Clicking Past Each Other: Rediscovering Common Ground Between IS and HCI Disciplines

Full Paper

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Abstract

Despite their shared focus on human-centered systems, Information Systems (IS) and Human–Computer Interaction (HCI) disciplines have evolved into largely separate research communities represented by the AIS SIGHCI and ACM SIGCHI. Prior efforts to connect these communities have been short-lived and primarily institutional in nature. This study examines whether common ground exists by systematically comparing research and publication practices. We analyzed 2,422 conference papers from both communities using LLM-based information extraction and structural topic modeling. Specifically, we compared research topics, theoretical foundations, methods, user framing, sample sizes, institutional affiliations, and funding patterns. While both communities primarily focus on micro-level phenomena and share a strong interest in Human–AI Interaction, they differ in their epistemic orientation and methodological preferences. We advocate for collaboration grounded in shared phenomena, particularly Human–AI Interaction.

Keywords

Community Bridging, Information Systems, Human-Computer Interaction, Human–AI Interaction, LLM-Based Information Extraction, Structural Topic Modeling, Bibliometric Analysis.

Introduction

This study began with a brief moment of confusion in our hallway. Colleagues preparing for upcoming conferences casually mentioned their travel plans. While the *Human-Computer Interaction* (HCI) groups packed their bags for CHI, the *Information Systems* (IS) group prepared for ICIS or AMCIS. These conversations revealed that the IS and HCI disciplines, which had worked side-by-side in our institute for years, were in practice divided into two parallel communities: one rooted in IS, where HCI is treated as a research stream (Li and Zhang, 2005), and another with HCI as an independent field with its own traditions and priorities. As Grudin (2018) notes, this can lead to each community reinventing the work of the other. In times of rapid technological development—most recently exemplified by AI—specialization aimed at keeping pace tends to create separation, which makes bridge-building more important (and difficult) than ever. To analyze how this divergence emerged, we examine the historical and theoretical foundations of how HCI constructs its identity both within and beyond the boundaries of the IS discipline and potential approaches to discover new common ground between the communities.

The HCI community first organized in 1982 as the *Special Interest Group in Computer-Human Interaction* (SIGCHI) within the *Association for Computing Machinery* (ACM). Their flagship conference, the *Confer-*

ence on Human Factors in Computing Systems (CHI), was first held in 1982. Around that time, the IS community first held its flagship conference, the *International Conference on Information Systems* (ICIS), in 1980, and later founded its society, the *Association for Information Systems* (AIS), in 1994. The HCI community within the AIS was established as the *Special Interest Group on Human-Computer Interaction* (SIGHCI) in July 2001. HCI is considered by the IS community as one of their five main research streams, with a focus on applying HCI in organizational contexts (Li and Zhang, 2005). For this paper, we will use both official abbreviations, noting the irony that the communities chose names that differ by only a single, easily-misplaced character.

Attempts to 'bridge' both communities have already been made at the CHI in 2005 and 2018 (Djamasbi et al., 2018) and the ACIS in 2018 (Seymour et al., 2018). According to Grudin (2018), previous attempts lasted no more than a few years. Yet, senior scholars in both communities share the notion that both communities have the same intellectual ground (Djamasbi et al., 2018; Grudin, 2018; Seymour et al., 2018). Nonetheless, three main reasons for the separation are identified. First, IS researchers place great value on theory and aim to generalize their results (Gregor, 2006). In contrast, SIGCHI aims towards relevant and 'novel' contributions (Balestrini et al., 2015). Second, the different priorities seem to impact the methodical choices, with SIGHCI criticizing SIGCHI for its low sample sizes and poor statistical analysis (Grudin, 2018), a circumstance that is also criticized within SIGCHI (Kay et al., 2016). Third, terminology and publication practices differ between the communities (Grudin, 2018).

Previous 'bridging' approaches can largely be summarized by shared conference attendance between communities. It is suspected that the different esteem between conference papers and journal articles is also a reason why previous approaches have failed (Grudin, 2018; Djamasbi et al., 2018). At least for the German 'Wirtschaftsinformatik,' we cannot fully agree with this notion, as recent VHB publication rankings list the CHI among the "A" conferences, the top grade on par with the ICIS. However, Chen (2024) showed that the different venues seem to self-reinforce this separation, as SIGCHI mostly cites itself.

To overcome this separation, Grudin (2018) advocated against institutional approaches and instead for exchanging understandings, priorities, methods, terminology, and topics currently under research. Instead, a transdisciplinary solution to the same problems should be found (Seymour et al., 2018). Consequently, the research question guiding this paper is: *What are the problems both communities are concerned with, and which theoretical and methodical approaches do each community use?*

To the best of our knowledge, no study has systematically investigated this issue. In addition, since the last 'bridging' workshop, eight years ago, new topics and methods have emerged, motivating the need for a new positioning on the subject matter. The aim of this study is descriptive, pointing towards "Human-AI Interaction" as a potential common ground that could be used to bridge both communities. The following section provides a brief overview of the IS and HCI disciplines and their current developments. We then outline our bibliometric analysis and present our findings. We conclude by discussing the common ground between the two communities and suggesting how to advance further.

Theoretical Foundations of the Disciplines

Information Systems

The following overview of the disciplines is not exhaustive, but aims to provide the reader with the necessary foundation to follow the subsequent argumentation.

IS, as a discipline, has been described as being concerned with the study and design of IS in organizational contexts (Benbasat and Zmud, 2003). The discipline also addresses the role of digital technologies in social life and societal contexts (Avgerou, 2000; Bryant et al., 2013). A central element of the discipline is the IT artifact, which has been recognized as a defining but historically under-theorized element of IS research (Orlikowski and Iacono, 2001). More generally, IS is widely understood as a socio-technical discipline that examines the interaction between technical systems and social contexts (Bostrom and Heinen, 1977). Traditionally, the field has maintained a strong organizational and managerial focus, emphasizing the role of digital technologies in supporting organizational goals and activities (Hirschheim and Klein, 2012). In particular, IS research has highlighted the importance of digital technologies for value creation and organizational performance (Melville et al., 2004). Recently, the scope of the discipline has expanded to include emerging phenomena such as digital platforms, layered modular architectures, data-driven innovation, and AI (Yoo et al., 2024).

IS is a structurally pluralistic discipline. Behavior-oriented research primarily pursues explanatory and predictive objectives, whereas design science research pursues prescriptive and artifact-oriented objectives (Gregor, 2006). Behavioral IS research is theory-driven, empirically grounded, and primarily concerned with explaining and predicting phenomena (Hevner et al., 2004) related to the development, use, and impact of IS. The core lies in theory development and hypothesis testing. Design science research addresses the development and evaluation of IT artifacts for solving organizational problems. Iterative build-evaluate cycles prevail. Fundamental to this is a strong integration of practice and research (Hevner et al., 2004). IS is characterized by interdisciplinarity, which is reflected in theoretical pluralism (Lim et al., 2013), sometimes perceived as fragmentation. Psychology, economics, sociology, strategy, organizational science, statistics, and communication are relevant in this context (Lim et al., 2013). Historically, the discipline has struggled not only with fragmentation but also with an "identity crisis" and a lack of its own theoretical core (Mueller and Urbach, 2017). Following Gregor (2006), IS research encompasses theories for analysis, explanation, prediction, explanation and prediction (as a combined category), and design and action, thereby reflecting the field's dual commitment to explanatory understanding and prescriptive artifact construction.

The research focuses on various levels: the individual (acceptance, use), groups (coordination, collaboration), organizations (processes, governance, transformation), interorganizational networks, and society (Avgerou, 2000). The organizational (meso) level has traditionally been a central focus (Melville et al., 2004), although the individual level has also been extensively studied, particularly in research on technology acceptance and use (Venkatesh et al., 2003). Methodological pluralism that prevails in the discipline is perceived as a strength (Loos et al., 2013). Typical methods include surveys, experiments, econometric analyses, qualitative case studies, artifact design and evaluation studies (Hevner et al., 2004; Sarker et al., 2025). In addition, advanced computer-assisted methods (e.g., machine learning, digital trace data, process mining) and multi-method designs that combine epistemologically proximate and distant approaches are increasingly being used (Sarker et al., 2025).

Human-Computer Interaction

HCI is often anchored in the definition formulated by SIGCHI: HCI concerns the design, evaluation, and implementation of interactive computer systems for human use, and the study of major phenomena surrounding them (Hewett et al., 1992). This wording is intentionally expansive: it positions HCI simultaneously as (1) a discipline for creating interactive artifacts and (2) a discipline of inquiry into the human, technical, and socio-cultural phenomena that arise around those artifacts. This breadth of HCI can best be understood through the notion of successive "waves" (or paradigms) that broadened both the object of study and the epistemic repertoire of the field (c.f. Bødker, 2006). The first wave, shaped by computer science, human factors, and engineering, foregrounded pragmatic concerns such as efficient operation and error avoidance in the context of few and exclusive mainframe computing systems (Harper et al., 2008). The second wave, shaped strongly by psychology, shifted attention to the cognitive processes involved in using and designing increasingly personal and graphical systems, such as PCs, in their specific context of use. The emergence of the WWW, social media, and mobile computing initiated a third wave of HCI that viewed the vast diversity of user groups, user contexts, and different interaction technologies through the lens of social sciences and product design (Harper et al., 2008). Today, the explosive growth of research on human-centered AI in HCI has arguably resulted in a fourth wave, in which human-AI collaboration, control, trust, and autonomy are at the center stage (Shneiderman, 2022). This progression captures two important trajectories that continue to define the field: a move from designing for an abstract 'general user' towards understanding specific user groups and contexts of practice, and a move from pragmatic *usability*, as standardized in ISO 9241-11, towards a broader notion of *user experience* (UX). Contemporary HCI treats interactive technologies as situated and value-laden interventions in everyday life, work, learning, health, and leisure. Consequently, HCI must address not only immediate task performance but also longer-term contextual consequences, such as adoption and appropriation, trust and risk perception, emotional attachment, social inclusion and exclusion, and the distribution of benefits and burdens across stakeholders.

HCI has no unified theory and different, sometimes conflicting, epistemic traditions. Early influences from human factors introduced quantitative models and lab experiments to predict and measure perceptual-motor capabilities and constraints. A paradigmatic example is Fitts's law, grounded in experiments on the speed–accuracy trade-off in goal-directed movement. Cognitive theory and cognitive psychology became a major influence: The Model Human Processor and the GOMS (goals, operators, methods, and selection rules) family of models began enabling predictions of task execution time and provided a bridge between cognitivist models and practical interface engineering. Further core ideas from cognitive theory include mental models and the gulfs of execution and evaluation, which help explain why interfaces can be learnable or confusing and why an iterative user-centered design process is required. In the 1990s and 2000s, HCI increasingly recognized that cognition and action are embedded in social practice and dynamic contexts. Activity theory and theories of embodiment were widely adopted in HCI, together with a push for a more physical, tangible, and social computing. The influential vision of ubiquitous computing also introduced novel devices and argued that computation should become invisibly embedded into the social and physical world and needs better design to reduce the burden of usage and configuration (Harper et al., 2008). To achieve this, computation must be designed with a deep understanding of target audiences and the context of use. As a result, qualitative and interpretive approaches, including grounded theory, have become a major and well-established strand of HCI research.

At the micro-level of moment-to-moment interaction, the focus is on perceptual-motor control, cognitive processing, and the immediate feedback loop between the user's action and the system's response. Controlled experiments and quantitative methods dominate these studies. At the situated context level, HCI treats interaction as embedded in physical, social, and organizational environments . Qualitative methods—observation, interviews, focus groups, and contextual inquiry—and their thematic analysis are essential for uncovering constraints and practices. Across these levels, iterative design and prototyping are not auxiliary activities but rather central methodological pillars for eliciting user feedback or collecting behavioral data.

Methods

Data Collection

To examine how these communities function, we analyzed the primary outputs of their work, namely, scientific papers. Because sourcing the entirety of the ACM or AIS databases is unfeasible, we focus on conference papers, as they represent the primary venues for rapid dissemination in both IS and HCI.

For the AIS, we selected the HCI tracks organized by SIGHCI at four major conferences: ICIS, ECIS[1], AMCIS, PACIS, and the SIGHCI proceedings. Unfortunately, the AIS eLibrary does not consistently preserve historical track information. To obtain additional papers, we searched past conference websites and consulted the SIGHCI newsletter to verify the existence of HCI tracks. We contacted the track chairs to obtain information on the papers. Although the response rate was low, we collected 989 papers from SIGHCI ranging from 2003 to 2024.

For the ACM, we focused on CHI, which serves as the flagship venue for SIGCHI. Because CHI covers a wide range of topics (e.g., hardware development), we needed to narrow the set of papers to those related to the IS discipline. We used ACM CCS codes to filter the papers. To derive a set of CCS codes representing the IS domain, we compiled a list of unique keywords used in top IS journals[2] from 1982 to 2025 and selected all the CCS codes that matched these keywords. Using these CCS codes as proxies for the IS domain, we collected 1,433 papers from the CHI conference, ranging from 2016 to 2025.

We included full papers and excluded extended abstracts and poster papers. We collected 2,422 papers from both communities. To enable further processing, we used a locally running Docling OCR model to convert each PDF file into a machine-readable Markdown file.

[1]Not to be confused with the EICS conference or "The ACM SIGCHI Symposium on Engineering Interactive Computing Systems."
[2]The top IS journals were determined using the 2024 German VHB ranking (ranks A+ to B) in the discipline of "Wirtschaftsinformatik."

LLM-Based Information Extraction

To compare the two communities, we required both metadata and full-text information from the papers. The metadata was straightforward to analyze. We used Crossref's *Open Funder Registry* (OFR) to extract funding information from the acknowledgments sections. To extract key attributes from the full text, we explored automated approaches. LLM-based information extraction is currently regarded as state-of-the-art for this purpose (Ateia et al., 2025). We adopted a zero-shot, context-injection approach. Specifically, we created a prompt template specifying the role ("research assistant"), the instruction ("Extract the attributes defined below..."), an attribute schema, the desired output format (JSON), and a placeholder for the paper.

To iteratively refine the prompt template, we created an evaluation dataset consisting of 15 randomly selected papers from each community sample. One author manually extracted the attributes specified in the prompt template from these papers. We tested the prompt on each paper using a state-of-the-art LLM (gemini-3-pro-preview). During this phase, several shortcomings of the prompt template were identified and addressed.

Once the prompt template was refined, we conducted a large-scale evaluation using 22 different open-weight and proprietary models on the evaluation dataset. We accessed all models via a single API using openrouter.ai. To measure the LLM performance, we applied exact string matching for attributes with predefined categories, such as Unit of Analysis, User Framing, Sample Size, and Paradigm. For attributes where minor spelling variations should be tolerated (e.g., Institutions, Funding, Country, Questionnaire, Theories), we used the Levenshtein distance. For attributes with greater variability, such as Topics, Methods, and Methodology, we employed bidirectional *Natural Language Inference* (NLI) to assess semantic coherence. For each LLM query, we calculated the average score across all attributes. Each paper was queried three times by each of the 22 LLMs to account for model randomness.[3]

Based on manual inspection of selected LLM outputs during the prompt-refinement stage, scores in the range of 0.7–0.8 can be considered close to human.[4] Deviations are largely attributable to the Levenshtein and NLI scoring, as we chose not to apply hard cutoffs. Of the 22 models evaluated, twelve can be considered to operate at a human level for extracting relatively simple attributes from scientific papers. Two attributes consistently received low scores across all LLMs: Research Paradigm and Methodology. We attribute this to the zero-shot prompting setup, which requires more detailed definitions and examples of what we consider a 'paradigm' or 'methodology.' Consequently, we excluded these two attributes from analyses. In addition to the average score for each model, we also considered the inference costs and whether the model is open-weight or proprietary. Interestingly, OpenAI's gpt-oss-20b achieved the highest score among the open-weight models while also being among the least expensive (even its larger sibling, gpt-oss-120b performed worse). Proprietary models (GPT, Claude, Gemini) outperformed the open-weight models overall. Yet, the performance gap was sufficiently small that we selected gpt-oss-20b, run locally on one author's laptop, to extract attributes for all 2,433 papers.

Structural Topic Modeling

Because LLM-based information extraction is relatively new, we additionally conducted a *structural topic modeling* (STM) analysis on the full-text Markdown files, using community as a covariate. Although STM is more difficult to interpret, it provides a form of triangulation to validate the LLM-based approach.

Results

Attribute-level Comparison between Communities

We first present the differences and similarities between the two communities based on the attributes extracted using the LLM and metadata. For open-ended attributes (e.g., topics, theories, methods), we report only those values that appear in both communities and restrict the presentation to the ten most frequent.

[3] We considered setting the temperature parameter to 0; yet, for LLMs with reasoning capabilities such as Gemini 3, Google recommends using the default temperature setting for better results (https://ai.google.dev/gemini-api/docs/gemini-3).
[4] For supplementary materials, with additional tables, figures, and data, please visit https://osf.io/qaz4x.

The comparative analysis of *topics* revealed thematic priorities across the two communities (Figure 1). While "human–ai interaction" is the dominant topic in both, it accounts for a substantially larger share of SIGCHI papers (26.7%) than SIGHCI papers (16.1%). Conversely, SIGHCI devotes a higher proportion to "platform ecosystems" (10.4% vs. 7.1% in SIGCHI) and places greater emphasis on "trust" (3.4% vs. 1.0%). A pronounced disparity is observed in the coverage of "large language models," which appear in 3.8% of SIGCHI papers but are nearly absent from the SIGHCI sample (0.1%).

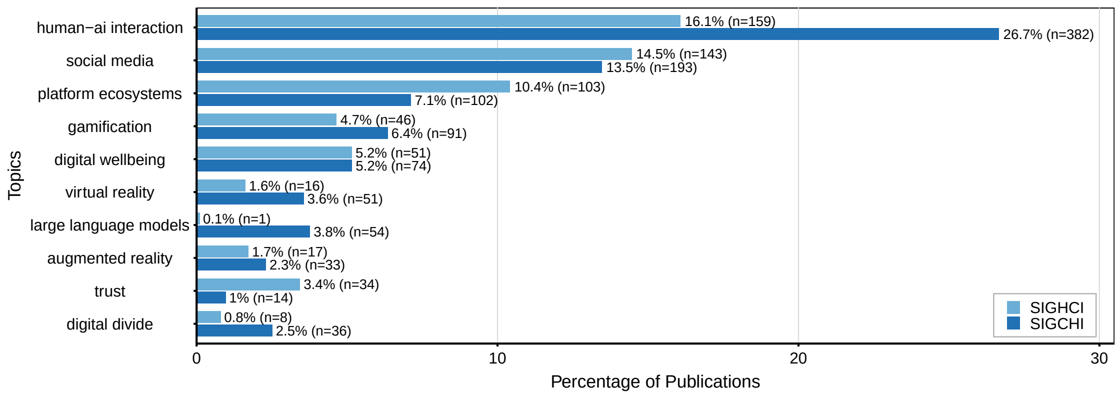
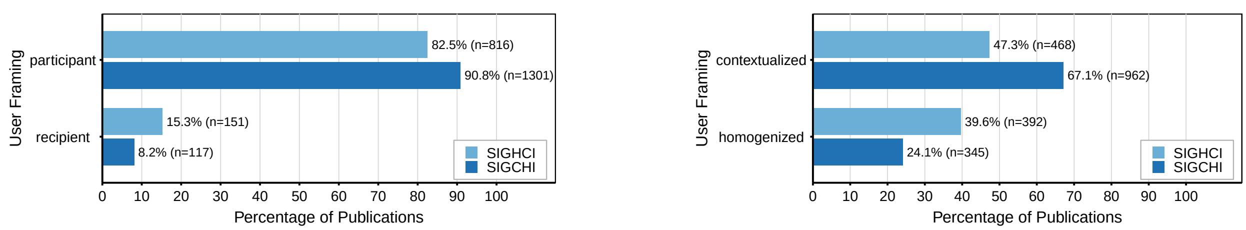


Figure 1. Comparison of Topics between Communities (Top 10)

The *unit of analysis* shows that both communities are focused on the micro (individual) level, with 93.7% of papers in SIGHCI and 92.9% in SIGCHI falling into this category (see online appendix).

Analysis of *user framing* revealed clear differences between the communities (Figure 2). Although both predominantly frame users as active "participants," this tendency is more pronounced in SIGCHI (90.8%) than in SIGHCI (82.5%), with SIGHCI exhibiting a higher proportion of "recipient" framing (15.3% vs. 8.2% in SIGCHI). The nature of these descriptions also differs substantially: SIGCHI papers largely favor "contextualized" framing (67.1%), whereas SIGHCI papers are less likely to contextualize users (47.3%) and rely more heavily on "homogenized" representations (39.6% vs. 24.1% in SIGCHI).



(a) Participant vs. Recipient **(b) Contextualized vs. Homogenized**

Figure 2. Comparison of User Framing between Communities

As illustrated in Figure 3, a disparity in the application of *theories* between the communities becomes visible, with SIGHCI consistently exhibiting a higher prevalence of the listed theories than SIGCHI. This divergence is evident in the use of the *Technology Acceptance Model* (TAM), which appears in 10.5% of SIGHCI papers but only 1.5% of the SIGCHI papers. Similar patterns emerge for other theories: the Theory of Planned Behavior is used in 3.1% of SIGHCI studies versus 0.5% in SIGCHI, and the Elaboration Likelihood Model is referenced in 2.3% of SIGHCI papers but only 0.2% of SIGCHI research.

The distribution of *methods* reveals the preferences of the communities (Figure 4). Surveys are the dominant method in both, appearing in 87.4% of SIGCHI papers and 79.6% of SIGHCI papers, but other methods diverge markedly. SIGCHI papers favor qualitative and observational approaches substantially more than SIGHCI; for instance, interviews are used in 45.6% of SIGCHI papers compared to only 12.7% of SIGHCI papers, and video recording is nearly five times more prevalent in SIGCHI (9.8%) than in SIGHCI (2.0%). Con-

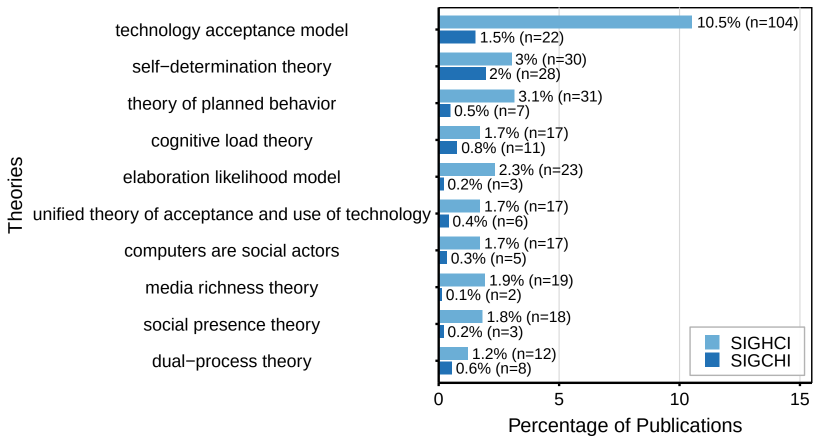


Figure 3. Comparison of Theory between Communities (Top 10)

versely, SIGHCI shows a stronger inclination towards quantitative and experimental methods, with *Structural Equation Modeling* (SEM) appearing in 12.4% of its papers versus 1.3% for SIGCHI, and experiments being used in 8.5% of SIGHCI papers compared to 1.1% in SIGCHI.

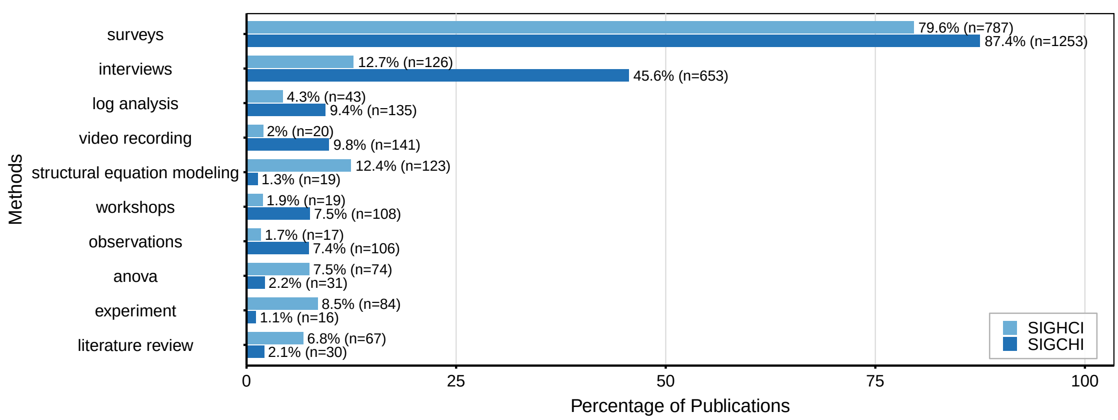


Figure 4. Comparison of Methods between Communities (Top 10)

The analysis of *questionnaires* usage supports this (Figure 5). SIGCHI papers show a focus on workload and system evaluation, with the *NASA Task Load Index* (NASA-TLX) appearing in 5.3% of papers compared to 1.1% in SIGHCI, and the System Usability Scale used more frequently by SIGCHI (3.1%) than by SIGHCI (1.2%). In contrast, SIGHCI papers prioritize constructs related to user perceptions: Perceived Usefulness is the most common questionnaire in SIGHCI (3.2% vs. 0.5% in SIGCHI), and both Perceived Ease of Use and Trust are more prevalent in SIGHCI (2.5% each) than in SIGCHI (0.3% vs. 0.8%).

Figure 6 shows the distribution of *sample sizes*. The median sample size for SIGHCI (Mdn = 150) was substantially higher than that for SIGCHI (Mdn = 31).

Differences also exist in *authors' institutional affiliations* across the two communities (see online appendix). SIGCHI papers are heavily dominated by authors from leading U.S. research institutions; for example, Carnegie Mellon University accounts for 6.1% of SIGCHI papers but only 0.6% of SIGHCI papers. Similarly, the University of Washington and the University of California are far more strongly represented in SIGCHI (4.7% and 3.6%, respectively) than in SIGHCI. In contrast, SIGHCI exhibits stronger contributions from the National University of Singapore, which represents 4.2% of SIGHCI papers versus 1.0% in SIGCHI, and McMaster University, which contributes 3.9% of SIGHCI output compared to 0.1% in SIGCHI. Industry-based research from Microsoft Research is also almost exclusively found in SIGCHI.

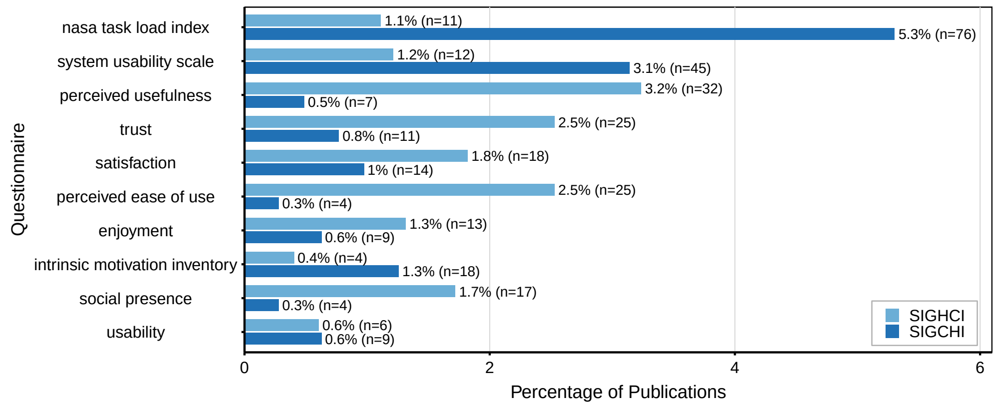


Figure 5. Comparison of Questionnaires between Communities (Top 10)

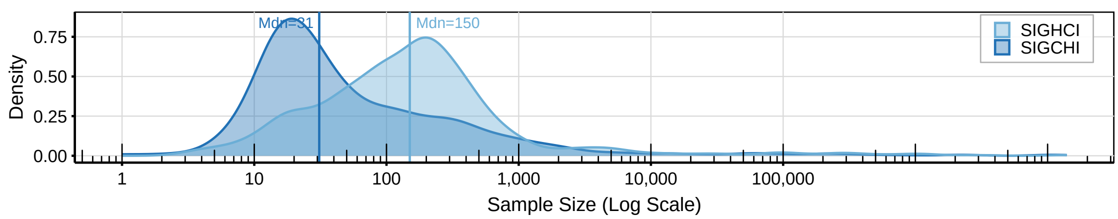


Figure 6. Comparison of Sample Sizes between Communities

For funding, only 19.7% of SIGHCI papers mentioned external funding, in contrast to 66% in SIGCHI (see online appendix). Both communities are mostly funded by national governments, according to the classification by OFR. There is more direct industry funding in SIGCHI (9.9% compared to 3.3% in SIGHCI).

Triangulation via Topic Modeling

SIGCHI exhibits a significantly higher mean topic proportion, particularly in areas such as "Input techniques," "Data visualization," "Fabrication," and "Generative design," as well as in "Social media" and "Online communities" (see online appendix). By contrast, SIGHCI shows a stronger emphasis on "Technology acceptance," which is its most prevalent topic. "Usable security" is the only other topic for which SIGHCI displays a significantly higher proportion than SIGCHI. "Human–AI decision making" is the sole topic where the difference between the two communities is not statistically significant.

Discussion

Both communities share characteristics rooted in their disciplinary profiles. They are interdisciplinary and follow a pluralistic methodological approach (Schwinghammer et al., 2025). The push towards the design science methodology in IS appears to narrow the gap between the communities (Hevner et al., 2004). Both are artifact-driven (Orlikowski and Iacono, 2001; Hewett et al., 1992) and pursue explanatory goals. No differences seem to exist in the unit of analysis, as both communities focus on the micro (individual) level, while on the organization-level, phenomena are comparatively less frequently addressed. This is notable given IS's historical emphasis on organizational and societal contexts (Avgerou, 2000; Bryant et al., 2013).

However, differences emerge in the publication practices of both communities. SIGCHI works in small-scale experimental setups, explaining the difference in participant framing over SIGHCI. This relates to the long-lasting trend in HCI from designing for a "general user" to individuals. Small-scale setups also explain the rare use of quantitative methods in general compared to SIGHCI. The past critique of its lack of theoretical grounding (Mueller and Urbach, 2017) in the IS disciplines appears to have reversed. SIGHCI frequently uses theory in contrast to SIGCHI, which is evident in larger sample sizes and quantitative methods aimed towards generalizable results, supporting previous observations (Djamasbi et al., 2018). Yet, theory in SIGHCI is dominated by the use of TAM, which can also be seen in the presence of its items in the questionnaires. Interestingly, questionnaires used by SIGHCI often rely on theory-derived constructs (e.g., 'perceived usefulness'), whereas SIGCHI frequently employs standardized instruments such as the NASA-TLX. In contrast, SIGCHI's less frequent explicit reference to formal behavioral theories are notable, given its origins in human factors and psychology. One possible explanation may lie in the"novelty effect" (Balestrini et al., 2015) and disincentivised incremental developments in the SIGCHI community (Djamasbi et al., 2018).

To pave the way forward, we found that the topic of *Human-AI Interaction* is a common research interest in both communities. We see this as confirmation of a 'fourth wave' of HCI research. The great changes AI imposed on the micro levels (which both communities are converged with at the moment) may introduce novel phenomena at the meso and macro levels. Changes in AI-supported interactions (which SIGCHI is focusing on) affect organizational decision-making and may lead to societal changes, which SIGHCI is predestined to research. Besides AI as a domain-specific topic, new research methods become available within communities as AI tools are used, for example, in large-scale qualitative research or rapid prototyping. This paper embodies this duality, as we used an LLM to systematically summarize vast amounts of literature from both communities, which might help researchers to inform and reflect on their communities. However, the use of AI poses risks that have been explained in detail elsewhere. In this study, we acknowledge that the LLM-based approach may have resulted in some extraction errors that affect specific attributes. We provide a full list of papers with the extracted attributes and the prompt template in the online appendix.

Future research could use this dataset to apply more detailed analyses, such as corpus comparison to highlight differences in terminology or a citation coupling analysis. The latter approach proved difficult because the AIS eLibrary does not provide properly indexed references. Our sample should be extended to include other conferences and journals, as we focused on HCI areas that are aligned with IS. Content-wise, the research surrounding Human-AI Interaction should be explored in detail: What are the theoretical and methodical approaches concerning Human-AI Interaction in both the SIGHCI and SIGCHI communities, and how can the combined efforts establish a mutually beneficial collaboration? Interestingly, the topic has been present since 2004 in SIGHCI and appeared in 2016 in the SIGCHI sample. This motivates future research on how this topic has gradually developed. To provide more actionable suggestions for using Human-AI Interaction as a bridging topic, we recommend collecting additional data from scholars in both communities.

Conclusion

Eight years after the last 'bridging' approaches, we found both communities to be largely unchanged. Instead of calling for new institutional initiatives, we recommend focusing on shared problems that can be tackled while honoring each community's distinct priorities and strengths. Human–AI Interaction is one such problems: it offers an opportunity for SIGHCI and SIGCHI to connect by reusing each other's existing work and by presenting new research in ways that are accessible and reusable across communities.

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