Creating Research Frameworks to Bridge the Divides in HCI Research

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Abstract
I present various ways to bridge the divides between AIS SigHCI and ACM SigCHI, including the development of research frameworks as boundary objects between the two fields. An example framework is presented.

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ACM Classification Keywords
H.1.2. Information Systems: User/Machine Systems—Human factors.

Introduction
Research in Human-Computer Interaction has long been fragmented across different disciplines, with research occurring under the disciplinary umbrella of computer science, library and information sciences, industrial engineering, business and management, and various subfields of psychology. While some researchers work in more than one of these areas, most HCI research is relatively siloed, with each discipline having their own scientific and professional organizations.

Bridging the divides between these areas is a formidable task, and in this paper, I will only address the divide between research conducted under the auspices of the Association for Information Systems' SIG in Human Computer Interaction (AIS SigHCI) and the Association for Computing Machinery's SIG in Computer-Human Interaction (ACM SigCHI).

Analysis of Research Focus

The practical mission of the AIS SigHCI[1] is "To promote research related to human-computer interaction within business, managerial, and organizational contexts", while the mission of the ACM SigCHI[2] is to enable its members to "invent and develop novel technologies and tools, explore how technology impacts people's lives, inform public policy, and design new interaction techniques and interfaces".

Based on its mission, my own experiences attending AIS SigHCI meetings, and an analysis of the Best Paper award nominees during the last five years of meetings, I argue that members of this organization primarily conduct technology research at a conceptual level: many of its top papers are about "information technology" in general (cf. [9,16,21,42,46]), rather than a specific technology, let alone a specific system (this also seems true for journal papers, which in the IS field are usually more comprehensive). Even the technology-specific papers often focus on generalizable interaction principles (cf. [8,11,17,25]) rather than the specific design of the technology presented. Moreover, almost every paper cites at least one fundamental theory or model (such as the Technology Acceptance Model [10] or the task-technology fit theory [18]). As such, AIS SigHCI research is almost invariably summative and incremental in nature, but lower in ecological validity.

Based on a similar analysis of ACM SigCHI meetings, I argue that members of this organization primarily conduct research with high ecological validity and often direct practical applicability. Many of its Best Papers introduce a new technology or interaction technique (cf. [4,7,34,44,47,48]), and while evaluation is considered a requirement (91% of the papers from 2014 contain a user study [5]), it is not the focus of the research. Consequently, the median at CHI 2014 was 18, with 42% of the studies taking a qualitative approach [5]. Awards are often given to papers that cover novel topics or interaction paradigms. As such, ACM SigHCI research is comparatively more formative and disruptive in nature, but not very paradigmatic, and thus lower in "accumulative" contributions.

Both the AIS SigHCI and the ACM SigCHI are not just open to academics, but also to industry professionals. The ACM SigCHI seems most successful in involving industry: many CHI papers are authored or co-authored by industry researchers, and industry recruitment is an important aspect of the CHI conference. Aside from writing papers, industry researchers and practitioners often conduct HCI research with the goal of improving the usability or user experience of their products. Based on my own experience with such industry HCI research, I argue that such research falls into three categories: user-centered design [1], "discount" usability evaluation [36], and multivariate ("A/B") testing [29]. This research is very formative and practical in nature, at the expense of scientific contribution and generalizability.

[1] http://sighci.org/index.php?page=about

[2] https://sigchi.org/about/mission-statement/

Given the differences in research focus, it is understandable that members of the AIS SigHCI the and ACM SigCHI barely overlap. Both organizations produce valuable knowledge about human-computer interaction, so more synergy in knowledge and practices between the fields (and with industry practitioners) would certainly be beneficial.

Boundary Objects

Carlile investigates how differences in knowledge and practices between disciplinary teams can be both a barrier and a source of innovation in product development [6]. Drawing upon the literature on "communities of practice", he demonstrates that knowledge is often localized, embedded and invested in practice. In this context, *boundary objects* are objects that are shared and shareable across-practice, and thus function as a means to cross the divide between disparate communities of practice. Drawing upon Star's original definition [43], Carlile identifies three types of boundary objects, each with their own function: repositories/tools, forms/methods, and maps/models.

Repositories and tools provide a shared language to represent knowledge between communities, thereby creating *syntactic* alignment. In this light, I note that AIS SigHCI researchers often limit themselves to journal articles when citing related work. In the ACM SigCHI community, however, a lot of the work never gets published in a journal. Researchers should thus strongly consider including ACM conference papers in their literature review. This will increase their ability to situate their work within the context of the state-of-the-art. Likewise, many ACM SigCHI researchers are unaware of the wealth of measurement scales available in repositories such as the Inter-Nominological Network[3]. Rather than developing new measurement scales, researchers should consider adopting measurement scales from (and contributing measurement scales to) this repository, thereby increasing the opportunity to compare constructs across studies.

Forms and methods provide shared tools for discovering and explicating knowledge between communities, thereby creating *semantic* alignment. In this light, I note that the ACM SigCHI community uses highly innovative evaluation practices: many evaluations are multi-method, involve high-fidelity prototypes, and intricate observation methods such as experience sampling. The AIS SigHCI community, on the other hand, seems most rigorous when it comes to the statistical evaluation of research results, often employing rigorous psychometric evaluation and Structural Equation Modeling (SEM). A mutual understanding of (and appreciation for) these methods could result in better semantic alignment. Moreover, some methods could be hybridized, e.g., while SEM has traditionally been used to model survey data, it can also be applied to experimental data, and modern SEM approaches have been extended to allow generalized and multi-level models that allow the integration of behavioral (e.g. clickstream) data.

Maps and models provide shared vehicles for resolving conflicts, thereby mutually transforming the knowledge in each community and thus creating *pragmatic* alignment. In this light, I suggest the development of research frameworks that integrate research across the

[3] http://inn.theorizeit.org/

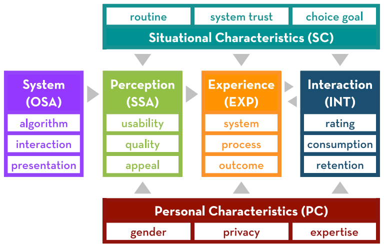

Figure 1: User-Centric Evaluation Framework for Recommender Systems

various conceptual levels at which HCI research occurs. I envision such frameworks to consist of two parts: 1) a middle range "EP" (Explanation and Prediction) type theory of interaction within a specific HCI subfield and 2) a classification of constructs (either measured, observed, or manipulated) that are of specific interest in this subfield. The framework can be used to integrate research at all levels: conceptual and concrete, observational and experimental, lab- or field-based. The EP type theory can be conceptually related to a more general theory (e.g. TAM), and thereby satisfies the desire of the AIS SigHCI community to create generalizable, incremental research. The constructs provide linkage points for measurement scales and (operationalizations of) experimental manipulations, introducing paradigm to ACM SigCHI research. Importantly, keeping only a weak linkage between the theory and the constructs allows for the framework to be extensible to novel research in this subfield—a prominent desire of the ACM SigCHI community.

Example Research Framework

In Knijnenburg et al. [27] we present a framework for the user-centric evaluation of recommender systems (Figure 1). This framework is rooted in higher-level theories within IS (cf. TAM [10]) and HCI (cf. Hassenzahl [20]), and links the objective characteristics of recommender systems (e.g. their algorithm, interaction mechanism, and presentation style) to the users' experience and interaction via perceptual concepts (e.g. usability, recommendation quality, and appeal). The effects in this model may be moderated by personal and situational characteristics.

As a model, the framework provides a means for *pragmatic* alignment of user-centric research in recommender systems. The paper also includes a repository of measurement scales for syntactic alignment. Finally, the framework integrates experimental, survey-based, and behavioral data into a single model, allowing for the semantic alignment of various research practices under a common framework.

The framework has seen considerable adoption among researchers in the ACM subfield of recommender systems (e.g. [2,3,12,13,19,32,35,38,40,41,50]), and has recently been recognized in the IS community as well (e.g. [14,15,22,30,31,33,37,39,45,49]). Moreover, the framework has been used as a vehicle for a book chapter [26], an industry brief [28], and several tutorials [23,24,24] on the user-centric evaluation of information systems, introducing experimental design, psychometrics, and SEM to an audience of researchers and practitioners previously unfamiliar with these techniques.

Conclusion

The divide between the AIS SigHCI and ACM SigCHI communities can be seen as both a barrier and a source of innovation in research practices. Using Carlile's theory [6], I have made several recommendations that can bring syntactic, semantic, and pragmatic alignment to these communities of practice. Most importantly I argue for the development of research frameworks that can be used to integrate research from these two communities. I hope that the presented example of a framework for the user-centric evaluation of recommender systems provides inspiration for other researchers to develop similar frameworks for their respective subfields of HCI research and disseminate them across the boundaries of the AIS SigHCI and the ACM SigCHI communities.

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