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The Sharply Decreasing Disruptiveness of HCI

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Abstract

How creative is HCI research? Although creativity has been a notable theme in HCI, the landscape of the creativity of HCI research itself remains unclear. In this paper, we address this by measuring the disruptiveness of HCI research, one important dimension distinguishing the level of creativity, through a large-scale data-driven bibliometric analysis. By quantitatively tracing its evolution over the past 40 years, we find that the disruptiveness of HCI is decreasing sharply, even at a faster speed than the global average across all fields. We characterize the patterns shown by the themes, knowledge use, and authorship of disruptive papers in HCI, and identify how they associate with disruptiveness, e.g., the positive relationship between author freshness and disruptiveness. Based on our results, we discuss practical implications to improve and secure disruptiveness and creativity in HCI.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**.

Keywords

Creativity, disruptiveness, bibliometric analysis, human-computer interaction

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1 Introduction

Creativity has been a long-standing focus of the Human-Computer Interaction (HCI) community [28, 40]. For example, "what new ideas or approaches are introduced" has been a key criterion for reviewers' evaluations of paper quality in the ACM CHI Conference on Human Factors in Computing Systems (CHI), the flagship venue in HCI [13]. While a significant body of HCI literature has sought to develop specific creative support tools to enhance the creativity of practitioners including HCI professionals [27, 40], few research efforts have gone beyond tool development to investigate the creativity inherent in HCI research itself. Nevertheless, a better understanding of and improved strategy for the creativity of HCI research is not only valuable for individual researchers to identify promising directions and position their contributions, but also crucial for our entire community to enjoy healthy and sustainable development.

The gap in the essential characterization of the creativity of HCI can be partly attributed to the lack of objective and established methods for quantifying research creativity. Although bibliometric analyses have proven effective in shedding light on certain aspects of HCI [10, 43, 56], scalable insights into the research creativity of HCI remain elusive without effective metrics to differentiate the level of a study's creativity. Fortunately, the recent introduction of the disruptiveness index offers a promising solution [29, 65]. Built upon how the emergence of an innovation changes the attention in the citation network, the disruptiveness index distinguishes the degree to which the contribution of the innovation is uniquely recognized and reveals the degree of changes that the innovation triggers [65, 88]. Since its introduction, disruptiveness has gained widespread adoption as a novel dimension for assessing creativity [52]. Following these works and aiming to unpack key patterns regarding creativity within HCI, the present study investigates the disruptiveness of HCI research. Specifically, we ask the following research questions:

- **RQ1**: What is the extent of disruptiveness of HCI?
- **RQ2**: What are the themes of disruptiveness in HCI?
- **RQ3**: What characterizes the knowledge use of disruptiveness in HCI?
- **RQ4**: Who publishes disruptive works in HCI?

To answer them, we conduct a large-scale bibliometric analysis of all regular papers and research notes from four premier HCI venues: ACM CHI, CSCW, UbiComp, and UIST conferences, spanning from 1982[1] to 2023 , which we further corroborate by three alternative methods to represent HCI. Leveraging citation patterns of subsequent research to recognize the unique contribution of a paper [64, 88], we distinguish its level of disruptiveness, i.e., the extent to which it disrupts versus develops/consolidates the existing literature. Our results show that the disruptiveness of HCI has been declining over time, with an even sharper decrease than the overall trend in science. Although the number of disruptive papers increases, its growth rate lags heavily behind the rapid expansion of HCI research. We trace the evolution of the main themes of disruptiveness in HCI and uncover the underlying patterns, e.g., a shift from the predominant focus on system development to growing concerns over social issues. We characterize the knowledge use of disruptiveness in HCI, revealing that disruptive papers tend to build on fewer, older, and less popular prior studies; although the average citation counts of disruptive works may not stand out, disruptive studies are more likely to acquire exceptionally high citation counts.

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[1] This was the first year that at least one of the conferences was held.

We present the evolution of the top countries (including territories) and institutions contributing disruptive papers and demonstrate a positive correlation between author freshness and disruptiveness. Based on our results, we discuss the underlying tensions and contributing factors of (non-)disruptiveness in HCI and outline possible endeavors to preserve and enhance disruptiveness in HCI. As such, our work not only provides crucial insights for individuals aiming to conduct more influential, disruptive, and creative HCI research, but also lays the groundwork for fostering a healthier and more sustainable future for the HCI community as a whole.

2 Related Work

2.1 Creativity in HCI

Creativity and creative work have been important themes and pursuits within HCI [28, 40]. The theoretical basis of creativity in HCI studies can be broadly classified into four strands, each with varying epistemic positions [40]. The first line of scholars regard creative work as problem-solving [22, 77], demonstrating the scientific aspect and formalizability of the creative process and highlighting the applicability of "structured methods" and "externalized guidelines" [23]. However, some essential yet often invisible work may be overlooked [40]. The second line of researchers see creative work as cognitive emergence [42] and contend that the creative process can be modeled as an alternating combination of diverse generation and convergent analysis [2, 19]. However, this perspective may risk missing serendipitous insights between these alternating steps [39]. Thirdly, some literature emphasizes the interactions with the material world and the reliance on in-context knowledge [71, 79], treating creative work as embodied actions. This fosters situated and contextual understanding in HCI, but hampers the translation of particularities to general lessons [40]. Finally, grounded in activity theory, the fourth epistemic position views creative work as expert activities mediated by tools [6, 47]. This underscores the fit between tools and contexts, but poses challenges in accommodating diverse practices and identifying representative target users [40, 48].

These strands of theories on creativity have motivated abundant related HCI research [28, 40], most of which concentrates primarily on the development and evaluation of digital creativity support tools [27, 40]. In comparison, relatively few studies seek to interrogate the creativity of HCI research itself, although it is essential not only for individual researchers to situate themselves within the community, but also for the field of HCI as a whole to achieve healthy development and growth [45]. Wobbrock and Kientz [87] contribute to this by categorizing research contributions in HCI. By classifying and exemplifying empirical research, artifact, methodological, theoretical, dataset, survey, and opinion contributions [87], they reveal how knowledge produced by HCI research is constructed and judged. Van Berkel and Hornbæk [82] further extend this to implications from HCI research and uncover how implications for methodology, theory, the HCI community, design, practice, policy, and society can be made. However, it remains unclear how the creativity of HCI research has been evolving over time and what characteristics shape the creativity of HCI research. The current work contributes to these by investigating the disruptiveness of HCI.

2.2 Creativity and Disruptiveness

Considering the essential role of creativity in research and development, past scholars have dedicated themselves to quantifying creativity and unpacking the underlying mechanisms of creative innovation. Along the pursuit of novel creation, an increasing number of empirical and theoretical studies indicate that novelty rarely emerges in isolation, but rather largely stands upon existing works yet recombines and reconfigures them in unique ways [25, 81, 85]. For example, Uzzi et al. [81] suggest that research grounding tail atypicality in conventional knowledge is the most impactful. A paper's long-term impact also relies heavily on its knowledge priors [54], and the surprisal incurred by unusual content and context combinations predicts high impact [74].

This high reliance of novel creative innovation on past knowledge leads to the willingness to distinguish how a work provides new knowledge for combinations. Motivated by the desire to delineate new entities' departure from the existing trajectories, disruptiveness (or disruption) quantifies the unique dimension of the extent to which an innovation shapes people's attention to or away from extant innovation in a network of innovations [29]. Although the metric has not been proposed for long, disruptiveness has been quickly recognized and grown to be a popular measurement of creativity recently: it effectively reflects how likely an innovation disrupts versus develops science and technologies [65, 88]. For example, Park et al. adopt this metric to examine the temporal patterns of disruptiveness and caution that science and technologies are becoming less disruptive over time [65]. Some other scholars focus on factors influencing the disruptiveness of innovations. For example, Li et al. [52] highlight the presence of a trade-off between productivity and disruptiveness, where increased productivity is associated with lower disruptiveness. Wu et al. [88] discover that small teams are more likely to disrupt, whereas large teams tend to develop the existing works more. Xu et al. [89] delve deeper into the structure of teams, revealing that flat teams with a larger ratio of leaders are more likely to disrupt established routines. However, Lin et al. [53] reveal that remote collaborations are more likely to cultivate developing work because distance hinders co-conception of knowledge.

In sum, this related literature provides the basic knowledge of what scientific disruptiveness is like and how it is characterized in general. However, variations may exist across fields and some general phenomena may not apply for specific fields [15, 90]. Moreover, it remains unclear how the circumstances within HCI compare with science in general and what specific contents characterize the landscape of HCI over time, which are essential for the further development of our HCI community. We seek to achieve these by offering a detailed understanding of disruptiveness in HCI.

2.3 Bibliometric Analysis of HCI

Bibliometric analysis, i.e., the quantitative study of scientific literature, has been a rigorous and powerful approach for the understanding of science and publications in general and field characteristics in specific [9, 21], especially when the abundance of the literature makes comprehensive surveys impracticable [12]. Therefore, a line of research has leveraged bibliometric analyses to understand the overall picture and characteristics of the HCI community [12].

Specifically, through visualizing the author co-citation network, co-authorship network, and hybrid network of topical terms and cited articles, past literature has identified the presence of dense author clustering and emerging trends such as ubiquitous computing [12]. Other important facts in HCI are similarly pointed out, e.g., the degree distribution of the coauthorship and citation network of HCI conferences follows power law [33], and the topics within the field are diverse yet drastically changing [56]. Kaye reveals that the size of the author team increases and female authors grow in their presence through statistical analysis of CHI [43], and Bartneck and Hu further illustrate that HCI publications are concentrated towards top countries and institutions by quantifying CHI authorship [5]. However, these bibliometric analyses also reveal that high selectivity may not translate into high impact in HCI [33], and neither does the recognition of awards [5]. Moreover, Cao et al. find that although HCI research is more likely to be translated to patents, the time lag of the technology transfer process is ever-increasing [10]. Through unveiling these important facts, important implications and suggestions are proposed [5, 10, 56].

The effectiveness and objectivity of bibliometric analyses have also facilitated the understanding of sub-components and sub-communities of HCI. For example, by tracking word usages and evolution, they help to identify the meanings and practices of key HCI concepts such as "interaction" [37, 38] in human-computer interaction and "intelligent" [83] in intelligent user interfaces. Other studies focus on specific disciplines in HCI, investigating the themes, research networks, and citation practices of accessibility [16, 57, 70, 84], child-computer interaction (CCI) [30], computer-supported collaborative learning (CSCL) [44, 80], computer-supported collaborative work (CSCW) [17, 18, 36, 41], human-agent interaction (HAI) [60], human-robot interaction (HRI) [4], and ubiquitous computing [55]. Furthermore, some studies have also attempted to identify the status and patterns of HCI in specific countries, including Australia [59], Brazil [3], India [31], Korea [50], and New Zealand [62].

However, although the existing literature has powerfully indicated important aspects of HCI, it has not covered the creativity of HCI research. We fill this gap by investigating the time evolution of disruptiveness of HCI research and unpacking the factors characterizing disruptiveness in HCI.

3 Method

In this section, we introduce how we conduct bibliometric analyses to understand the disruptiveness of HCI papers by showing the datasets we use and the details of our data processing procedure.

3.1 Dataset

ACM metadata. We first collect high-quality data of HCI papers from the ACM digital library. By exporting citation information of papers published in premier HCI venues from the ACM digital library, we obtain the metadata of these papers, including title, abstract, author-specified keywords, year of publication, DOI identifier, etc. For the few papers where some of these fields are missing (e.g., abstracts and keywords), we manually add them back based on the information from their electronic PDF files. Moreover, we document the specific venues of the papers according to the ACM digital library. This avoids the encounter of incorrect venue classifications in public datasets [10], thereby ensuring that only relevant papers are included.

OpenAlex metadata. We further use OpenAlex [67] data to complement the ACM metadata and provide more comprehensive bibliometric information. Specifically, OpenAlex is a leading large-scale open dataset that records not only the publication information of the scientific literature but also the connections between different works. Designed as an open alternative to the paywalled bibliometric knowledge bases, OpenAlex has been increasingly popular and widely adopted since the retirement of its precursor, the Microsoft Academic Graph (MAG) dataset [78]. It offers detailed information on papers' disambiguated authors, institutions, references, and related concepts (i.e., fields of study in MAG) that can be distinguished with unique identifiers and that are unavailable in the ACM metadata. In the current work, we focus on articles (including preprints) from OpenAlex to ensure fair comparisons.

3.2 Data Processing

Data selection. Seminal work in bibliometrics has indicated that a few top venues can represent the core literature of a field [8]. Therefore, in our main results, we align with Cao et al. [10] to focus on four premier HCI venues for our analyses: the ACM CHI Conference on Human Factors in Computing Systems (CHI), the ACM Conference on Computer-Supported Cooperative Work and Social Computing (CSCW), the ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp), and the ACM Symposium on User Interface Software and Technology (UIST). These venues are selected because of their representativeness of the frontier of HCI research: they are among the most prestigious and influential venues for HCI publications and papers from these venues are all related to HCI according to the scope of the venues.

We take several further steps to enhance the data quality of papers from these selected premier HCI venues. First, some early UbiComp conferences are published by Springer rather than ACM. To address this, we add the data of those papers back by retrieving their bibliometric information from the original publisher. Second, CSCW and UbiComp conferences start from 2017 to publish their accepted research papers in journal formats in the CSCW issues of the Proceedings of the ACM on Human-Computer Interaction (PACMHCI) and the Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT) respectively. To reflect this, we treat papers from these two sources as the continuations of the corresponding venues, which are included in the procedure of the ACM metadata collection. Third, to enhance the comparability and representativeness of papers, we include only papers published as research articles and notes in these four venues between 1982, the first year at least one of the venues was published, and 2023, excluding all other publication types such as extended abstracts, posters, and keynotes.

To further validate the robustness of our findings, we consider three more approaches to representing HCI[2]: (1) the top 20 venues

[2] In our main results, we focus on findings derived from the four premier HCI venues rather than alternative approaches due to (1) better quality control enabled by strict venue selection and (2) the substantial manual effort needed for data cleaning and checking. To ensure an accurate delineation of HCI, we focus on these four venues

with the highest h5-index according to Google Scholar, (2) continuous venues sponsored by ACM Special Interest Group on Computer-Human Interaction (SIGCHI), and (3) papers recognized as related to HCI according to OpenAlex. The details of the three alternative methods for identifying HCI papers are shown in Appendix A.

Data linking. We link data from the ACM digital library and OpenAlex metadata using the DOIs of the papers. Specifically, DOI (Digital Object Identifier) is a unique identifier assigned to an article or document, which is available in both the ACM dataset and the OpenAlex dataset. However, for some early HCI papers, a single paper may be published in multiple forms, leading to the presence of multiple DOIs according to ACM. We eliminate the duplicates through metadata cross-referencing to make sure that each HCI paper is recorded only once. We then match the data by querying the OpenAlex API with the DOIs provided by the ACM dataset.

Calculation of disruptiveness. Disruptiveness quantifies the degree to which a paper disrupts (versus develops or consolidates) the existing literature by assessing how the focal paper is cited along with its knowledge bases, i.e., its references [65, 88]. When a paper is disruptive, its unique contributions to the literature are more likely to be recognized and future work is relatively more likely to cite only the focal paper itself rather than citing it together with its references; however, when a paper is developing or consolidating the existing knowledge, subsequent work is relatively more likely to acknowledge both the focal paper itself and its references. As such, a paper's level of creativity is reflected in the extent to which subsequent papers consider it sufficient to use the paper as supporting knowledge independently. Mathematically, disruptiveness can be quantified with the following index D:

$$D = \frac{n_f - n_b}{n_f + n_b + n_o}$$

Here n_f denotes the number of future papers citing only the focal paper (but none of its references), n_b represents the number of future papers citing both the focal paper and any of its references, and n_o is the number of future papers citing any of its references but not the focal paper.

By definition, D varies between -1 and 1. Fig. 1 visualizes the circumstances with decreasing D, i.e., $D = 1$, $0 < D < 1$, $D = 0$, $-1 < D < 0$, and $D = -1$, respectively. It can be indicated from the figure that when D drops from the maximum of 1 to the minimum of -1, citing papers change from citing only the focal paper (and none of its references) to citing both the focal paper and its references. Therefore, a larger D represents a higher likelihood of not being cited together with a work's knowledge base, translates to more recognition of the unique contribution of the work itself, and indicates higher disruptiveness.

Table 1 lists the most disruptive papers in the four premier HCI venues of HCI, CSCW, UbiComp, and UIST, respectively. It can be inferred from the table that the most disruptive papers are mostly the ones that propose new techniques or concepts, although their citation counts vary significantly. This corroborates the effectiveness of the metric of disruptiveness. Moreover, high citations may not indicate high disruptiveness as well. For example, for highly-cited papers primarily develop prior work rather than proposing new directions, e.g., "*Signed Networks in Social Media*" [51], a CHI 2010 paper with top 0.1% citations that extends the "*Slashdot Zoo*" [46] based on the theory of *structural balance* [11], negative disruptiveness is spotted. Indeed, the disruptiveness of a paper's disruptiveness and citation numbers only slightly correlate with each other (Pearson's $r = 0.020$ for all papers). These indicate that disruptiveness depicts an aspect that vastly differs from academic impact, which citation numbers delineate.

Other variables. In our analyses, we measure the citations of each paper by counting the number of articles (preprints included) that cite the paper according to OpenAlex. We identify the topics of the papers based on the concept tagging assigned by the OpenAlex deep-learning-based concept classifier. Because human-computer interaction (HCI) is on level 1 in the OpenAlex concept hierarchy, we use concepts that are one level lower, i.e., concepts at level 2, to depict the (sub)topics of papers in HCI. For keywords, we use the author-specified ones we retrieve from ACM metadata and normalize them to lower cases to get keywords better aligned. As for references, we use the information from OpenAlex wherever possible. In terms of affiliations, we leverage authors' affiliated institutions as detailed by OpenAlex and match them to countries according to OpenAlex. When assigning papers to these affiliations, we make sure that a single paper contributes one credit to each of the participating institutions or countries: for example, a paper with an author from both the U.S. and the U.K. and two more authors from the U.S. will be calculated as a U.S.-based paper once and a U.K.-based paper once. Furthermore, we calculate an author's career age when publishing a paper as the number of years between that paper and their first publication in their career, where the same name-disambiguated author is identified with unique OpenAlex IDs. However, there may be the possibility that multiple authors are mistakenly merged into the same ID. We seek to address this by considering only careers where the intervals between two consecutive publications are no longer than 5 years as valid (changing the threshold to 10 years reaches qualitatively similar results). New authors are consequently defined as those with career ages of 0.

Data summary. The metadata of a total of 17,476 papers from the four premier HCI venues are extracted, among which 10,267 are published in CHI between 1982 and 2023, 3,342 are published in CSCW between 1986 and 2023, 2,150 are published in UbiComp between 2001 and 2023, and 1,717 are published in UIST 1988 and 2023. To meaningfully calculate the disruptiveness of the papers, we need to make sure that the papers 1) have reference information and 2) have been cited by other papers. Adopting these constraints, we arrive at 16,193 papers, where 9,747 are from CHI, 3,020 are from CSCW, 1,837 are from UbiComp, and 1,589 are from UIST.

4 Results

4.1 RQ1: What is the extent of disruptiveness of HCI?

The disruptiveness of HCI papers is drastically decreasing. One first and simple delineation of disruptiveness is whether the contribution of a paper is more likely to be uniquely acknowledged (rather than being cited along with its references). In this way, we identify disruptive papers as those with a disruptiveness index

where the quality of the papers is comparable and where we can practically afford to make several rounds of careful data cleaning and validation.

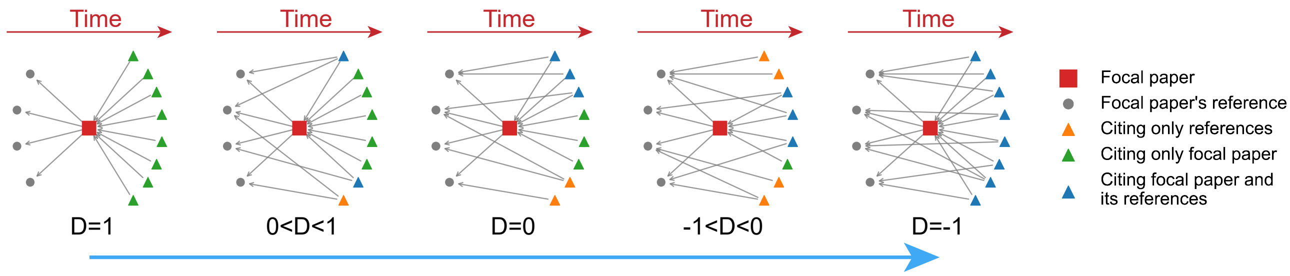
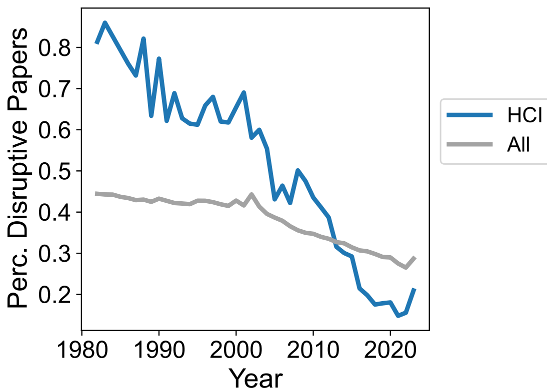


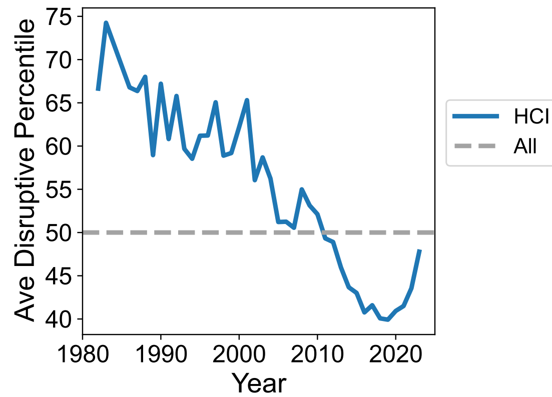
Figure 1: Schematic illustration of disruptiveness and the corresponding local citation network around the focal paper with decreasing disruptiveness D.

Table 1: Most disruptive papers in CHI, CSCW, UbiComp, and UIST, respectively.

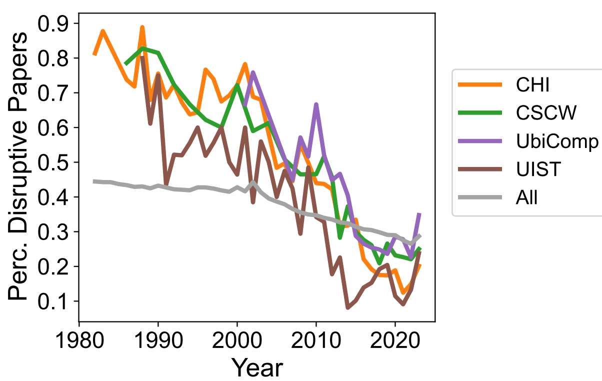
Title	Disruptiveness	Citation	Year
CHI			
Whisper: A Wristwatch Style Wearable Handset	0.914	32	1999
Bridging the Paper and Electronic Worlds: The Paper User Interface	0.866	86	1993
Labeling Images with a Computer Game	0.840	1489	2004
A Toolkit for Strategic Usability: Results from Workshops, Panels, and Surveys	0.830	103	2000
Reflexive Loopers for Solo Musical Improvisation	0.810	17	2013
CSCW			
Knowledge-Domain Interoperability and an Open Hyperdocument System	0.609	42	1990
Awareness and Coordination in Shared Workspaces	0.262	1556	1992
Blogging as Social Activity, or, Would You Let 900 Million People Read Your Diary?	0.254	307	2004
Why CSCW Applications Fail: Problems in the Design and Evaluation of Organizational Interfaces	0.204	581	1988
Computer-Supported Cooperative Work: Examples and Issues in One Federal Agency	0.179	10	1986
UbiComp			
Instant Inkjet Circuits: Lab-Based Inkjet Printing to Support Rapid Prototyping of UbiComp Devices	0.376	248	2013
Smart-Its Friends: A Technique for Users to Easily Establish Connections between Smart Artefacts	0.175	154	2001
ElectriSense: Single-Point Sensing Using EMI for Electrical Event Detection and Classification in the Home	0.108	311	2010
WebClip: A Connector for Ubiquitous Physical Input and Output for Touch Screen Devices	0.107	3	2013
IoT Inspector: Crowdsourcing Labeled Network Traffic from Smart Home Devices at Scale	0.099	66	2020
UIST			
Automation and Customization of Rendered Web Pages	0.337	151	2005
Citrine: Providing Intelligent Copy-and-Paste	0.320	45	2004
Pssst: Side Conversations in the Argo Telecollaboration System	0.316	12	1995
Pop through Mouse Button Interactions	0.279	24	2001
Don't Click, Paint! Using Toggle Maps to Manipulate Sets of Toggle Switches	0.259	27	1998



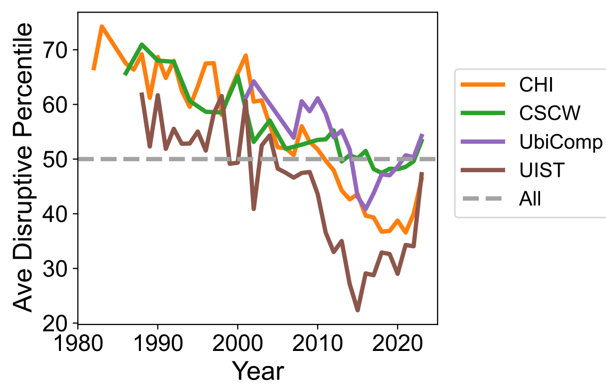
(a) Percentage of disruptive papers over time.



(b) Average disruptiveness percentile over time.



(c) Percentage of disruptive papers across venues.



(d) Average disruptiveness percentile across venues.

Figure 2: The decrease of disruptiveness in HCI over time.

$D > 0$ in the same way as Lin et al. [53] and Li et al. [52]. Fig. 2(a) shows the percentage of disruptive papers in the four premier HCI venues (blue line) and the percentage of disruptive papers in science (gray line) over time, respectively. In line with prior literature [65], we find that the overall disruptiveness of scientific papers drops significantly. However, the disruptiveness of HCI papers decreases even more sharply ($p < 0.001$, both ANCOVA and logistic regression with the interaction effect of time and HCI relevance). Specifically, 44.4% of the research papers published in 1982 were disruptive; in 2021-2023, the figure drops to 26.5%-28.7%. For papers from the four premier HCI venues, they used to be extremely more likely to be disruptive than the global average of the time, where 81.4% to 87.7% of the papers published in 1982 and 1983 were disruptive; however, in 2021-2023, the figure drops to 17.0%-21.8%, which was even lower than the average of all papers in this period.

The notable decrease of disruptiveness in HCI is also observed when we examine the average disruptiveness percentile of HCI papers instead (Fig. 2(b)). Specifically, taking the general decreasing disruptiveness of science into account, we compute the percentile of a paper's disruptiveness index D among all papers published in the same year, where larger values of percentiles correspond to higher disruptiveness. As revealed by Fig. 2(b), the average disruptiveness percentile of HCI papers from the four premier HCI venues drops significantly over time ($p < 0.001$, both ANCOVA and Ordinary Least Squares (OLS) regression with the interaction effect of time and HCI relevance): it diminishes from 64.0%-73.0% in 1982-1983 to 41.5%-47.8% in 2021-2023, changing from being high above the yearly median to lying below the yearly median in terms of disruptiveness. Taken together, HCI has been shifting to be less disruptive at a faster speed than all scientific papers and than all computer science-related studies (see Appendix B) in general.

In Fig. 2(c), we further unpack how the decrease of disruptiveness in HCI varies across the four premier venues of CHI, CSCW, UbiComp, and UIST. It can be inferred that disruptiveness is declining across all these four venues, especially for CHI and UIST. For example, 81.4%-87.8% of the CHI papers published in 1982-1983 were disruptive, but in 2021-2023, only 12.4%-20.2% of the published CHI papers had a disruptiveness score $D > 0$. CHI papers in 1982-1983 shared an average disruptiveness percentile of 63.9%-72.9%, but the figure dropped to 38.8%-45.0% between 2021 and 2023, remaining below 50% consistently. Similarly, for UIST, the percentage

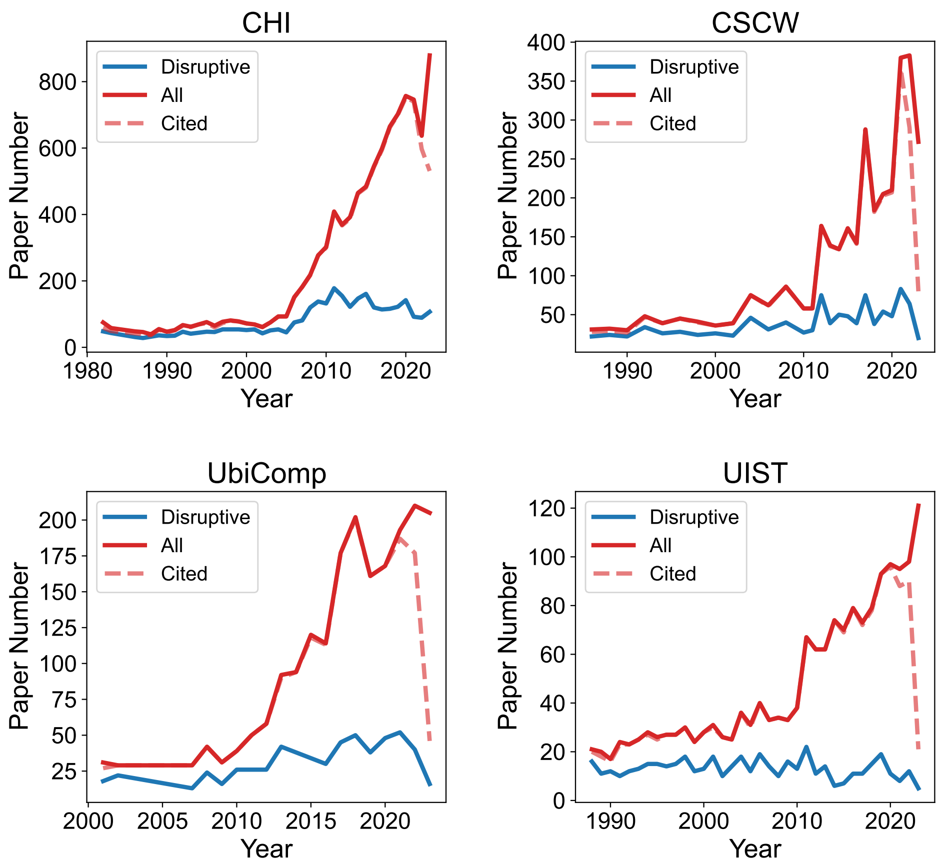


Figure 3: The number of disruptive papers and all papers published by ACM CHI, CSCW, UbiComp, and UIST over time, with the growth rate of disruptive papers not being commensurate with the expansion of HCI.

of disruptive papers dropped from 80% in 1988 to 9.1%-23.8% in 2021-2023, and the average percentile of disruptiveness lowered from 62.3% in 1988 to the minimum of 21.6% in 2015, and rose to 46.9% in 2023, which was consistently below 50%.

Slower growth rate of disruptive work than all work. To investigate how the decrease of disruptiveness in HCI occurs, we explore the number of disruptive papers (disruptiveness $D > 0$) and all published papers across the four premier HCI venues over time. As shown in Fig. 3, the number of disruptive papers in CHI, CSCW, and UbiComp is indeed increasing. Even for UIST, the number of disruptive papers remains relatively stable. However, the total volume of papers in all these four venues is increasing substantially, especially in recent years. For example, 75 papers were published by CHI in 1982, and the number remained to be 72 in 2000. The number of CHI papers then grew quickly to 302 in 2010, 757 in 2020, and reached 879 in 2023. In contrast, 48 out of the 59 papers with both references and citations from CHI 1982 were disruptive. The number remained to be 52 out of 72 in 2000, rose to 132 out of 300 in 2010, 142 out of 752 in 2020, and then 107 out of 531 in 2023 (some recent papers have not had enough time to get citations and therefore the disruptiveness index is not applicable yet). Therefore, the decrease in disruptiveness is not primarily a matter of the disappearance of disruptive works. However, the growth rate of disruptive works does not match up with that of the explosion of published papers. As a result, the percentage of disruptive works and the average percentile of disruptiveness fall off.

These observed trends are robust to data selection. As shown in the Appendix, we conduct three sets of robustness tests (1) taking alternative approaches for identifying HCI papers (see Appendix B), (2) removing self-citations (see Appendix C), and (3) adopting an alternative time-aware measurement of disruptiveness, CD2 (see Appendix D). We observe qualitatively similar trends, which further corroborate the drastic decrease of disruptiveness in HCI.

4.2 RQ2: What are the themes of disruptiveness in HCI?

To uncover what constitutes disruptiveness in HCI, we examine the main themes of disruptive papers in the four premier HCI venues across time. Specifically, we investigate the top algorithmically extracted objective topics and author-specified subjective keywords of disruptive HCI papers in different time periods and the corresponding patterns they show.

Table 2: Top topics of disruptive papers in HCI across time.

1982-1990			1991-2000			2001-2010		
Topic	**Freq.**	**Perc.**	**Topic**	**Freq.**	**Perc.**	**Topic**	**Freq.**	**Perc.**
Bubble	93	0.744	Citation	276	0.604	Context	117	0.547
User interface	87	0.750	Bubble	100	0.617	Bubble	105	0.471
Software	45	0.833	Work	81	0.692	Process	97	0.577
Work	43	0.782	User interface	73	0.603	Task	87	0.372
Set	30	0.750	Software	40	0.541	User interface	85	0.489
Task	26	0.650	Usability	34	0.642	Work	81	0.450
Citation	25	0.893	Research center	32	0.640	Set	79	0.494
Process	19	0.731	Task	31	0.585	Field	77	0.570
User experience design	16	0.640	Collaborative software	29	0.725	Usability	74	0.552
Graphics	16	0.727	Process	26	0.722	Mobile device	73	0.525
2011-2015			**2016-2020**			**2021-2023**		
Topic	**Freq.**	**Perc.**	**Topic**	**Freq.**	**Perc.**	**Topic**	**Freq.**	**Perc.**
Context	117	0.362	Context	116	0.202	Context	67	0.184
Social media	112	0.434	Process	101	0.205	Work	48	0.146
Work	109	0.324	Set	93	0.193	Social media	48	0.213
Set	104	0.322	Social media	89	0.248	Perception	47	0.187
Process	98	0.328	Work	82	0.153	Set	43	0.171
Task	91	0.296	Task	77	0.197	Task	38	0.165
Mobile device	76	0.266	Wearable computer	62	0.173	Process	36	0.117
Bubble	63	0.297	Virtual reality	62	0.193	Politics	29	0.171
Usability	61	0.349	Perception	59	0.174	Virtual reality	27	0.114
Field	57	0.320	Politics	56	0.183	Wearable computer	27	0.165

Evolving topics: top topics are broadening in scope, but may not indicate greater probabilities of disruptiveness. Table 2 shows the top 10 topics (i.e., concepts from OpenAlex) of disruptive papers, their corresponding frequencies of occurrence, and the percentage of disruptive papers pertaining to the topic in different years in the four premier HCI venues. In terms of the specific topics, we observe a remarkable evolution of disruptiveness with distinctive traits within the field of HCI. First, the scope of HCI disruptiveness seems to be broadening from focusing primarily on the technical aspects of computer science systems, e.g., bubble, user interface, and software management, to attending also to the social aspects of social media and politics. Second, disruptive innovation evolves as new approaches for human-computer interactions become available, for example, collaborative software between 1991 and 2000, mobile devices between 2001 and 2015, social media from 2011 on, and wearable computers from 2016 on. Third, some traditional HCI topics such as work and set have been present among the top topics over time. This highlights that some cores of the HCI remain the same over time, and novel contributions to these core areas are consistently made as time passes.

Nevertheless, the top topics may not have larger proportions of disruptive papers. For example, the percentage of disruptive papers regarding user experience design was 64.0% in 1982-1990, which was vastly lower than the average of 76.9% in HCI at the time. This highlights that it is not some specific major topics with extremely high disruptiveness that contribute to disruptiveness in HCI. Instead, disruptive papers are distributed across topics and sometimes even less towards some prevalent topics. However, the large number of studies pertaining to those topics may compensate for the lower probability of disruptiveness, resulting in their prominent contributions to disruptiveness in HCI.

Evolving keywords: increasingly specified, broadened to social facets, and closely tracing technological advancements. The objectively extracted topics depict only part of the picture of disruptiveness in HCI. To take what themes authors themselves regard as important into consideration, we turn to keywords specified by disruptive papers in HCI. Table 3 displays the most frequent keywords among disruptive papers, the corresponding frequencies of mentioning, and the percentages of disruptive papers related to the keywords in different time periods in HCI. Compared with the algorithmically-extracted topics, the keywords show visible differences and the frequencies of the keywords are lower. These are easy to understand because authors' intention to highlight certain aspects and thus add them as keywords may differ. For example, some recent advancements in task management may be present, but the authors may not regard them as worthy of explicitly mentioning because they may seem too vague or ordinary. Differences in authors' preferences for keyword specification also lead the keywords to diverge, which consequently reduces the frequencies of the most prominent keywords.

Interesting trends are also observed when we look into the keywords of disruptive HCI papers themselves. First, top keywords have been growing to be increasingly specified and diverse over time. For example, the more general themes of user interface, design, and input devices were among the top three keywords in

Table 3: Top keywords of disruptive papers in HCI across time.

1982-1990			1991-2000			2001-2010		
Keyword	**Freq.**	**Perc.**	**Keyword**	**Freq.**	**Perc.**	**Keyword**	**Freq.**	**Perc.**
user interface	5	0.833	cscw	51	0.637	ubiquitous computing	38	0.521
design	4	1.0	virtual reality	36	0.75	privacy	35	0.603
input devices	3	1.0	user interface design	25	0.862	cscw	35	0.486
user interface management systems	3	0.333	information visualization	24	0.615	ethnography	34	0.642
object-oriented programming	3	1.0	visualization	23	0.676	collaboration	32	0.478
programming environments	2	1.0	groupware	22	0.478	visualization	27	0.628
software engineering	2	1.0	world wide web	22	0.759	mobile computing	27	0.692
usability	2	1.0	hypertext	21	0.84	computer-mediated communication	26	0.531
eye movements	2	1.0	multimedia	20	0.69	awareness	25	0.481
learning	2	1.0	user interface	20	0.69	children	22	0.629
2011-2015			**2016-2020**			**2021-2023**		
Keyword	**Freq.**	**Perc.**	**Keyword**	**Freq.**	**Perc.**	**Keyword**	**Freq.**	**Perc.**
social media	53	0.457	social media	52	0.23	social media	35	0.246
crowdsourcing	43	0.326	augmented reality	40	0.328	covid-19	21	0.313
twitter	37	0.578	virtual reality	40	0.17	machine learning	19	0.224
privacy	33	0.347	privacy	38	0.242	privacy	18	0.188
design	32	0.296	crowdsourcing	35	0.205	augmented reality	18	0.196
collaboration	25	0.347	machine learning	24	0.216	virtual reality	17	0.101
mobile	24	0.375	collaboration	24	0.282	deep learning	12	0.231
education	21	0.538	accessibility	23	0.187	accessibility	11	0.098
ubiquitous computing	20	0.426	design	20	0.168	mental health	10	0.204
visualization	20	0.364	internet of things	18	0.295	pandemic	9	0.409

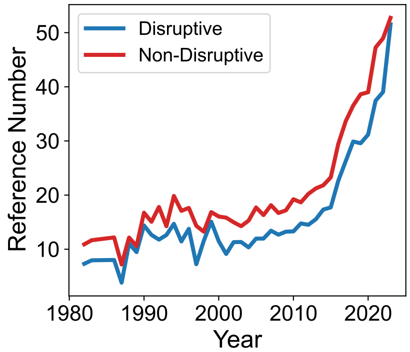
1982-1990, and cscw and ubiquitous computing, i.e., the core themes of the CSCW and UbiComp conferences, were extremely prevalent in 1991-2010 and in 2001-2010, respectively. However, more specific keywords and keywords that are indirectly related to HCI have emerged as top keywords of HCI in recent years, e.g., crowdsourcing in 2011-2020, education in 2011-2015, and accessibility in 2016-2023, as well as machine learning in 2016-2023 and deep learning, COVID-19, and mental health in 2021-2023. This indicates the specification and broadening scope of the fertile ground for HCI innovation. Second, keywords also turn from focusing primarily on techniques to also considering the societal aspect. For example, social media has remained a top keyword since the period of 2011-2015, and similar circumstances are also observed for themes such as education (2011-2015). Third, the evolution of disruptive research in HCI closely follows the technological advancements and the corresponding shifts in interaction formats. For example, cscw and groupware came into sight in 1991-2000, followed by ubiquitous computing and mobile computing during 2001-2010, social media in 2011-2023, and machine learning in 2016-2023.

4.3 RQ3: What characterizes the knowledge use of disruptiveness in HCI?

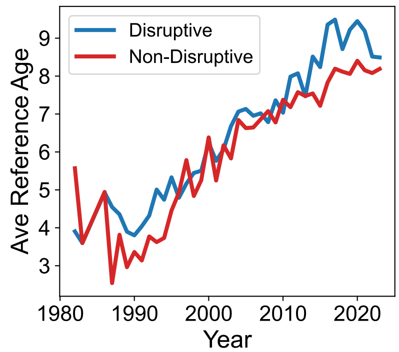
Themes only provide the basic contour of disruptiveness in HCI. To gain deeper insights into the construction of disruptive HCI papers, we turn to the knowledge use of disruptiveness in HCI and explore how disruptive work in HCI uses prior knowledge and how the knowledge they produce is used. Specifically, we investigate the relationship between disruptiveness and (1) referencing behaviors and (2) citation patterns in HCI.

Fewer, older, and less popular references for disruptive papers. Fig. 4 compares the referencing behaviors (i.e., knowledge combination) of disruptive (disruptiveness $D > 0$) and non-disruptive (disruptiveness $D \leq 0$) HCI papers over time. In terms of the number of references, as shown in Fig. 4(a), although it grows for both disruptive and non-disruptive papers over the years, the number of references for disruptive papers is consistently smaller than that for non-disruptive papers ($p < 0.01$ for most years since 2000, t-test)[3]. This indicates that disruptive HCI papers need relatively less

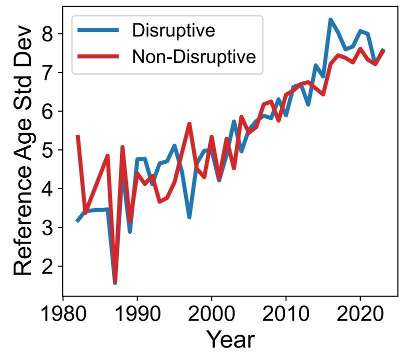
[3] Non-significant differences are observed only in the most recent year of 2023, where many papers have not acquired the citations needed for distinguishing disruptiveness yet and the sample sizes are thus relatively small.



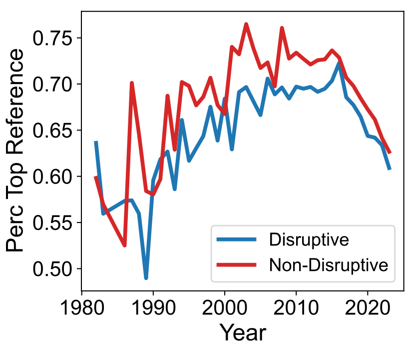
(a) Reference number across disruptive and non-disruptive HCI papers.



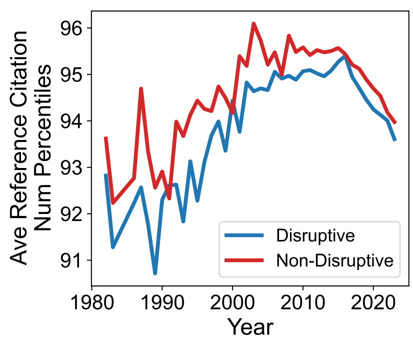
(b) Average reference age across disruptive and non-disruptive HCI papers.



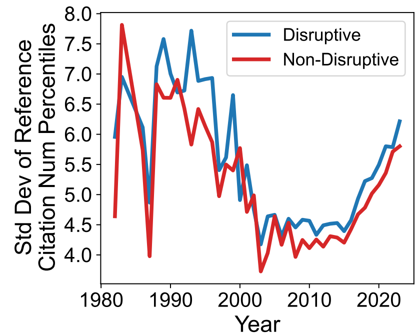
(c) Standard deviation of reference age across disruptive and non-disruptive HCI papers.



(d) Percentage of top 5% popular papers in references across disruptive and non-disruptive HCI papers.



(e) Average of reference citation number percentiles across disruptive and non-disruptive HCI papers.



(f) Standard deviation of reference citation number percentiles across disruptive and non-disruptive HCI papers.

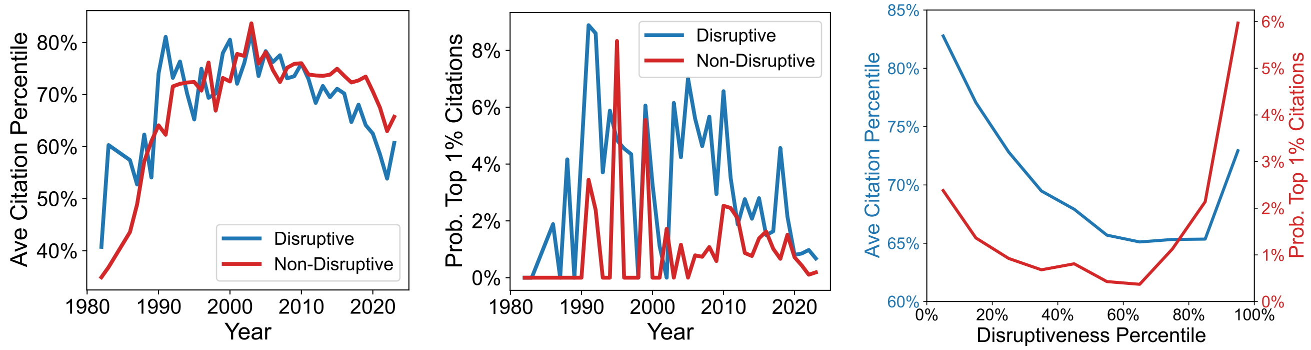
Figure 4: Differences in referencing behaviors across disruptive and non-disruptive papers in HCI, with disruptive papers drawing on fewer, older, and less popular studies.

prior literature to situate their contributions than non-disruptive ones.

One other important aspect of referencing is the age of the knowledge [61, 88]. We gauge the age of a reference by the difference between the year that the current paper references the prior literature and the year that the prior literature was published. Based on this, we further calculate the average age of a paper's references and the standard deviation of the ages of a paper's references, which we depict in Fig. 4(b) and Fig. 4(c), respectively. It can be concluded from the figures that although the standard deviation of reference age is comparable for disruptive and non-disruptive HCI papers, the average age of references for disruptive papers is larger, especially in recent years ($p < 0.001$ for all but the very recent years since 2014, t-test). For example, the average reference ages of disruptive HCI papers published in 2020, 2021, 2022, and 2023 were 9.45, 9.19, 8.51, and 8.49, respectively; for non-disruptive ones, the same numbers dropped to 8.40, 8.15, 8.08, and 8.19, respectively.

Furthermore, knowledge creation is also inherently influenced by the importance of the knowledge upon which it is based [54]. We measure this by the popularity of the references, which is quantified by the references' citation percentiles among papers published within the same year. Fig. 4(d) displays the percentage of the top 5% most popular literature referenced by disruptive and non-disruptive HCI papers, respectively. We find that although seminal past literature constitutes the vast majority of references in both disruptive and non-disruptive papers, disruptive HCI papers are relatively less likely to be built upon the most popular past literature ($p < 0.05$ for most years since 2008, t-test). Similarly, when we examine the average popularity of references quantified by the average of citation number percentiles of a paper's references (see Fig. 4(e)), we find that the references of disruptive papers are stably less popular than those of non-disruptive papers on average ($p < 0.05$ for most years since 2008, t-test). As for the heterogeneity of a paper's reference popularity, as indicated by Fig. 4(f), the standard deviation of the popularity of a paper's references is larger for disruptive HCI papers than non-disruptive ones on average ($p < 0.05$ for most years since 2014, t-test). Therefore, disruptive HCI papers are more likely to build their work upon less prominent past literature.

Lower average citations but higher probability of top citations for disruptive papers. As for citation patterns (i.e., knowledge contribution and usage), Fig. 5(a) and Fig. 5(b) display the average citation percentiles and the probability of hit papers with top 1% citations across disruptive and non-disruptive HCI papers



(a) Average citation percentile across disruptive and non-disruptive HCI papers.

(b) Probability of top 1% citations across disruptive and non-disruptive HCI papers.

(c) Average citation percentile and probability of top 1% citations across different disruptiveness percentiles.

Figure 5: Average citation percentile and probability of top 1% citations with respect to disruptiveness in HCI, where disruptive papers may not exhibit higher average citations but are more likely to have top 1% citations.

over time. Here citation percentiles are calculated based on all scientific articles published within the same year. We find that although sometimes disruptive papers had more citations in the early years, from about 2010 on, the average citation percentile of disruptive papers is consistently lower than that of non-disruptive papers (see Fig. 5(a)). However, the trend alters when the probability of acquiring the top 1% most citations is examined instead (see Fig. 5(b)): in most years, especially from 2002 on, disruptive papers are more likely to garner citations ranking the top 1%. This reveals that although disruptive papers may not acquire high citations on average, they are more likely to stand out and be extremely impactful.

To gain a more nuanced understanding of the relationship between citations and disruptiveness, we delve into how the average citation percentiles and the probability of top 1% citations change with respect to the percentiles of disruptiveness. Here the citation percentiles and disruptiveness percentiles are identified through comparisons with all articles published in the same year, and higher percentiles indicate larger citations and disruptiveness. For better delineation of the observed patterns, we further aggregate the disruptiveness percentiles into deciles. As evident in Fig. 5(c), the average citation percentile declines as the disruptiveness of HCI papers increases from the least 10% to the top 10%-20%. Although the average citation percentile then rises a bit when disruptiveness further increases to the top 10%, it is still vastly smaller than the least disruptive ones (i.e., most developing ones). Specifically, the least 10% disruptive HCI papers share an average citation percentile of 82.2%, whereas for the top 10% most disruptive ones, a paper's citation ranks 72.9% on average. However, this is not the case for the acquisition of exceptionally high citation counts. The probability of publishing papers with top 1% citations declines from 2.4% to 0.4% when the disruptiveness of an HCI paper changes from the least 10% to the top 30%-40%. However, it then increases to 6.0% for the top 10% disruptive ones, underscoring the impressive reward that high disruptiveness can bring about. Taken together, disruptiveness may not translate to high citations on average but is more likely to trigger top 1% citations. These patterns are especially prominent for the least and most disruptive papers in HCI.

4.4 RQ4: Who publishes disruptive works in HCI?

Furthermore, we investigate who publishes disruptive works in HCI by uncovering (1) the top contributing countries (or territories) and institutions over time and the patterns they show, and (2) how authors' prior experience influences disruptiveness.

Consistent contribution of the U.S., U.K., and Canada, along with the recent emergence of Asian countries such as China. To understand the top contributors to disruptiveness in HCI, we identify the top countries and territories that disruptive HCI works come from across different time periods. To better capture the potential changes resulting from the recent surge in HCI publications, we group the recent years into finer-grained intervals of five years as opposed to the ten-year intervals used for earlier periods. As reflected by Fig. 6, the United States has consistently been the most important country-level fertile ground of disruptiveness in HCI over time. Across all time periods, it has been publishing more than three times as many as the secondary country-level contributor. The United Kingdom and Canada remained the second and the third between 1982 and 2020, until they changed to the third and fourth during 2021-2023. These changes seem to be resulted from the recent rise of Asian countries such as China. For example, China was not among the top 10 within the landscape of disruptiveness in HCI from 1982 to 2000. It ranked tenth during 2001-2010, changed to sixth during 2011-2015, quickly rose to fourth during 2016-2020, and even came to second place during 2021-2023.

Top contributions may not be attributed to a high probability of disruptiveness. To further unpack how these countries and territories contribute to the landscape of disruptiveness in HCI, we examine the percentage (or probability) of disruptive papers from the top countries and territories in HCI across time (see Fig. 7, where the dashed vertical line indicates the global average). We find the top country-level contributors to disruptiveness in HCI may not be the ones with an exceptionally high probability of producing disruptive works. Indeed, U.S.-based authors publish disruptive papers at probabilities centering around the global average; Canadian (1982-2023), French (1991-2023), and German (2011-2023) studies

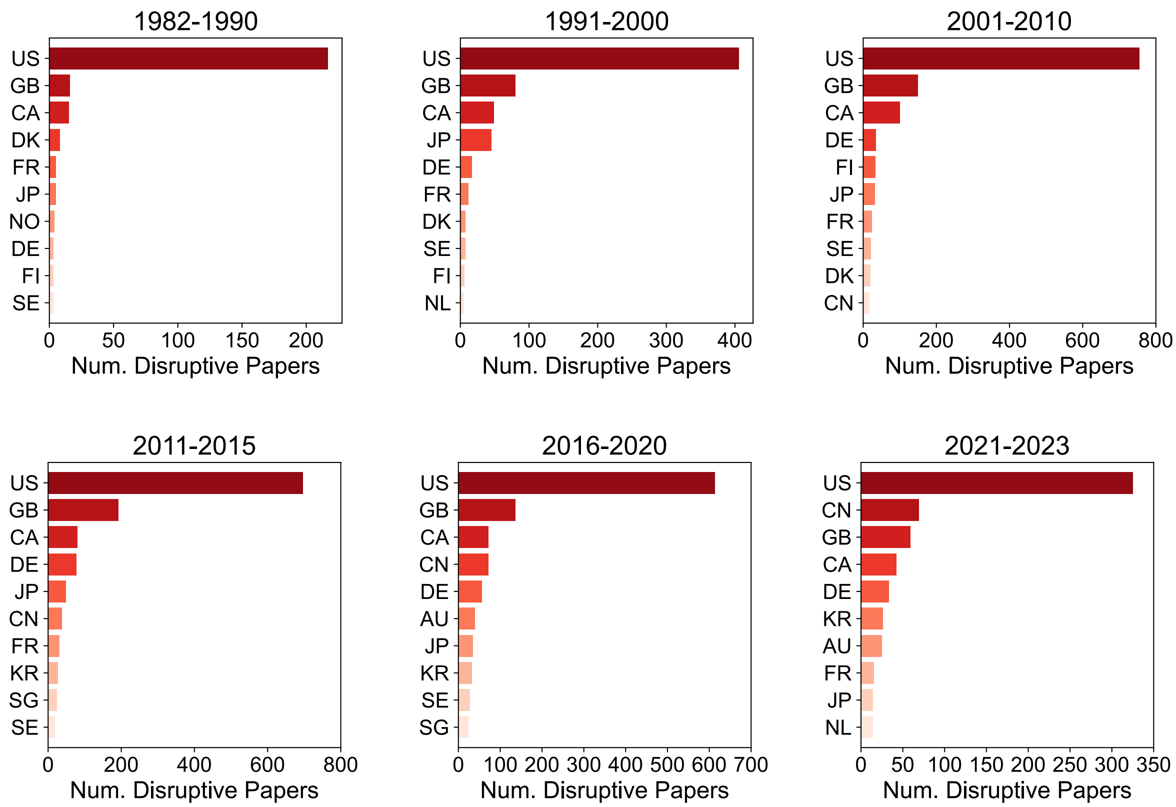


Figure 6: Top countries and territories publishing disruptive HCI papers over time.

are even less likely to be disruptive than an average HCI paper. These results emphasize that the top countries do not seem to exhibit a privilege in unearthing disruptive ideas; rather, their large volume of HCI publications enables them to accumulate advantages in contributing disruptive works. Moreover, the average percentages of disruptive papers for all top countries and territories are vastly decreasing. This indicates that the sharp decline of disruptiveness in HCI is not attributed to certain specific countries but is instead a general phenomenon within the field. Similar patterns are identified when we examine the leading cities contributing to disruptiveness in HCI (see Appendix E).

Growth of the University of Washington and Tsinghua University, but no longer previous industrial giants such as PARC and IBM. For a more fine-grained understanding of the contributors of disruptiveness in HCI, we delve into the institutions publishing the most disruptive HCI studies over time. As depicted in Fig. 8, several universities, e.g., Carnegie Mellon University, Georgia Institute of Technology, and Stanford University have long been among the top institutional-level contributors to disruptiveness in HCI. For example, Carnegie Mellon University was the largest contributor to disruptiveness in HCI in 2001-2020 and the second largest one in 1982-2000 and 2021-2023. However, some important industrial players no longer come into sight in recent years. For example, Palo Alto Research Center used to publish the most disruptive papers between 1982 and 2000, but dropped to sixth during 2001-2010 and is no longer visible among the top 10 institutions from 2011 on. Similar circumstances have also been observed for IBM, Apple, Intel, etc. Indeed, industrial companies took up 4/10 and 5/10 among the top 10 institutions in 1982-1990 and 1991-2000, respectively; however, only 1/10 (Microsoft) of the top institutional contributors were from industry in 2016-2020, and even none of the top institutional publishers of disruptive HCI papers were from industry in 2021-2023. Replacing these industrial companies are some increasingly important universities. For example, the University of Washington was not among the top 10 institutions between 1982 and 2000, but it rose to fourth place in 2001-2010, ranked second between 2011-2020, and then ascended to first place between 2021 and 2023. Similarly, Tsinghua University was not among the top producers of disruptiveness in HCI before 2020. However, it quickly rose to the third recently between 2021 and 2023.

Divergent percentage of disruptiveness across institutions. Fig. 9 further depicts the percentages of disruptive papers in HCI for top institutions across time. Substantial discrepancies in the probability of publishing disruptive HCI papers across institutions are observed. For example, Stanford University, Massachusetts Institute of Technology, and the University of California, Irvine have long been more likely to contribute disruptive works, whereas for

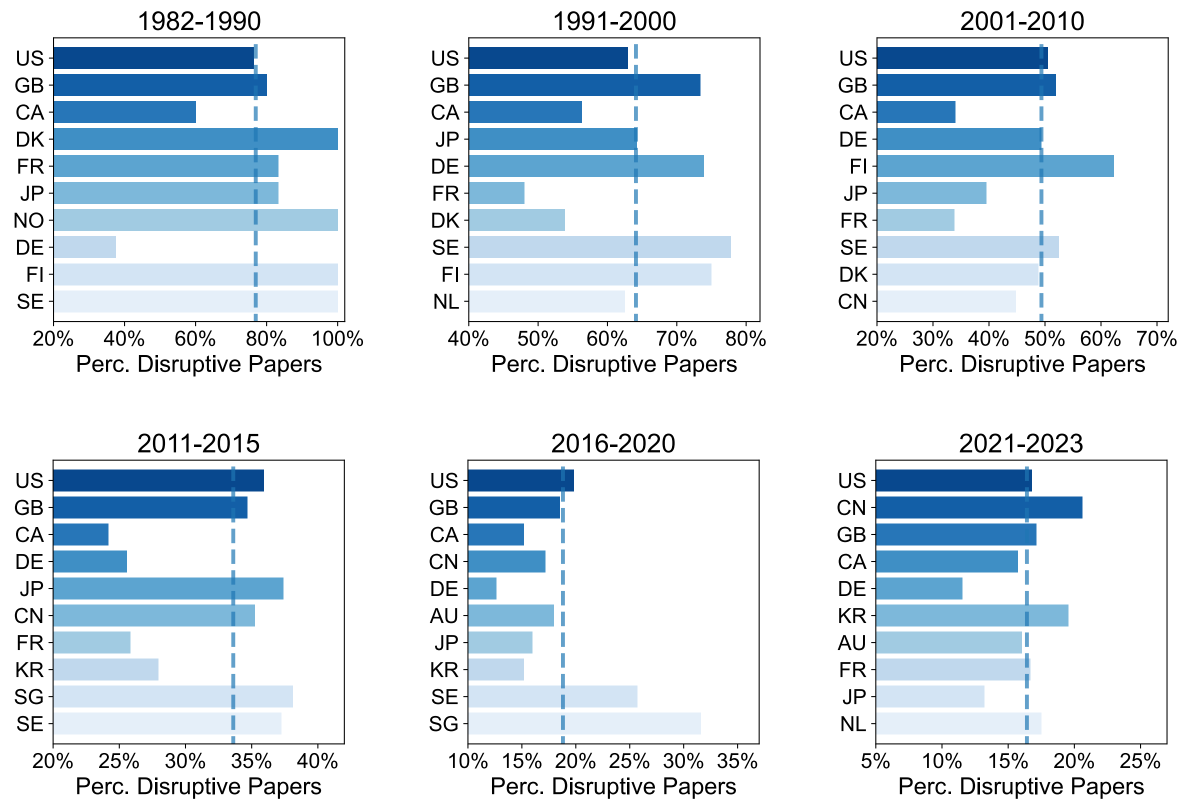


Figure 7: Percentage of disruptive HCI papers published by top countries and territories over time.

Carnegie Mellon University and the University of Washington, the ratios of disruptive works fluctuate. Moreover, the recently emerging top institutions of authorships, e.g., Tsinghua University, contribute disruptive papers with likelihoods above the global average in recent years. This hints that some of these emerging institutions may be especially effective in bringing about novel disruptive ideas in HCI.

Fresh authors are more likely to publish disruptive HCI papers. Authors' affiliated countries and institutions do not fully capture all aspects of their behavioral traits related to publications. Existing literature suggests that authors' past experience and expertise also significantly influence the papers they publish [20, 91]. On the one hand, authors' past engagement with publications can cause the chaperone effect [72] and can be translated to familiarity with the literature. This helps them better discern the important directions and research gaps, which can lead to higher probabilities of disruptiveness. On the other hand, authors' familiarity with certain existing attempts may also lay constraints on the paradigms to follow and limit the range of ideas that they attend to [20], which may result in lower probabilities to produce disruptive works. Taking these competing possibilities into account, we seek to understand how authors' past expertise is associated with disruptiveness in HCI in reality.

Specifically, Fig. 10(a) illustrates the distribution of papers with different percentages of new authors (left axis) and the corresponding percentages of disruptive HCI papers they publish (right axis). We find that as the percentage of new authors in a paper increases, the probability that it is disruptive rises accordingly: when 0%-20% of the authors have not published any papers before, they share a probability of 29.4% to contribute disruptive papers; the probability rises to 48.0% when 60%-80% of the authors are new and even to 72.6% when more than 80% are new authors without prior publication records. However, the four premier venues of HCI are indeed dominated by papers with relatively few brand-new authors: studies with fewer than 20% new authors represent 75.1% of papers with a calculable disruptiveness index in these venues.

Similar circumstances are observed when we analyze the maximum career age of a paper's authors instead. As Fig. 10(b) depicts, a greater maximum career age is associated with a lower likelihood of publishing disruptive papers. For authors with fewer than 5 years of experience in science, 66.4% of their papers are disruptive. The percentage decreases to 28.3% when the authors' maximum career age increases to 20-25 years, which then fluctuates around 25%-30% as the maximum career age of a paper's authors continues to grow. However, only 2.3% of the papers from the four premier HCI venues are authored by teams with a maximum career age between 0-5 years, whereas those whose maximum career ages exceed 20 years publish 57.9% of HCI publications. Taken together, we find that

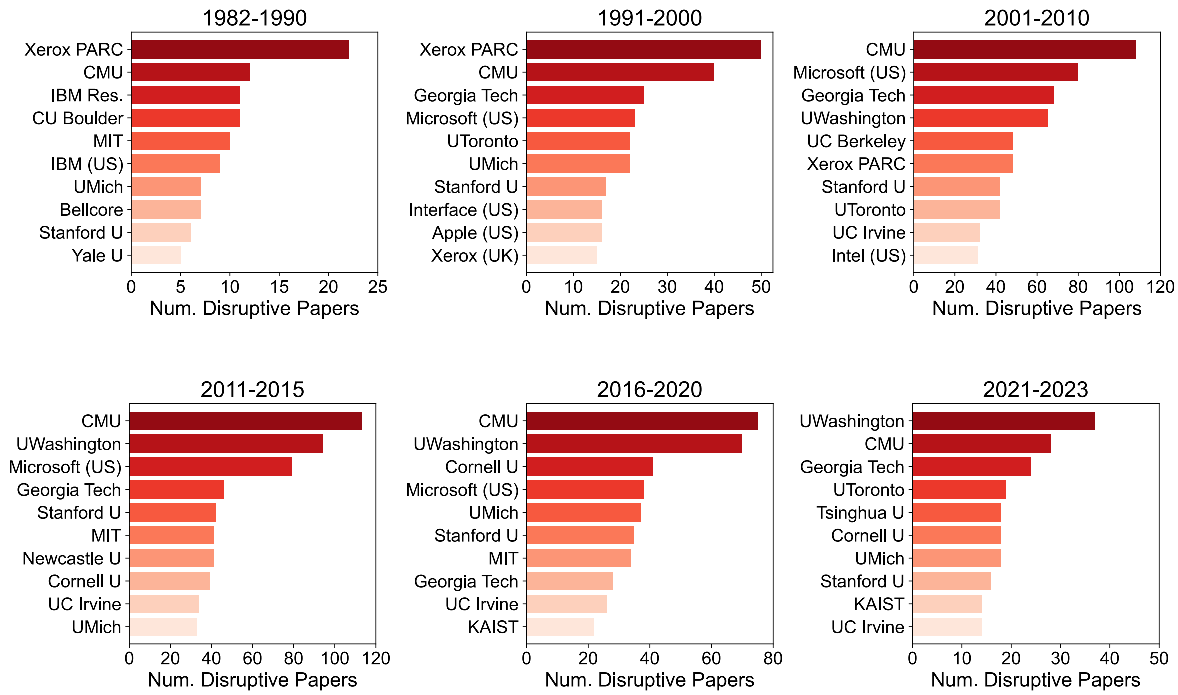


Figure 8: Top institutions publishing disruptive HCI papers over time.

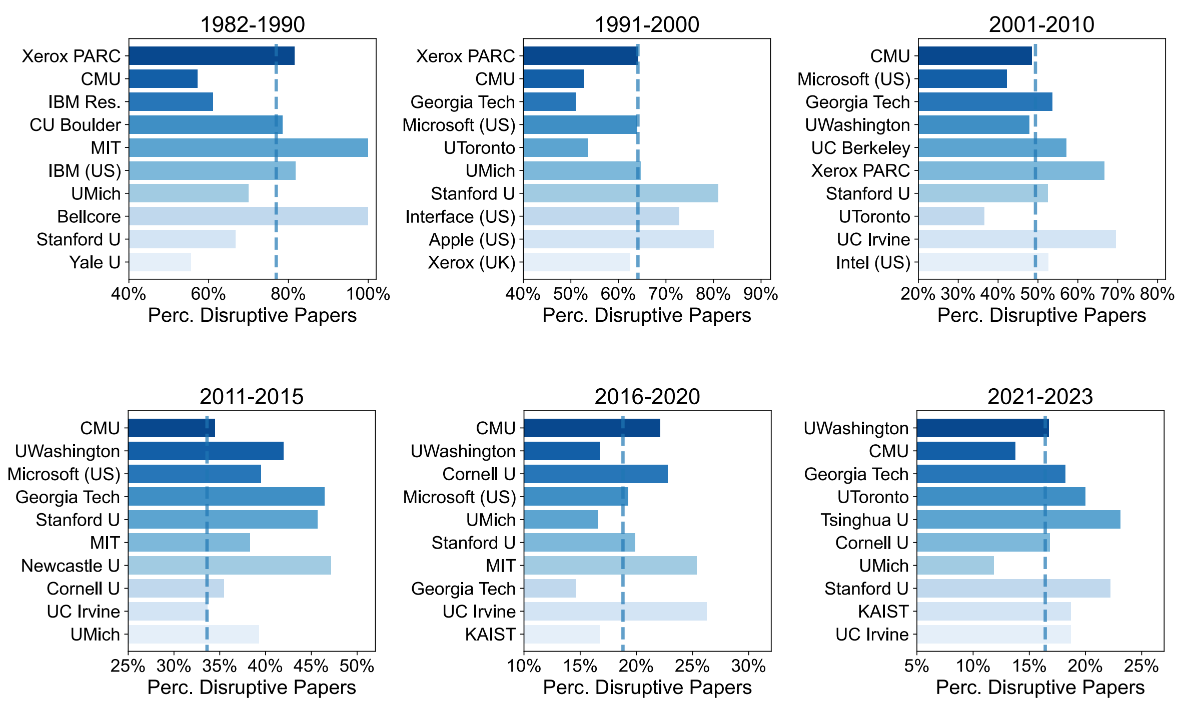
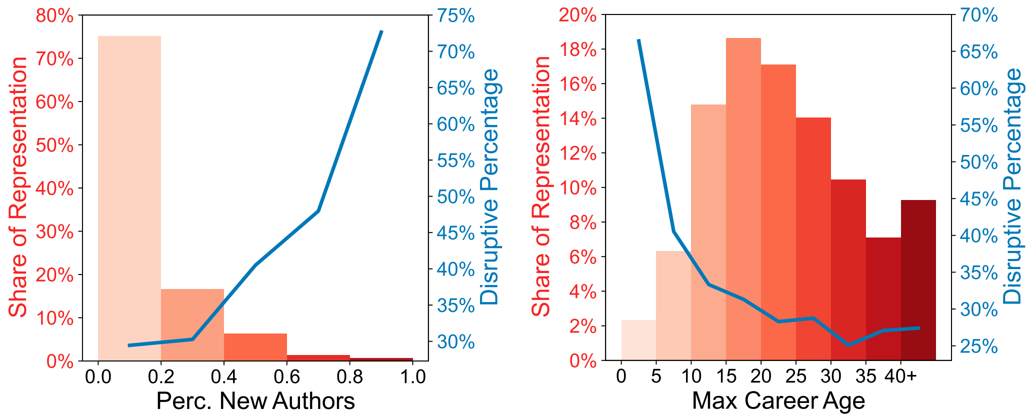


Figure 9: Percentage of disruptive HCI papers published by top institutions over time.



(a) The distribution of the percentage of new authors and its relationship with disruptiveness for HCI papers.

(b) The distribution of authors' maximum career age and its relationship with disruptiveness for HCI papers.

Figure 10: The positive relationship between author freshness and disruptiveness in HCI.

fresh teams with a larger proportion of new authors and lower career age are more likely to produce disruptive work. However, their representation in these HCI venues is relatively limited.

5 Discussions

5.1 The Sharp Decline of Disruptiveness of HCI

As shown in the main results, a sharp decline of disruptiveness can be observed in HCI over time. What is even more noteworthy is that although disruptiveness in science and technology drops in general [65], the disruptiveness of HCI falls at an even significantly faster rate than the global average, the trend of which is robust and consistent across venue selection.

One of the contributing factors can be researchers' reference behaviors. As we show in Fig. 4(a), the average number of references cited in CHI papers has been growing quickly, especially in recent years. Considering that more references may render increased difficulties in disrupting all related prior knowledge [68], lower disruptiveness is relatively more likely to be anticipated. To a certain degree, this can be attributed to HCI's increasing highlight on discussions of related work. An adequate review of related previous work has been among the top criteria for reviewers' judgment of HCI papers [13], and we increasingly encounter with and recommend better communication with the prior literature to situate a manuscript and highlight its uniqueness when acting as authors and reviewers in HCI. This helps to tease out the focal paper's unique contributions, but risks lowering down authors' willingness to uniquely cite a single previous study and may even push them to incorporate not-so-relevant literature into the reference lists. As a result, the quantitatively measured disruptiveness is more likely to go down. Furthermore, in-context understanding and contributions are increasingly noted and underscored in HCI [40, 48]. This benefits surfacing user groups' situated context-dependent opinions and needs, tailoring technologies to their personalized interests and concrete usages, and improving user experiences [49]. However, these circumstances are more likely to contribute incremental development rather than disruption of the existing attempts, and out-of-box or even paradigm-shifting work is less present. As a result, a lower probability of disruptiveness is brought upon.

Another possible contributing factor is the expansion of the field. In HCI, a surge in the number of papers has been observed in recent years (see Fig. 3). Prior literature has manifested that more papers may not translate into knowledge advances; instead, cognitive overload and research competitions may hinder creative ideas due to the lack of the cognitive slack necessary for novelty [14]. Even worse, if the knowledge space of a field is relatively fixed, producing highly novel and creative work becomes more challenging. However, recent years have spotted the consolidation of research contributions and criteria for paper judgment in HCI [13, 87]. Although they help researchers (especially novice researchers) to better highlight their contributions, they also risk confining out-of-the-box ideas that do not fit the norms of current HCI practices. For example, some paradigm-shifting and disruptive works may find it hard to identify an appropriate subcommittee, the selection of which is a must for CHI submissions. In response to this, the authors may adjust their papers according to the intended subcommunity, risking curtailing the disruptiveness of the work correspondingly. This could be particularly prominent in the most prestigious HCI venues, where the high standards for papers and the potential recognition associated with publications in these venues may drive authors to more intentionally make substantial efforts on adjustments. As a result, we observe a steeper decrease of disruptiveness in these venues as shown in Appendix B. Fortunately, this is addressable given the interdisciplinary nature of HCI: the HCI community has a long history and tradition of welcoming diverse methodologies and paradigms [32, 63]. When expanded directions and subfields are further welcomed and appreciated, knowledge advances should be promoted and ignited by new ideas.

The decline in disruptiveness also points to the trade-offs regarding the essential tension between tradition and risky innovation. When the rewards of risk-taking fail to outweigh the potential loss incurred by failures, scientists become less inclined to take such risks [26]. Disruptive works usually involve taking risks [75], but they may not always lead to tangible benefits: although high disruptiveness indicates a higher probability to acquire top 1% yearly-normalized citations, it may not result in higher average citation counts (Fig. 5). Therefore, for scholars who more conservatively focus on average expected returns, pursuing the risk-taking disruptive works may not seem to be an efficient strategy. However, it is exactly the risky and less redundant research that accelerates scientific progress and pushes the boundaries of knowledge further [69], both of which are vital for the sustainable development of a field. Given that the most disruptive papers are most likely to obtain extremely high citations (as we discuss and show in Fig. 5), fostering an environment that emphasizes landmark contributions rather than quantity or average impact may encourage researchers to undertake more disruptive work.

The peer review system can also subtly influence the declining disruptiveness of HCI. Following the norms of science, HCI venues recruit peer reviewers to determine and ensure the validity and credibility of scientific knowledge [58] and evaluate a paper's contribution to HCI [13]. These reviewers play a crucial role in delineating the boundaries of HCI and maintaining the knowledge constructs of the HCI community. However, reviewers are not infallible and may sometimes exhibit a conservative stance towards disruptive and risky studies [7, 75], making papers that challenge the existing paradigms more seriously criticized and thus less likely to be published [76]. Given the high standards upheld by HCI reviewers in the paper selection process, authors may be hesitant to choose disruptive projects for fear of criticism, which may in turn result in the decreasing disruptiveness of HCI. Moreover, the adoption of a "revise and resubmit" or revision process in HCI [13] rather than a rebuttal phase in some other computer science conferences [24, 86] may also contribute to the decline. Whereas rebuttals primarily encourage authors to respond to reviewers' comments and clarify their points [24, 86], in resubmissions, authors more frequently follow reviewers' suggested modifications and substantially adjust their papers according to reviewers' advice. This can be beneficial for improving the overall quality of the papers and helping unconventional submissions fit into the community. However, the increased adherence to existing norms may also risk diminishing the disruptive nature of the manuscript.

Overall, although HCI's highlight on building heavily on related studies, strong emphasis on context-dependent contributions, and fast expansion with consolidated research norms help distinguish it as a community, it may come at the expense of impairing extremely creative work and disruptiveness. This may be further compounded by the trade-offs regarding risk-taking and peer reviews. As a result, a sharp decrease in the disruptiveness of HCI is engendered.

5.2 Relevant Factors of Disruptive HCI Papers

Our depiction of the evolution and characteristics of disruptiveness in HCI also reveals the associations between various relevant factors and disruptiveness. For example, as demonstrated in our results, the knowledge base of disruptive papers may differ from that of non-disruptive ones: disruptive papers tend to build upon fewer, older, and less popular references. This indicates that pursuing the most popular topics may not be conducive to making research disruptive; instead, less explored areas may serve as potent sources of disruptiveness. This is also reflected in our depiction of the evolving main themes of disruptiveness in HCI. As we have discussed in our results, top topics and keywords of disruptive HCI papers may not always predict high disruptiveness. Therefore, to sustainably maintain the disruptiveness of HCI, our community should continue encouraging diversity in research focuses rather than concentrating solely on a few prevalent directions and reserve some attention to relatively older and less popular topics instead of exclusively pursuing the most timely and trending ones.

We also discover that freshness rather than expertise is more likely to trigger disruptiveness: HCI papers published by both teams with larger percentages of new authors and authors with shorter career spans are more likely to be disruptive. This shows that among the competing positive effects (e.g., better topic identification) and negative impacts (e.g., limited focus) brought by prior experience, the latter tends to dominate. According to recent findings, this is primarily because freshness can steer researchers away from conventional thinking and stereotypes, thus enhancing originality [91], whereas aging scientists are more likely to adhere to familiar knowledge and critique emerging ideas [20]. Therefore, in light of the empirical patterns observed in our study, we emphasize attracting new researchers to HCI to promote disruptiveness and creativity fueled by fresh perspectives.

Furthermore, we observe that the top contributors of disruptiveness in HCI may not have higher percentages of disruptive papers. Such findings imply that historically non-dominant countries and institutions may bring about new possibilities to the landscape of disruptiveness of our community. This is further supported by the relatively higher percentages of disruptive papers that emerging institutions publish (see Fig. 9), and recent studies' increasing recognition of the positive impact of diversity on science [1, 35, 66, 90]. With novel cultural contexts, alternative ways of thinking, and even different situated technological practices, scholars from historically non-dominant backgrounds have the potential to uncover novel and insightful dimensions for and introduce unusual and disruptive ingredients to HCI. However, we find that contributors with these possibilities, e.g., those from the Global South, are significantly underrepresented in the top players of HCI and the landscape of disruptiveness. Therefore, it is recommended for our community to develop targeted strategies to improve global participation to further embrace disruptive studies.

5.3 Implications

Our study provides concrete and actionable implications for our HCI community to improve disruptiveness and alleviate, or even reverse, the sharp decline in disruptiveness we observe in HCI.

Welcoming new directions and unconventional studies. As discussed in previous sections, popular topics and established knowledge bases do not necessarily foster disruptiveness, whereas expanding into new directions may lead to innovation. Therefore, it is crucial for our HCI community to cultivate an atmosphere that embraces new directions. This is particularly important for highly disruptive studies, which may seem unconventional at first. Although such studies have the potential to spark exciting future research, they may struggle to fit within existing subcommunities or subcommittees. Therefore, it is worth considering the incorporation of "other" types of contributions alongside the existing ones and adopting an open and welcoming attitude toward unconventional research that may not adhere closely to the established paradigms in HCI but could significantly contribute to our community. Furthermore, some relevant venues in other communities, e.g., the AAAI Conference on Artificial Intelligence (AAAI), the International Joint Conference on Artificial Intelligence (IJCAI), and The Web Conference (WWW), have set up special tracks that publish papers in the same proceedings while adopting slightly different criteria for publication. Similar attempts may also help our community embrace new directions and unconventional works.

Encouraging risky yet innovative research. Leading HCI venues employ a peer-review process to assess and ensure the quality of submissions. Although guidelines for reviewers are provided, the responsibility often falls on the reviewers themselves to balance different aspects of evaluation [73], e.g., among significance, originality, and research quality [13]. Disruptive papers are usually riskier and more innovative. Some of them may lack established evaluation methods or fail to demonstrate impressive rigor. To facilitate the publication of disruptive works, we recommend that reviewers in HCI more carefully balance originality with other aspects of the manuscripts and avoid excessive criticism of imperfect yet thought-provoking research. As such, risky yet innovative research would be encouraged. Moreover, allowing authors to revise and resubmit their work [13] is also a valuable option to help these works address deficiencies and meet publication standards. However, as we have discussed before, this may also risk weakening the disruptiveness of certain works when we fit them into the norms of HCI. It is therefore worth considering properly combining (1) rebuttals for clarifying and defending authors' points and (2) revisions for improving paper quality following reviewers' comments. Some possible examples that we can learn from include the ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD), the ACM Conference on Computer and Communications Security (CCS), and the USENIX Security Symposium (USENIX Security).

Supporting fresh authors. As highlighted in the preceding sections, fresh authors with relatively limited prior experience are more likely to contribute disruptive work because they are less constrained by established traditions. Therefore, one possible pathway to improving disruptiveness is to better scaffold fresh authors and help them avoid the pitfalls of inexperience that might hinder their work from being accepted. Some sister venues, e.g., the International AAAI Conference on Web and Social Media (ICWSM), have recently introduced mentoring programs for first-time authors. We argue that our community can also explore similar initiatives to support fresh authors and thereby foster disruptiveness.

Facilitating wider participation. According to our previous discussions, it may be valuable to facilitate wider participation, especially those from the historically underrepresented population and those from the Global South, to secure disruptiveness in HCI by encouraging novel practices. Some previous experience indicates that holding conferences in those regions can be an important step: for example, holding CSCW 2011 in Hangzhou encouraged the participation of more Chinese authors [34]. However, too few of the top HCI conferences are held out of developed countries: the four premier ones we primarily investigate have only been held in developing countries twice (CSCW 2011 in Hangzhou, China and UbiComp 2011 in Beijing, China). Some other communities have been diversifying their selections of conference sites: for instance, the International Conference on Learning Representations (ICLR) was held in Kigali, Rwanda in 2023. Our HCI community may consider similar attempts.

Emphasizing representative masterpieces. Disruptiveness in HCI may also benefit from an emphasis on representative works rather than overall productivity or average citation counts. As we have shown previously, disruptive HCI papers may not necessarily receive more citations on average, but share a larger probability to rank within the top 1% of citations among papers published in the same year. To encourage disruptive studies, cultivating an environment that values standout contributions should help. For example, placing greater emphasis on representative works in funding decisions and researcher promotion processes is recommended.

5.4 Limitations and Future Work

Although disruptiveness serves as a powerful method for differentiating disruptive ideas from those that consolidate and develop existing knowledge, it does not capture all nuanced aspects of creativity. Future research is encouraged to dissect other facets beyond disruptiveness and delve into detailed qualitative insights (e.g., through interviews with HCI researchers) to gain a more profound understanding of the creativity of HCI. Moreover, our dataset only includes published papers, and we therefore do not consider rejected manuscripts. Future studies could extend our analyses to include unaccepted manuscripts and delineate a more thorough picture of disruptiveness in HCI, e.g., through uncovering its relationship with acceptance rates and empirically demonstrating the role of the review process. Furthermore, we focus on four premier venues to identify prominent patterns regarding disruptiveness in HCI. Although these venues effectively represent the knowledge frontier of HCI and the main patterns are corroborated by several alternative identifications, we welcome future research to extend our results to other representations of HCI research to further validate the generalizability of our study. Lastly, our study is descriptive in nature and we refrain from making causal claims based on our findings. We hope that future work will build upon this foundation to explore causal relationships in greater depth.

6 Conclusions

In this paper, we investigate the creativity of HCI by probing the disruptiveness of research papers published in ACM CHI, CSCW, UbiComp, and UIST between 1982 and 2023. We discover that HCI has been experiencing a decline in disruptiveness that is even steeper than the average of science. The landscape of disruptiveness in HCI is evolving, but top temporal themes and contributors of disruptiveness may not translate to higher probabilities of disruptive paper. Instead, factors such as narrower, older, and less famous knowledge bases and the inclusion of more fresh authors are linked to disruptiveness, which may be more likely to incur exceptionally high citations rather than high average impacts. By further discussing the potential drivers of (non-)disruptiveness of HCI, we provide practical implications for the HCI community to embrace a more creative and lively future.

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References

[1] Bedoor K AlShebli, Talal Rahwan, and Wei Lee Woon. 2018. The preeminence of ethnic diversity in scientific collaboration. *Nature communications* 9, 1 (2018), 5163.

[2] John Baer. 2003. Evaluative thinking, creativity, and task specificity: Separating wheat from chaff is not the same as finding needles in haystacks. In *Critical Creative Processes*. Hampton Press, 129–151.

[3] Simone Diniz Junqueira Barbosa, Milene Selbach Silveira, and Isabela Gasparini. 2017. What publications metadata tell us about the evolution of a scientific community: the case of the Brazilian human–computer interaction conference series. *Scientometrics* 110 (2017), 275–300.

[4] Christoph Bartneck. 2011. The end of the beginning: a reflection on the first five years of the HRI conference. *Scientometrics* 86, 2 (2011), 487–504.

[5] Christoph Bartneck and Jun Hu. 2009. Scientometric analysis of the CHI proceedings. In *Proceedings of the SIGCHI conference on human factors in computing systems*. Association for Computing Machinery, New York, NY, USA, 699–708.

[6] Susanne Bodker. 2021. *Through the interface: A human activity approach to user interface design*. CRC Press.

[7] Kevin J Boudreau, Eva C Guinan, Karim R Lakhani, and Christoph Riedl. 2016. Looking across and looking beyond the knowledge frontier: Intellectual distance, novelty, and resource allocation in science. *Management science* 62, 10 (2016), 2765–2783.

[8] Samuel C Bradford. 1934. Sources of information on specific subjects. *Engineering* 137 (1934), 85–86.

[9] Robert N Broadus. 1987. Toward a definition of "bibliometrics". *Scientometrics* 12 (1987), 373–379.

[10] Hancheng Cao, Yujie Lu, Yuting Deng, Daniel Mcfarland, and Michael S Bernstein. 2023. Breaking Out of the Ivory Tower: A Large-scale Analysis of Patent Citations to HCI Research. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–24.

[11] Dorwin Cartwright and Frank Harary. 1956. Structural balance: a generalization of Heider's theory. *Psychological review* 63, 5 (1956), 277.

[12] Chaomei Chen, Gulshan Panjwani, Jason Proctor, Kenneth Allendoerfer, Serge Aluker, David Sturtz, Mirjana Vukovic, and Jasna Kuljis. 2006. Visualizing the Evolution of HCI. In *People and Computers XIX—The Bigger Picture: Proceedings of HCI 2005*. Springer, 233–250.

[13] Marshini Chetty, Bongshin Lee, and Phoebe Toups-Dugas. 2024. Guide to a Successful Submission. https://chi2025.acm.org/guide-to-reviewing-papers/

[14] Johan SG Chu and James A Evans. 2021. Slowed canonical progress in large fields of science. *Proceedings of the National Academy of Sciences* 118, 41 (2021), e2021636118.

[15] Mario Coccia and Lili Wang. 2016. Evolution and convergence of the patterns of international scientific collaboration. *Proceedings of the National Academy of Sciences* 113, 8 (2016), 2057–2061.

[16] Mark Colley, Taras Kränzle, and Enrico Rukzio. 2022. Accessibility-Related Publication Distribution in HCI Based on a Meta-Analysis. In *CHI Conference on Human Factors in Computing Systems Extended Abstracts*. Association for Computing Machinery, New York, NY, USA, 1–28.

[17] António Correia, Shoaib Jameel, Daniel Schneider, Benjamim Fonseca, and Hugo Paredes. 2019. The effect of scientific collaboration on CSCW research: A scientometric study. In *2019 IEEE 23rd International Conference on Computer Supported Cooperative Work in Design (CSCWD)*. IEEE, 129–134.

[18] António Correia, Hugo Paredes, and Benjamim Fonseca. 2018. Scientometric analysis of scientific publications in CSCW. *Scientometrics* 114 (2018), 31–89.

[19] Tim Coughlan and Peter Johnson. 2006. Interaction in creative tasks. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 531–540.

[20] Haochuan Cui, Lingfei Wu, and James A Evans. 2022. Aging scientists and slowed advance. *arXiv preprint arXiv:2202.04044* (2022).

[21] Naveen Donthu, Satish Kumar, Debmalya Mukherjee, Nitesh Pandey, and Weng Marc Lim. 2021. How to conduct a bibliometric analysis: An overview and guidelines. *Journal of business research* 133 (2021), 285–296.

[22] K Anders Ericsson. 1999. Creative expertise as superior reproducible performance: Innovative and flexible aspects of expert performance. *Psychological Inquiry* 10, 4 (1999), 329–333.

[23] Daniel Fallman. 2003. Design-oriented human-computer interaction. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 225–232.

[24] Angela Fan, Cheng Zhang, Danielle Belgrave, Jakub Tomczak, and Ulrich Paquet. 2024. NeurIPS 2024 Call For Papers. https://neurips.cc/Conferences/2024/CallForPapers

[25] Lee Fleming. 2001. Recombinant uncertainty in technological search. *Management science* 47, 1 (2001), 117–132.

[26] Jacob G Foster, Andrey Rzhetsky, and James A Evans. 2015. Tradition and innovation in scientists' research strategies. *American Sociological Review* 80, 5 (2015), 875–908.

[27] Jonas Frich, Lindsay MacDonald Vermeulen, Christian Remy, Michael Mose Biskjaer, and Peter Dalsgaard. 2019. Mapping the landscape of creativity support tools in HCI. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–18.

[28] Jonas Frich, Michael Mose Biskjaer, and Peter Dalsgaard. 2018. Twenty years of creativity research in human-computer interaction: Current state and future directions. In *Proceedings of the 2018 Designing Interactive Systems Conference*. Association for Computing Machinery, New York, NY, USA, 1235–1257.

[29] Russell J Funk and Jason Owen-Smith. 2017. A dynamic network measure of technological change. *Management Science* 63, 3 (2017), 791–817.

[30] Michail Giannakos, Zacharoula Papamitsiou, Panos Markopoulos, Janet Read, and Juan Pablo Hourcade. 2020. Mapping child–computer interaction research through co-word analysis. *International Journal of Child-Computer Interaction* 23 (2020), 100165.

[31] Aakar Gupta. 2015. Five years of IndiaHCI: A scientometric analysis. In *Proceedings of the 7th Indian Conference on Human-Computer Interaction*. Association for Computing Machinery, New York, NY, USA, 56–61.

[32] Steve Harrison, Deborah Tatar, and Phoebe Sengers. 2007. The three paradigms of HCI. In *Alt. Chi. Session at the SIGCHI Conference on human factors in computing systems San Jose, California, USA*. 1–18.

[33] Nathalie Henry, Howard Goodell, Niklas Elmqvist, and Jean-Daniel Fekete. 2007. 20 years of four HCI conferences: A visual exploration. *International Journal of Human-Computer Interaction* 23, 3 (2007), 239–285.

[34] Pamela Hinds, John C. Tang, and Jian Wang. 2011. From the Conference Co-Chairs. https://dl.acm.org/action/showFmPdf?doi=10.1145%2F1958824

[35] Bas Hofstra, Vivek V Kulkarni, Sebastian Munoz-Najar Galvez, Bryan He, Dan Jurafsky, and Daniel A McFarland. 2020. The diversity–innovation paradox in science. *Proceedings of the National Academy of Sciences* 117, 17 (2020), 9284–9291.

[36] Daniel B Horn, Thomas A Finholt, Jeremy P Birnholtz, Dheeraj Motwani, and Swapnaa Jayaraman. 2004. Six degrees of Jonathan Grudin: a social network analysis of the evolution and impact of CSCW research. In *Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work*. Association for Computing Machinery, New York, NY, USA, 582–591.

[37] Kasper Hornbæk, Aske Mottelson, Jarrod Knibbe, and Daniel Vogel. 2019. What do we mean by "interaction"? An analysis of 35 years of CHI. *ACM Transactions on Computer-Human Interaction (TOCHI)* 26, 4 (2019), 1–30.

[38] Kasper Hornbæk and Antti Oulasvirta. 2017. What is interaction?. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 5040–5052.

[39] Stacy Hsueh, Sarah Fdili Alaoui, and Wendy E Mackay. 2019. Deconstructing creativity: Non-linear processes and fluid roles in contemporary music and dance. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–21.

[40] Stacy Hsueh, Marianela Ciolfi Felice, Sarah Fdili Alaoui, and Wendy E Mackay. 2024. What Counts as 'Creative'Work? Articulating Four Epistemic Positions in Creativity-Oriented HCI Research. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–15.

[41] Michal Jacovi, Vladimir Soroka, Gail Gilboa-Freedman, Sigalit Ur, Elad Shahar, and Natalia Marmasse. 2006. The chasms of CSCW: a citation graph analysis of the CSCW conference. In *Proceedings of the 2006 20th Anniversary Conference on Computer Supported Cooperative Work*. Association for Computing Machinery, New York, NY, USA, 289–298.

[42] James C Kaufman and Robert J Sternberg. 2010. *The Cambridge handbook of creativity*. Cambridge University Press.

[43] Joseph'Jofish' Kaye. 2009. Some statistical analyses of CHI. In *CHI'09 extended abstracts on human factors in computing systems*. Association for Computing Machinery, New York, NY, USA, 2585–2594.

[44] Andrea Kienle and Martin Wessner. 2006. The CSCL community in its first decade: development, continuity, connectivity. *International Journal of Computer-Supported Collaborative Learning* 1 (2006), 9–33.

[45] Vassilis Kostakos. 2015. The big hole in HCI research. *interactions* 22, 2 (2015), 48–51.

[46] Jérôme Kunegis, Andreas Lommatzsch, and Christian Bauckhage. 2009. The slashdot zoo: mining a social network with negative edges. In *Proceedings of the 18th international conference on World wide web*. 741–750.

[47] K Kuutti. 1996. Activity theory as a potential framework for human-computer interaction research. *Context and consciousness: Activity theory and human-computer interaction/MIT Press* (1996).

[48] Kari Kuutti and Liam J Bannon. 2014. The turn to practice in HCI: towards a research agenda. In *Proceedings of the SIGCHI conference on human factors in computing systems*. Association for Computing Machinery, New York, NY, USA, 3543–3552.

[49] Effie Lai-Chong Law, Virpi Roto, Marc Hassenzahl, Arnold POS Vermeeren, and Joke Kort. 2009. Understanding, scoping and defining user experience: a survey approach. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 719–728.

[50] Hyang-ee Lee, Ji Hong Park, and Yeseul Song. 2014. Research collaboration networks of prolific institutions in the hci field in korea: An analysis of the hci korea conference proceedings. In *Proceedings of HCI Korea*. Hanbit Media, Inc., Seoul, KOR, 434–441.

[51] Jure Leskovec, Daniel Huttenlocher, and Jon Kleinberg. 2010. Signed networks in social media. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1361–1370.

[52] Heyang Li, Claudio J Tessone, and An Zeng. 2024. Productive scientists are associated with lower disruption in scientific publishing. *Proceedings of the National Academy of Sciences* 121, 21 (2024), e2322462121.

[53] Yiling Lin, Carl Benedikt Frey, and Lingfei Wu. 2023. Remote collaboration fuses fewer breakthrough ideas. *Nature* 623, 7989 (2023), 987–991.

[54] Jiazhen Liu, Tamang Kunal, Dashun Wang, and Chaoming Song. 2023. Correlated Impact Dynamics in Science. arXiv:2303.03646 [physics.soc-ph] https://arxiv.org/abs/2303.03646

[55] Yong Liu, Jorge Goncalves, Denzil Ferreira, Simo Hosio, and Vassilis Kostakos. 2014. Identity crisis of ubicomp? Mapping 15 years of the field's development and paradigm change. In *Proceedings of the 2014 ACM International joint conference on pervasive and ubiquitous computing*. Association for Computing Machinery, New York, NY, USA, 75–86.

[56] Yong Liu, Jorge Goncalves, Denzil Ferreira, Bei Xiao, Simo Hosio, and Vassilis Kostakos. 2014. CHI 1994-2013: Mapping two decades of intellectual progress through co-word analysis. In *Proceedings of the SIGCHI conference on human factors in computing systems*. Association for Computing Machinery, New York, NY, USA, 3553–3562.

[57] Kelly Mack, Emma McDonnell, Dhruv Jain, Lucy Lu Wang, Jon E. Froehlich, and Leah Findlater. 2021. What do we mean by "accessibility research"? A literature survey of accessibility papers in CHI and ASSETS from 1994 to 2019. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–18.

[58] Robert K Merton. 1973. The sociology of science: Theoretical and empirical investigations. *The University of Chicago* (1973).

[59] Omar Mubin, Abdullah Al Mahmud, and Muneeb Ahmad. 2017. HCI down under: reflecting on a decade of the OzCHI conference. *Scientometrics* 112 (2017), 367–382.

[60] Omar Mubin, Max Manalo, Muneeb Ahmad, and Mohammad Obaid. 2017. Scientometric analysis of the HAI conference. In *Proceedings of the 5th international conference on human agent interaction*. 45–51.

[61] Satyam Mukherjee, Daniel M Romero, Ben Jones, and Brian Uzzi. 2017. The nearly universal link between the age of past knowledge and tomorrow's breakthroughs in science and technology: The hotspot. *Science advances* 3, 4 (2017), e1601315.

[62] David M Nichols and Sally Jo Cunningham. 2015. A scientometric analysis of 15 years of CHINZ conferences. In *Proceedings of the 15th New Zealand conference on human-computer interaction*. Association for Computing Machinery, New York, NY, USA, 73–80.

[63] Judith S Olson and Wendy A Kellogg. 2014. *Ways of Knowing in HCI*. Vol. 2. Springer.

[64] Joon Sung Park, Joseph O'Brien, Carrie Jun Cai, Meredith Ringel Morris, Percy Liang, and Michael S Bernstein. 2023. Generative agents: Interactive simulacra of human behavior. In *Proceedings of the 36th annual acm symposium on user interface software and technology*. Association for Computing Machinery, New York, NY, USA, 1–22.

[65] Michael Park, Erin Leahey, and Russell J Funk. 2023. Papers and patents are becoming less disruptive over time. *Nature* 613, 7942 (2023), 138–144.

[66] Kendall Powell. 2018. The power of diversity. *Nature* 558, 7708 (2018), 19–22.

[67] Jason Priem, Heather Piwowar, and Richard Orr. 2022. OpenAlex: A fully-open index of scholarly works, authors, venues, institutions, and concepts. *arXiv preprint arXiv:2205.01833* (2022).

[68] Xuanmin Ruan, Dongqing Lyu, Kaile Gong, Ying Cheng, and Jiang Li. 2021. Rethinking the disruption index as a measure of scientific and technological advances. *Technological Forecasting and Social Change* 172 (2021), 121071.

[69] Andrey Rzhetsky, Jacob G Foster, Ian T Foster, and James A Evans. 2015. Choosing experiments to accelerate collective discovery. *Proceedings of the National Academy of Sciences* 112, 47 (2015), 14569–14574.

[70] Zhanna Sarsenbayeva, Niels van Berkel, Danula Hettiachchi, Benjamin Tag, Eduardo Velloso, Jorge Goncalves, and Vassilis Kostakos. 2023. Mapping 20 years of accessibility research in HCI: A co-word analysis. *International Journal of Human-Computer Studies* (2023), 103018.

[71] Donald A Schön. 2017. *The reflective practitioner: How professionals think in action*. Routledge.

[72] Vedran Sekara, Pierre Deville, Sebastian E Ahnert, Albert-László Barabási, Roberta Sinatra, and Sune Lehmann. 2018. The chaperone effect in scientific publishing. *Proceedings of the National Academy of Sciences* 115, 50 (2018), 12603–12607.

[73] Nihar B Shah. 2022. Challenges, experiments, and computational solutions in peer review. *Commun. ACM* 65, 6 (2022), 76–87.

[74] Feng Shi and James Evans. 2023. Surprising combinations of research contents and contexts are related to impact and emerge with scientific outsiders from distant disciplines. *Nature Communications* 14, 1 (2023), 1641.

[75] Steven Si and Hui Chen. 2020. A literature review of disruptive innovation: What it is, how it works and where it goes. *Journal of Engineering and Technology Management* 56 (2020), 101568.

[76] Kyle Siler and David Strang. 2017. Peer review and scholarly originality: Let 1,000 flowers bloom, but don't step on any. *Science, Technology, & Human Values* 42, 1 (2017), 29–61.

[77] Herbert A Simon. 1973. The structure of ill structured problems. *Artificial intelligence* 4, 3-4 (1973), 181–201.

[78] Arnab Sinha, Zhihong Shen, Yang Song, Hao Ma, Darrin Eide, Bo-June Hsu, and Kuansan Wang. 2015. An overview of microsoft academic service (mas) and applications. In *Proceedings of the 24th international conference on world wide web*. Association for Computing Machinery, New York, NY, USA, 243–246.

[79] Lucy A. Suchman. 1987. *Plans and situated actions: the problem of human-machine communication*. Cambridge University Press.

[80] Kai-Yu Tang, Chin-Chung Tsai, and Tzu-Chiang Lin. 2014. Contemporary intellectual structure of CSCL research (2006–2013): A co-citation network analysis with an education focus. *International Journal of Computer-Supported Collaborative Learning* 9 (2014), 335–363.

[81] Brian Uzzi, Satyam Mukherjee, Michael Stringer, and Ben Jones. 2013. Atypical combinations and scientific impact. *Science* 342, 6157 (2013), 468–472.

[82] Niels Van Berkel and Kasper Hornbæk. 2023. Implications of Human-Computer Interaction Research. *Interactions* 30, 4 (2023), 50–55.

[83] Sarah Theres Völkel, Christina Schneegass, Malin Eiband, and Daniel Buschek. 2020. What is" intelligent" in intelligent user interfaces? a meta-analysis of 25 years of IUI. In *Proceedings of the 25th international conference on intelligent user interfaces*. Association for Computing Machinery, New York, NY, USA, 477–487.

[84] Lucy Lu Wang, Kelly Mack, Emma J McDonnell, Dhruv Jain, Leah Findlater, and Jon E Froehlich. 2021. A bibliometric analysis of citation diversity in accessibility and HCI research. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–7.

[85] Martin L Weitzman. 1998. Recombinant growth. *The Quarterly Journal of Economics* 113, 2 (1998), 331–360.

[86] Adrian Weller, Katherine Heller, Nuria Oliver, and Zico Kolter. 2023. ICML 2024 Author Instructions. https://icml.cc/Conferences/2024/AuthorInstructions

[87] Jacob O Wobbrock and Julie A Kientz. 2016. Research contributions in human-computer interaction. *Interactions* 23, 3 (2016), 38–44.

[88] Lingfei Wu, Dashun Wang, and James A Evans. 2019. Large teams develop and small teams disrupt science and technology. *Nature* 566, 7744 (2019), 378–382.

[89] Fengli Xu, Lingfei Wu, and James Evans. 2022. Flat teams drive scientific innovation. *Proceedings of the National Academy of Sciences* 119, 23 (2022), e2200927119.

[90] Yang Yang, Tanya Y Tian, Teresa K Woodruff, Benjamin F Jones, and Brian Uzzi. 2022. Gender-diverse teams produce more novel and higher-impact scientific ideas. *Proceedings of the National Academy of Sciences* 119, 36 (2022), e2200841119.

[91] An Zeng, Ying Fan, Zengru Di, Yougui Wang, and Shlomo Havlin. 2021. Fresh teams are associated with original and multidisciplinary research. *Nature Human Behaviour* 5, 10 (2021), 1314–1322.

A Alternative approaches to representing HCI

We adopt three additional ways to identify representative HCI venues and papers and validate the robustness of our findings.

Firstly, we consider an alternative broader scope of premier HCI venues by focusing on all research papers from the top 20 venues with the highest h5-index according to Google Scholar[4] (see Table 4). Similarly to our main text, we take into account the predecessors of the venues to improve the continuity of the data records. For example, for Proceedings of the ACM on Human-Computer Interaction, we include ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW), Annual

[4]https://scholar.google.es/citations?view_op=top_venues&hl=en&vq=eng_humancomputerinteraction

Table 4: Top 20 HCI venues with the highest h5-index according to Google Scholar.

Rank	Venue
1	CHI Conference on Human Factors in Computing Systems (CHI)
2	Proceedings of the ACM on Human-Computer Interaction
3	International Journal of Human-Computer Studies
4	International Journal of Human-Computer Interaction
5	IEEE Transactions on Affective Computing
6	Behaviour & Information Technology
7	Virtual Reality
8	Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies
9	International Journal of Interactive Mobile Technologies
10	ACM/IEEE International Conference on Human-Robot Interaction (HRI)
11	International Conference on Intelligent User Interfaces (IUI)
12	Annual ACM Symposium on User Interface Software and Technology (UIST)
13	ACM Designing Interactive Systems Conference (DIS)
14	IEEE Conference on Virtual Reality and 3D User Interfaces
15	ACM Transactions on Computer-Human Interaction (TOCHI)
16	Universal Access in the Information Society
17	IEEE Transactions on Human-Machine Systems
18	International Conference on Human-Computer Interaction (HCI International)
19	International Journal of Child-Computer Interaction
20	Frontiers in Virtual Reality

Symposium on Computer-Human Interaction in Play (CHI PLAY), ACM SIGCHI Symposium on Engineering Interactive Computing Systems (EICS), ACM Symposium on Eye Tracking Research and Applications (ETRA), ACM International Conference on Supporting Group Work (GROUP), ACM International Conference on Interactive Surfaces and Spaces (ISS) and its predecessor ACM International Conference on Interactive Tabletops and Surfaces (ITS), and International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI); for Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, we incorporate ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp) and ACM International Symposium on Wearable Computers (ISWC); for International Journal of Human-Computer Studies, we also retrieve papers published by its predecessor International Journal of Man-Machine Studies. Moreover, to ensure fair comparisons, we consider only regular papers (including short papers) with careful peer reviews of the full papers in these venues wherever distinguishable. Therefore, we remove invited talks, extended abstracts (including those presented as full papers but only have their abstracts peer-reviewed, e.g., publications from HCI International), demonstrations, etc. To make the data more comparable with those in our main analyses, we similarly focus on articles published between 1982 and 2023. In this way, data on a total of 42,118 papers are collected.

Secondly, similar to Cao et al. [10], HCI research can also be represented by papers from continuous venues sponsored by SIGCHI. Specifically, we regard sponsorship from SIGCHI as a demonstration of high relevance to and recognition by the HCI community. To ensure a better depiction and understanding of HCI, we eliminate the confounding effect of the occasionally held venues or venues that depart from being closely relevant to HCI across time, and retain only venues (1) with at least five proceedings/issues and (2) with at least one SIGCHI-sponsored proceeding or issue between 2020 and 2023. To make the papers more comparable to one another, for conference proceedings, we (1) keep only independently-held conferences and symposiums and remove workshops and (2) focus on research papers and notes unless some papers in other types are treated the same as research papers, e.g., pictorials at Conference on Creativity & Cognition (C&C). As such, based on the official information from SIGCHI[5], a total of 36 venues are identified, which we show in Table 5. In all, these venues publish a total of 37,289 papers between 1982 (the first year at least one venue starts to be published) and 2023.

Thirdly, another way to recognize HCI papers is using the "concept" label provided by OpenAlex. Specifically, using advanced natural language processing methods, OpenAlex tags recorded papers based on their relevance to hierarchically organized academic concepts[6]. These concept tags have been widely adopted as proxies of disciplines [52, 53, 89], although sometimes they may not be perfectly accurate. Following these studies, we define HCI papers as those tagged with the level-1 concept "human-computer interaction" in the concept hierarchy of OpenAlex. This leads to the identification of 879,054 HCI papers between 1982 and 2023.

In these approaches, we retrieve the basic bibliometric information of conference papers from their proceedings on the official websites and match them with their OpenAlex metadata by querying the API of OpenAlex with their DOIs. For journals, we look up papers pertaining to the venues using the "source" information according to OpenAlex and extract their bibliometric information from the database.

[5] https://dl.acm.org/sig/sigchi/publications
[6] https://docs.openalex.org/api-entities/concepts

Table 5: Continuous venues sponsored by SIGCHI.

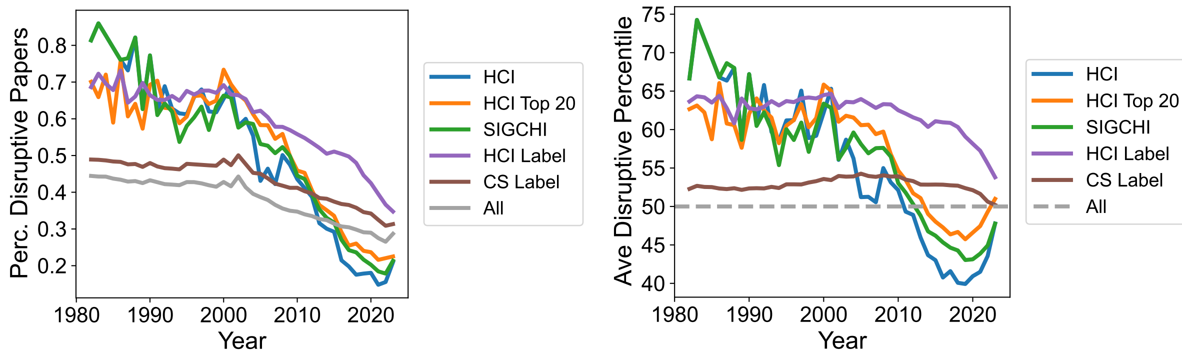
No.	Venue
1	International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI)
2	International Conference on Advanced Visual Interfaces (AVI)
3	Conference on Creativity & Cognition (C&C)
4	Annual Symposium on Computer-Human Interaction in Play (CHI PLAY)
5	CHI Conference on Human Factors in Computing Systems (CHI)
6	Conference on Human Information Interaction and Retrieval (CHIIR)
7	ACM SIGCAS/SIGCHI Conference on Computing and Sustainable Societies (COMPASS)
8	ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW)
9	ACM Conference on Conversational User Interfaces (CUI)
10	ACM Designing Interactive Systems Conference (DIS)
11	ACM SIGCHI Symposium on Engineering Interactive Computing Systems (EICS)
12	ACM Symposium on Eye Tracking Research and Applications (ETRA)
13	ACM International Conference on Supporting Group Work (GROUP)
14	International Conference on Human-Agent Interaction (HAI)
15	ACM/IEEE International Conference on Human-Robot Interaction (HRI)
16	ACM Conference on Hypertext and Social Media (HT)
17	International Conference on Multimodal Interaction (ICMI)
18	Annual ACM Interaction Design and Children Conference (IDC)
19	Brazilian Symposium on Human Factors in Computing Systems (IHC)
20	Conference on l'Interaction Humain-Machine (IMH)
21	ACM International Conference on Interactive Media Experiences (IMX)
22	International Symposium on Physical Design (ISPD)
23	ACM International Conference on Interactive Surfaces and Spaces (ISS)
24	ACM International Symposium on Wearable Computers (ISWC)
25	International Conference on Intelligent User Interfaces (IUI)
26	International Conference on Mobile Human-Computer Interaction (MobileHCI)
27	ACM International Symposium on Pervasive Displays (PerDis)
28	ACM Conference on Recommender Systems (RecSys)
29	ACM Symposium on Computational Fabrication (SCF)
30	ACM Symposium on Spatial User Interaction (SUI)
31	International Conference on Tangible, Embedded, and Embodied Interaction (TEI)
32	ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp)
33	Annual ACM Symposium on User Interface Software and Technology (UIST)
34	ACM Conference on User Modeling, Adaptation and Personalization (UMAP)
35	ACM Symposium on Virtual Reality Software and Technology (VRST)
36	International Web for All Conference (W4A)

B Analysis with alternative approaches to representing HCI

To validate the robustness of the trends we observe, we repeat our analysis with alternative approaches to representing HCI. Fig. 11 shows the disruptiveness of HCI and its comparison with all computer science (CS) related papers and all scientific articles over time. It can be inferred that across the top 20 HCI venues with the highest h-5 index according to Google Scholar, continuous venues sponsored by SIGCHI, and papers identified as HCI-relevant by OpenAlex, HCI is enduring sharper drops in both the percentage of disruptive papers and the average disruptiveness percentile compared with CS-related papers and all papers in general ($p < 0.001$ for all approaches, ANCOVA and logistic regression for disruptive papers and ANCOVA and OLS regression for disruptiveness percentiles). These results confirm the remarkable decline of disruptiveness in HCI. Moreover, comparing the results we obtain with different representations of HCI, we find that the decrease in disruptiveness for the four premier HCI venues, top 20 HCI venues, and SIGCHI-sponsored venues are all significantly sharper than that for papers with an HCI label ($p < 0.001$ for all circumstances, ANCOVA and regressions with the interaction effect of time and approaches for HCI representation). This indicates that the drastic decrease of HCI disruptiveness is particularly prominent in the prestigious frontiers of HCI.

C Analysis removing self-citations

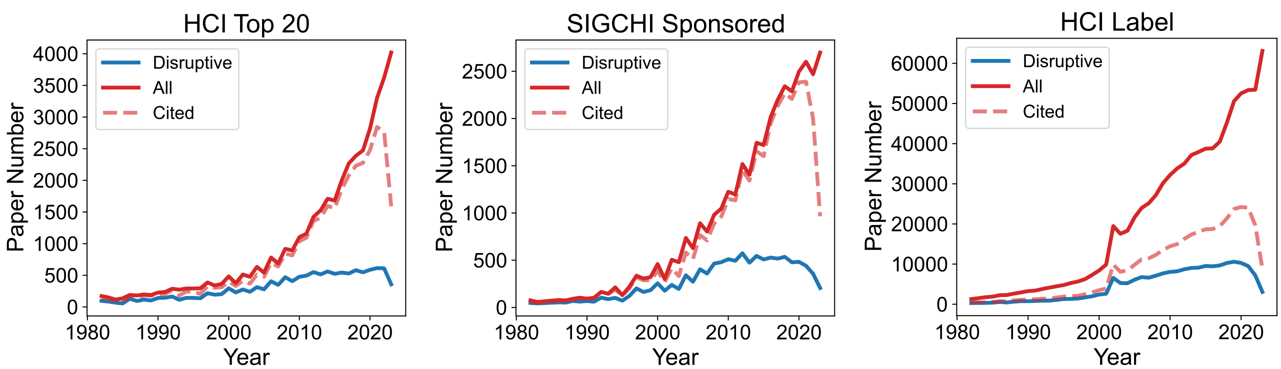
There may also be concerns that authors' self-citations could introduce potential bias in assessing disruptiveness. For example, authors' propensity to cite multiple works of their own may diminish the calculated disruptiveness of their research. Therefore, we conduct further analysis on an alternative circumstance where



(a) Percentage of disruptive papers over time.

(b) Average disruptiveness percentile over time.

Figure 11: The decrease of disruptiveness in HCI over time under alternative approaches to representing HCI.



(a) The number of disruptive papers and all papers in the top 20 HCI venues over time.

(b) The number of disruptive papers and all papers in continuous SIGCHI-sponsored venues over time.

(c) The number of disruptive papers and all papers labeled as related to the concept of HCI over time.

Figure 12: The number of disruptive papers and all papers published in different representations of HCI over time.

we only retain independent citations with no overlapping authors between cited papers and citation papers. As depicted in Fig. 13, the disruptiveness of HCI is still decreasing sharply when self-citations are removed: both the percentage of disruptive HCI papers and the average disruptiveness percentile of HCI papers are drastically decreasing from above the global average to below the average of science, and the expansion of HCI papers is a lot faster than the growth of disruptive HCI papers. These observations suggest the robustness of our main results.

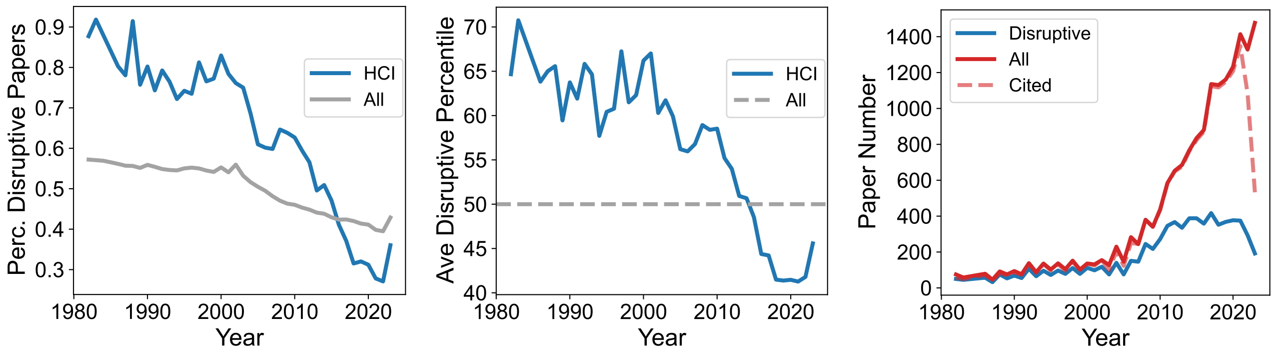
D Alternative time-aware measurement of disruptiveness and the corresponding analysis

In our main analysis, we leverage disruptiveness index D to dissect the local citation network around a paper and quantify its creativity and innovativeness. However, some people may be concerned about whether it may be influenced by the time for citation acquisition: it is likely that papers may be differently cited when the time lags between the cited paper and the citing paper vary. To address this, we echo Park et al. [64] to replicate our main results with an alternative time-aware measurement of disruptiveness, CD2:

$$CD2 = \frac{n_{f2} - n_{b2}}{n_{f2} + n_{b2} + n_{o2}}$$

Here the subscript 2 indicates only future papers published in 2 years since the focal paper's publication are retained, n_{f2} denotes the number of papers citing only the focal paper (but none of its references), n_{b2} is the number of papers citing both the focal paper and any of its references, and n_{o2} refers to the number of papers citing any of the focal paper's references but not the focal paper.

With this alternative time-aware measurement of disruptiveness, we replicate our analysis of the disruptiveness of HCI. We take only papers published between 1982 and 2021 into consideration to ensure that each paper has a full two years to acquire citations. Fig. 14 demonstrates the results we obtain with CD2 to quantify disruptiveness. Similarly to our main results, we find drastic decreases in both the percentage of disruptive papers and the average disruptiveness percentile in HCI ($p < 0.001$, ANCOVA and logistic regression for disruptive papers and ANCOVA and OLS regression

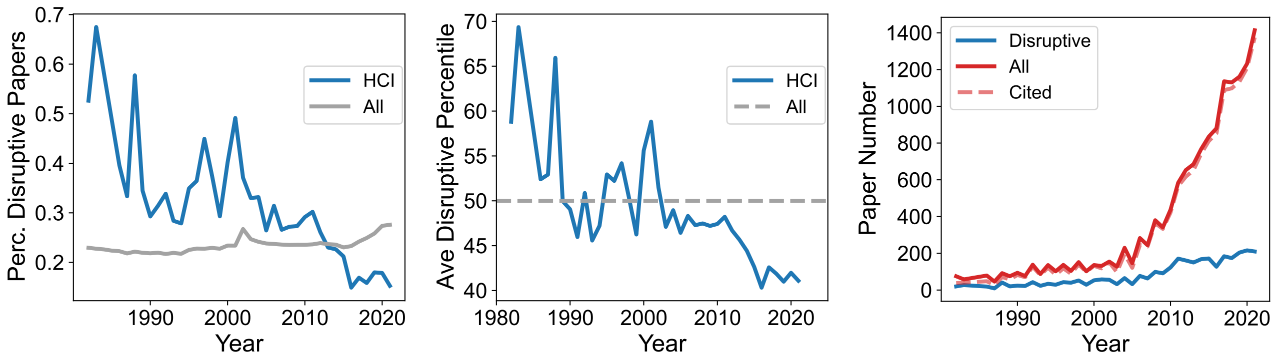


(a) Percentage of disruptive papers over time.

(b) Average disruptiveness percentile over time.

(c) The number of disruptive papers and all papers over time.

Figure 13: HCI disruptiveness with self-citations removed.



(a) Percentage of disruptive papers over time.

(b) Average disruptiveness percentile over time.

(c) The number of disruptive papers and all papers over time.

Figure 14: HCI disruptiveness with the time-aware measurement of disruptiveness CD2.

for disruptiveness percentiles). Moreover, the growth rate of disruptive HCI papers is slower than that of all HCI papers. Therefore, the robustness of our main results is once again substantiated.

E Top cities publishing disruptive works in HCI

In our main text, we investigate the top countries (or territories) and institutions contributing disruptive HCI works. To better understand the contributors to disruptiveness in HCI and verify the robustness of the identified patterns, we further examine the top cities publishing disruptive HCI papers.

Specifically, we retrieve the cities of authors' institutions using geographic information from OpenAlex, where each city is identified by a unique GeoNames city id. Fig. 15 and Fig. 16 illustrate the top cities publishing disruptive HCI papers and the corresponding percentages of disruptive papers they publish over time. As is evident, Pittsburgh has long been among the top cities publishing disruptive HCI papers, while some other previous leaders such as Palo Alto have gradually lost their lead. Their positions have been taken by emerging contributors such as Beijing and Hong Kong. Moreover, the percentage of disruptive papers drops significantly across top cities over time and the top contributing cities may not be more likely to publish disruptive papers. These findings substantiate that (1) the sharp decline of disruptiveness in HCI is a general phenomenon and (2) top contributors may not translate to higher probabilities of disruptive HCI papers.

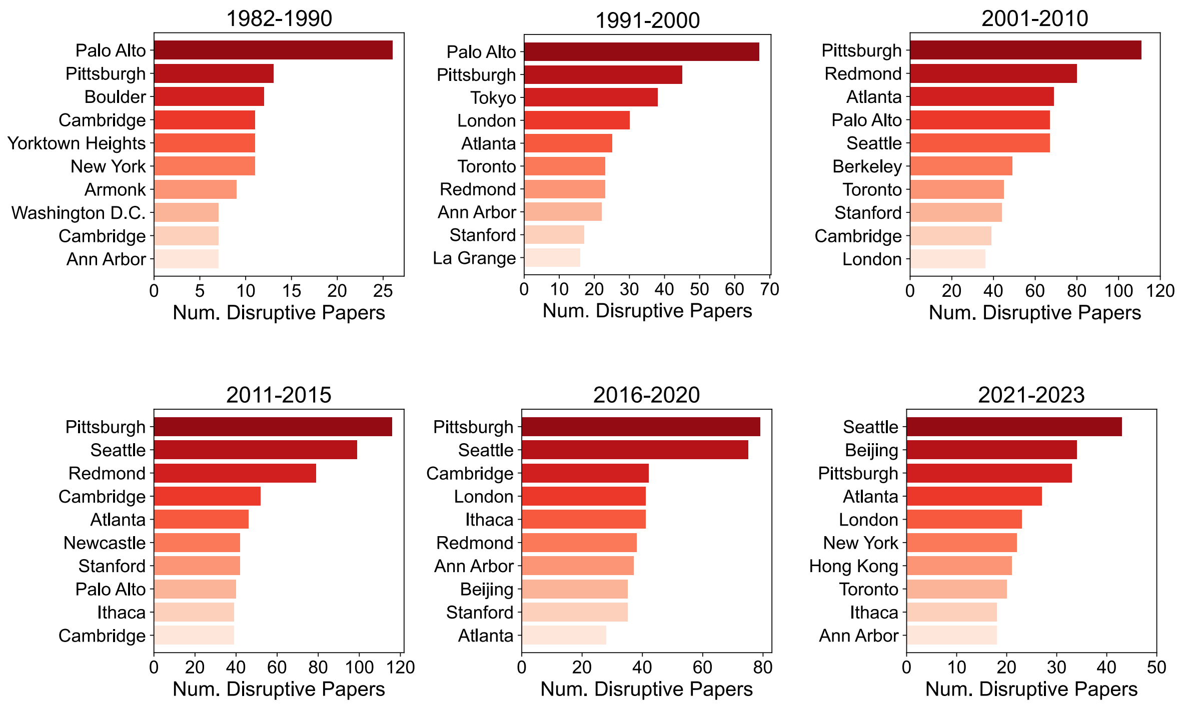


Figure 15: Top cities publishing disruptive HCI papers over time.

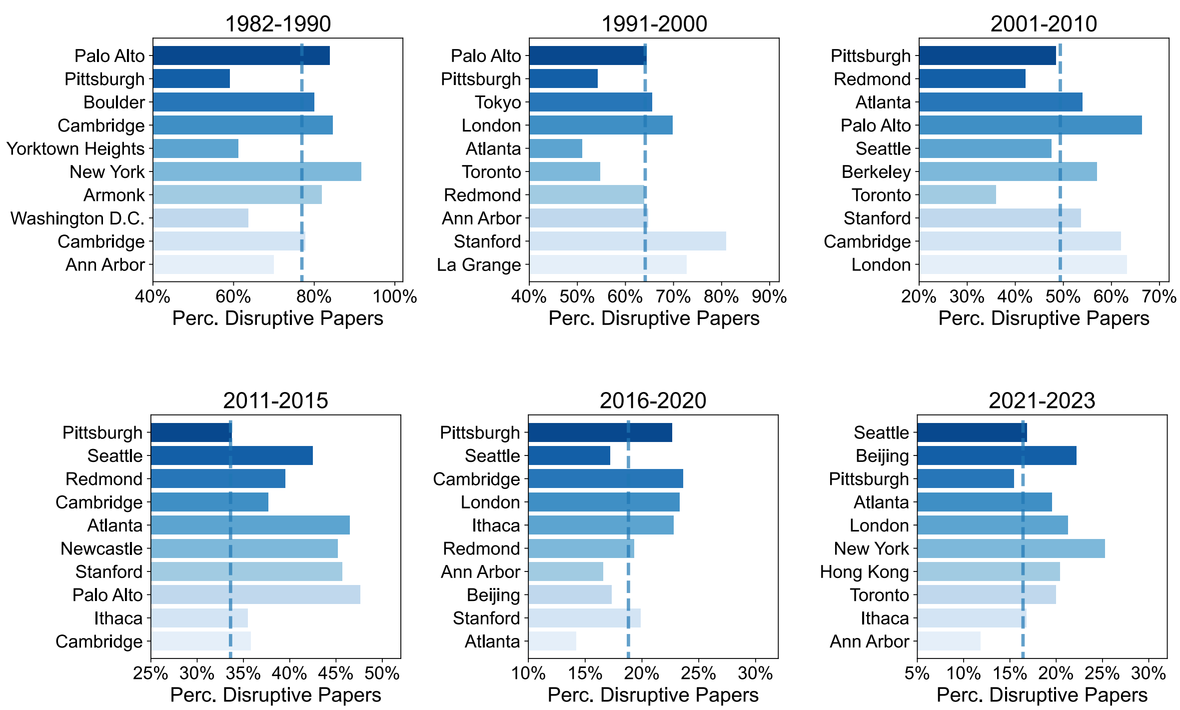


Figure 16: Percentage of disruptive HCI papers published by top cities over time.