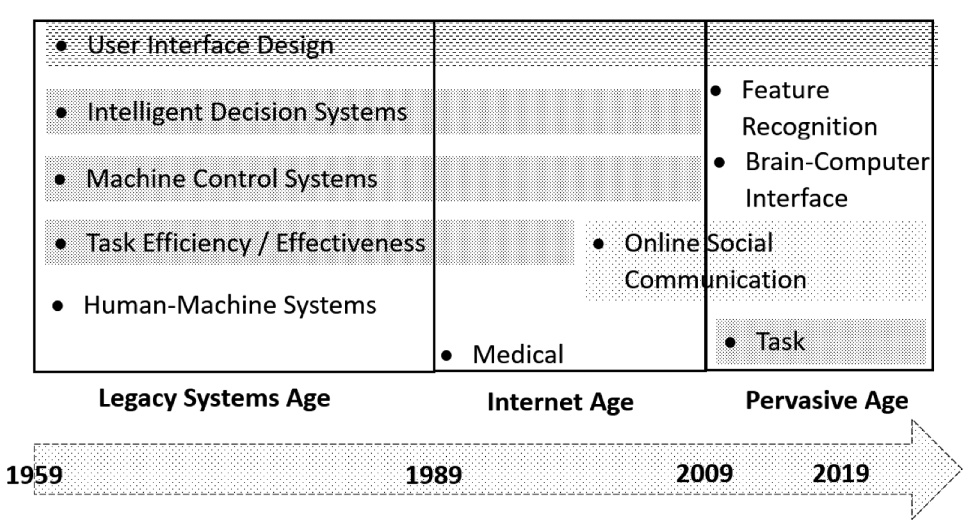


Figure 1. Developmental stages of the HCI studies.

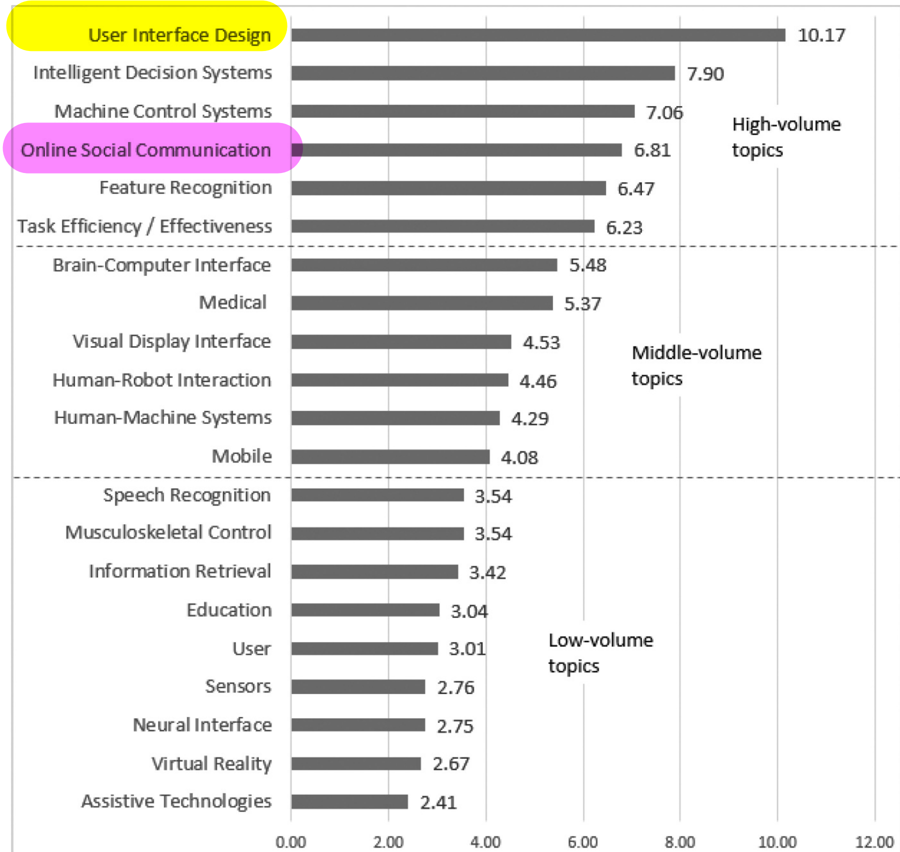


Figure 2. Topic volumes considering the total number of publications.

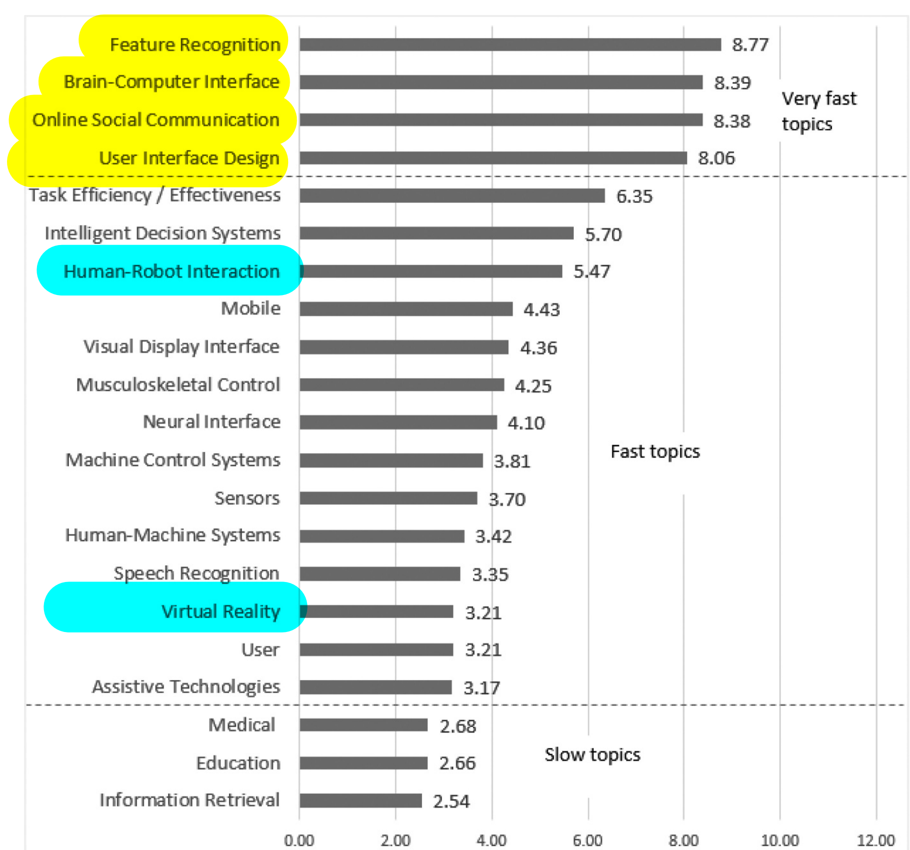


Figure 3. Speed of each topic considering the acceleration values.

research area. In the last 10 years HCI research covered almost all areas because computers became an integrated part of human life.

After 2009, pervasive computing technologies became popular (Botta et al., 2016), which was affected by the technological developments, such as cloud computing ca. 2008 (Satyanarayanan, 2015), and the Internet of things (Weyrich & Ebert, 2016) This trend also shows that the future stages possibly will evolve in shorter time periods (less than 10 years) concerning new technologies that also affect the HCI field. For instance, mobile cloud technologies are evolving and dominating mobile data traffic (Cisco, 2013), and context-aware systems are becoming important providing more adaptive user interfaces and mobile technologies (Qin et al., 2017). As seen from the change patterns in the last 60 years, we may expect to see faster changes in the near future. It is not wrong to say that these upcoming ages will take around 5–6 years.

5.4. Toward the emergence of sub-disciplines

When the topic sets considering the volume and acceleration values are analyzed (see Table 5), it can be seen that even “Brain–Computer Interface” is a younger topic with a high volume and rapid acceleration. This finding indicates that “Brain–Computer Interface” may emerge as a sub-discipline of the HCI field. As a burgeoning field, the importance of BCI studies has also been discussed in earlier studies (Wolpaw & Wolpaw, 2012). Similarly, the topics of “Human-Robot Interaction” (HRI) and “Mobile” are middle-aged; however, their volume is high and their acceleration is fast. Accordingly, these topics are also expected to be new sub-disciplines. HRI studies cover the robotic systems considering their design, behaviors and evaluation involving humans and robots interacting through communication (Goodrich & Schultz, 2007). Thus, topics, such as robotics and robot anatomy (Perez-Gaspar et al., 2016; Thrun, 2004), social learning and interaction, modalities and types of knowledge acquired through interactions, including vision, speech, and haptics, representing the world and the intentions of others, qualitative and quantitative evaluation methodologies, and ethics (Murphy et al., 2010) are all creating a baseline for the field which is also an evidence for HRI as a new discipline. Similarly, “User Interface Design”, “Intelligent Decision Systems” and “Task Efficiency/Effectiveness” can also be considered as classical sub-disciplines of the HCI field.

5.5. Transition from machine-oriented systems to human-oriented systems

Through the developmental ages of the HCI discipline, it can be seen that the discipline is evolving from machine-oriented systems toward more human-oriented systems. During the Legacy Systems Age, computers were mainly used by experts, so human centeredness was not a critical issue. However, as seen in the Pervasive Age, almost everybody is a computer user. Therefore, human-oriented system development is a critical issue in every project. For instance, “Sensors” is a young topic and one of the fast-developing topics. Through sensor technologies, detailed data about the behaviors of users, as well as the context of the systems can be collected. The behavioral analysis of this data yield information about the adaptation of the systems according individual differences and preferences, as well as contextual differences. The emergence of these context-aware adaptive systems is expected to affect HCI studies from all perspectives in the near future (Magnenat-Thalmann et al., 2016). This transition can also be seen from the Hornbæk et al. (2019)’s study analyzing the word “interaction” in the HCI studies and addressing feel, affective, cognitive themes (Hornbæk et al., 2019).

6. Conclusion

This study has attempted to shed light on the research landscape of the HCI discipline from 1957 to 2018. With this aim, a semantic content analysis based on topic-modeling was performed on the peer-reviewed journal articles to discover research themes and temporal trends for HCI. The methodology of the study is based on LDA, which is an unsupervised generative model for probabilistic topic modeling widely applied in text mining. Previous HCI trend studies are mainly based on quantitative and qualitative analysis of selected journals and articles. However, this study differentiates from the previous studies by its analysis methodology. By this way, it is possible to analyze a very long term (60 years) and thousands of articles. As a result, 21 topics demonstrating HCI research landscape were found at a finer granularity level. By analyzing and interpreting the age, volume and acceleration of these topics over a 60-year period, a systematic taxonomy exhibiting the evolution of HCI field was proposed.

More specifically, three main developmental ages of the evolution of the HCI field can be defined as Legacy Systems Age (1959–1989), Internet Age (1989–2009), and Pervasive Age (2009–2019). Furthermore, a number of the discovered topics, such as “Brain–Computer Interface”, “Human–Robot Interaction”, “Mobile”, “User Interface Design”, “Intelligent Decision Systems”, and “Task Efficiency/Effectiveness” can be considered as sub-disciplines that are possible to emerge from HCI in the near future. In the terms of the temporal trends of the discovered topic, since a transition on the HCI studies from machine-oriented systems toward human-oriented systems have been identified, the context-aware adaptive systems are expected to profoundly affect HCI studies in all dimensions. Thus, this study provides a deep understanding of this dynamic discipline by analyzing HCI studies conducted in the last 60 years. The findings of this study are expected to guide the field by providing a better understanding of the history of HCI, and thus illuminating its future in exploring potential research and application avenues in this lively field.

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