Data-Driven Approach to Human-Engaged Computing

Xiaojuan Ma
Hong Kong University of Science and Technology
Hong Kong SAR
mxj@cse.ust.hk

ABSTRACT

This paper presents an overview of the research landscape of data-driven human-engaged computing in the Human-Computer Interaction Initiative at the Hong Kong University of Science and Technology.

KEYWORDS

Engagement, data-driven, inference, analysis, application, machine intelligence, hybrid realities.

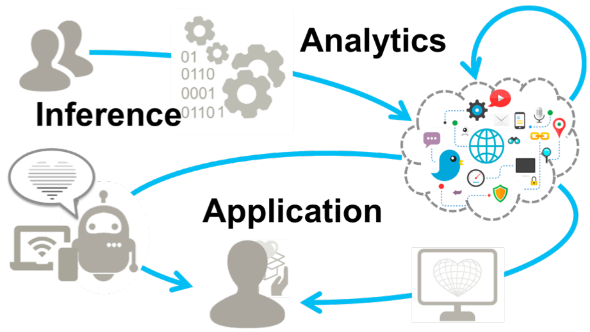

Figure 1: Overview of our research on data-driven human-engaged computing.

1 INTRODUCTION

Making technologies more engaging for human users is gaining increasing attention in academia and industry these days. It aims to equip computing devices and services with the abilities to perceive and understand users' attentional, emotional, cognitive, and behavioral engagement, as well as to manage and use such information to improve user interactions and experiences. In this paper, we present an overview of our research efforts on human-engaged computing (HEC) (Fig. 1). In particular, we take a data-driven approach to 1) inferring human engagement dynamicity from various signals, and 2) analyzing factors that engage users in online and offline activities in everyday life that can potentially be adopted in human-computer interaction (HCI). Then, we apply the resulting insights to two main application areas: achieving more engaging interaction experiences 3) with artificial intelligence (AI) via the design of emotionally and socially intelligent robots and agents; and 4) with non-AI entities (e.g., data and objects) via immersive hybrid realities. Last but not least, we experiment with the use of engagement ingredients to enrich user experiences in different contexts, ranging from education, e-commerce, health and wellbeing, to creativity.

2 ABOUT ENGAGEMENT

2.1 Definition of Engagement

In human-human interaction, engagement is “the process by which interactors start, maintain, and end their perceived connections to each other during an interaction” [21]. In the context of HCI, we take a more comprehensive definition that details the dimensions of engagement – considering it as “the attentional, emotional, cognitive, and behavioral connection that exists between a user and the task at hand at any point in time and possibly over time” ([22], adapted from [2], P. 2). Some literature takes a narrower definition of engagement that refers to only one of the following dimensions (Fig. 2).

Attentional Engagement concerns attention allocation and redistribution (e.g., [4]), which can be measured by gaze data collected via eye tracking.

Emotional engagement concerns users’ affective reactions such as interest, excitement and boredom (e.g., [10]), commonly measured using subjective questionnaires. Recently, researchers have explored the use of sensors to detect users’ affective states.

Cognitive engagement concerns psychological devotion to a task (e.g., [13]), such as active thinking and reflection, and can be measured by sensors like EEG (objective) or by self-reporting (subjective).

Behavioral engagement concerns physical participation and involvement (e.g., [7]), often measured by attendance, time spent, number of actions, and number of attempts.

2.2 Human-Engaged Computing

With the technology advancement, researchers and practitioners start looking into how to design synergized interactions between humans and technologies, with the goal of augmenting the capabilities of both parties and maximizing their capacities. In the article “Rethinking the Relationship between Humans and Computers”, Xiangshi Ren proposes that human-engaged computing aims to achieve “a state of optimal balance between engaged humans and engaging computers” [20].

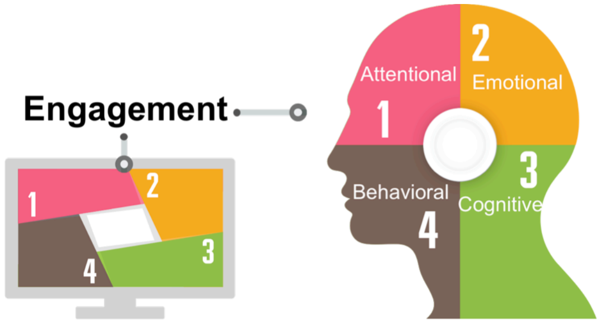

Figure 2: Components of Human-Engaged Computing (HEC): engaged human and engaging computer.

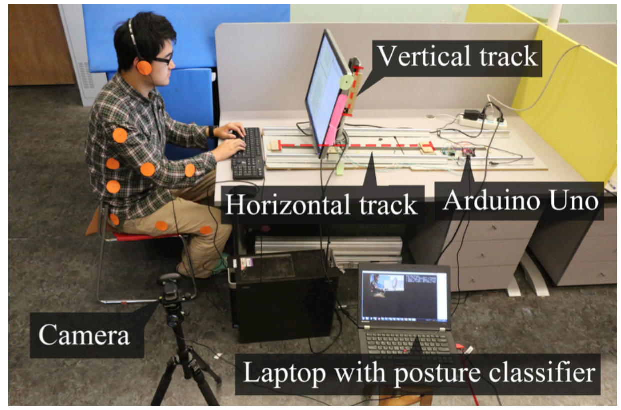

Figure 3: Example setup to detect posture [34].

There are two essential research components of this notion: *engaged humans* and *engaging computers* (Fig. 2). The former requires the ability for computers (in a general sense) to perceive and understand the states and changes of human engagement. The latter demands feature(s) in a technological design that can motivate and facilitate humans to establish connections with it. Our group proposes to take a data-driven approach, i.e., leveraging rich data about humans, computers, and assorted interactions from diverse sources, to infer user engagement dynamicity and analyze engaging factors for design inspiration. Based on the derived insights, we further explore the creation of engaging experience with AI systems and non-AI entities.

3 RESEARCH LANDSCAPE OF HEC

3.1 Inference (Engaged Humans)

The main goal of the *Inference* research component is to sense and model human engagement dynamicity in real-time, i.e., the states, transitions, and fluctuations of engagement – a single dimension or multiple dimensions as an integrated measure. We have been exploring the use of three types of signals as engagement cues: social signal, physiological signal, and behavioral signal.

Social signals are “communicative or informative signals that, either directly or indirectly, provide information about social facts, namely social interactions, social emotions, social attitudes, or social relations” [26]. In other words, social signals are indicators of attentional, emotional, and even cognitive engagement in interpersonal interactions, which can potentially be transferred to other interaction contexts. Common social signals include gaze, facial expressions, vocal behaviors, proxemics, gesture, posture, and other body languages. Our group investigates non-intrusive methods to capture social signals during an interaction, using sensors like cameras and microphones. Fig. 3 shows an example setup of a posture detection system [34]. In actual applications, the sensors are better embedded in the environment.

Physiological signals are readings produced by physiological processes of human beings, including but not limited to heartbeat rate (ECG/EKG signal), respiratory rate and content (capnogram), skin conductance (EDA signal), muscle current (EMG signal), brain electrical activity (EEG signal), etc. Research has shown that physiological signals can serve as cues of attentional (e.g., [9]) and emotional engagement (e.g., [1]). We have previously experimented with extracting emotional cues from pulse [33] and skin conductance data [24] (Fig. 4)

Behavioral signals are actions and activities performed during an interaction or on an interface online or offline, such as conversational acts, text input, clicks, scrolling, page switch, emoji usage, likes, check-ins, etc. Some of these are task-specific, but they all suggest users’ level of behavioral, cognitive, and sometimes emotional engagement. We have been mining behavioral signals from different sources, such as gameplay data [12], social media data [29], social commerce data [31], multimedia data [25], and public service data [6].

We can use the different types of engagement signals individually or collectively, according to the application context and needs.

3.2 Analytics (Engaging Computers)

The purpose of our *Analytics* research component is to identify engaging factors people may encounter in their everyday life. In particular, we are interested in what engages users when they interacting with other humans or with physical / virtual entities.

Our research on *engagement with social actors* concerns a) characteristics of individuals that tend to attract other people to

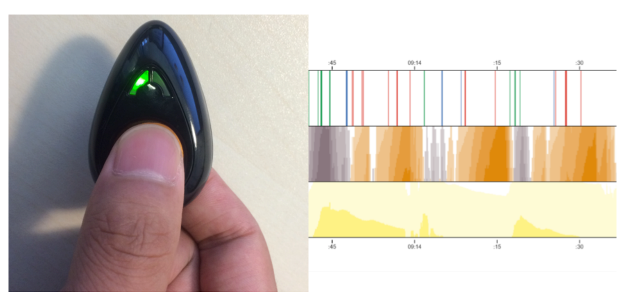

Figure 4: Monitoring skin conductance using Pip sensor and sample readings [24].

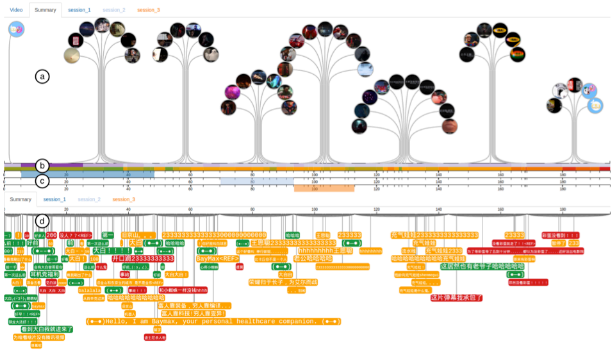

Figure 5: Analysis of viewer engagement during live video commenting [25]: (middle) video timeline; (top) summary of video scenes, height encoding intensity of behavioral engagement; (bottom) comments posted during video watching, color encoding sentiment.

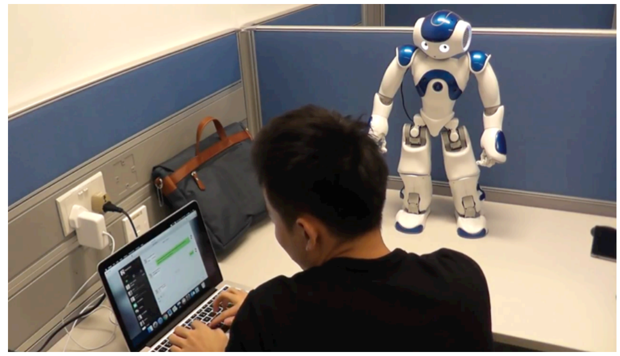

Figure 6: Example of engagement sensing and handling in human-robot interaction; the user disengaged from his conversation with the robot to work on a task on the computer [23].

participate in activities with them e.g., personality [30] and structure of their intimacy network [11]; and b) strategies people used to directly or indirectly manage others' engagement [29] e.g., money gifting.

Our research on *engagement with physical and virtual entities* intends to capture tangible and nontangible properties that make something more engaging than others. Our studies have covered a wide spectrum of design space, ranging from appearance (e.g., cuteness [19]), layout (e.g., product arrangement on e-comerce site [31]), medium (e.g., food for social messaging [28] and data display [27]), to semantics (e.g., associations in humor [3]).

To give an example, Fig. 5 shows a visualization of viewer engagement on an online video sharing platform, by analyzing the live commenting data [25]. We can gain an idea about which part of a video is engaging and why, and how viewers engage one another to create an illusion of co-watching.

3.3 Application I: Engagement with AI Systems

Our first application of insights drawn from inference and analytics is designing engaging experiences with Artificial Intelligent (AI) systems, naming robots and virtual agents (HRI / HAI). More specifically, we would like to augment AI systems with emotional and social intelligence, enabling smoother, more effective, and more enjoyable human-AI collaboration.

For example, we compare the efficacy of two disengagement handling techniques (dominant / explicit versus submissive / implicit) adapted from human-human interaction, when employed by a physical robot to manage potential interaction breakdowns with a human user [23]. During the entire process, the robot closely monitors the user's shift of engagement by social and behavioral signals. We have also experiment with applying these two traits on a virtual agent to deal with user challenges such as verbal abuse and sexual harassment [30].

3.4 Application II: Engagement with Non-AI Entities

Our second application focuses on non-AI entities in a computing system, such as data and traditional interface elements. We use engaging factors (e.g., appearance, medium, semantic, etc.) identified previously to inform the design of these entities across the **reality–virtuality** continuum. In other words, a design can live in conventional digital media, in "ambient media" situated in everyday life [14], or a combination of both. As a result, these designs could be of better assistance in areas like informatics (e.g., healthcare [17] and wellness [24], photo archive [15], etc.), narratives (e.g., video synopsis [25], paper-craft [35], etc.), persuasion (e.g., volunteerism [8] and healthy aging [32]), and recommendation (e.g., e-commerce [31], travel [5], and transportation [6]).

In the work shown in Fig. 7, we use crowdsourcing techniques to infer users' allocation of attentional and cognitive engagement when looking at digital medical graphics [16]. Guided by the results, we can use optimization algorithms to automatically improve the perceptual effectiveness of the information display during physician-patient communication.

In another work, we conduct meta-synthesis of daily anecdotes about how breakage of technology may lead to engagement of (restoring, reinforcing, or promoting) online and offline interpersonal communication [18]. Based on the findings, we propose a Breakage-to-Icebreaker (B2I) design process, i.e., embedding icebreaking mechanisms into existing products and services to create opportunities for users to interact and reflect while enjoying the original functionalities (Fig. 8).

4 CONCLUSIONS

This paper provides a brief overview of the research on data-driven human-engaged computing (HEC) conducted in the Human-Computer Interaction Initiative at the Hong Kong University of Science and Technology. We summarize our works related to two essential components of HEC: engaged humans

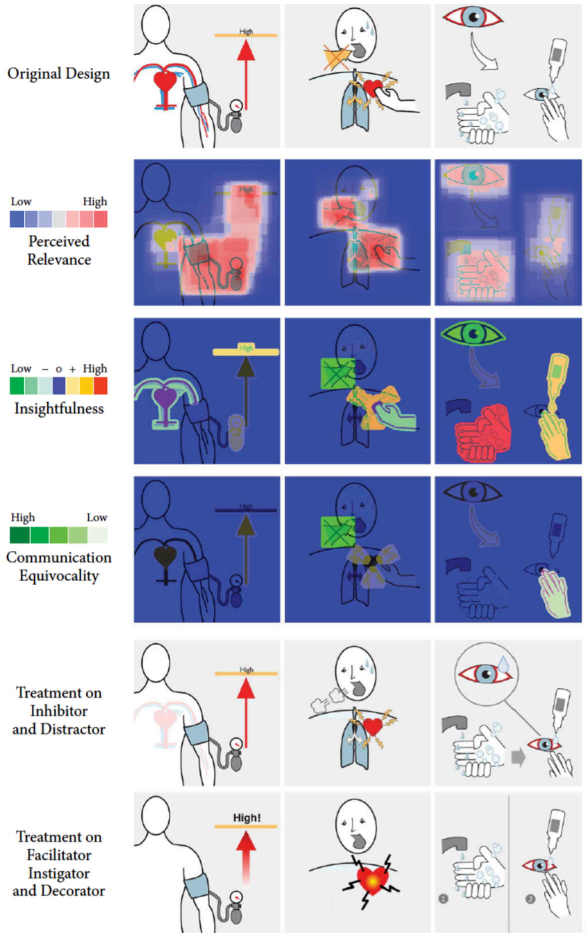

Figure 7: User attentional and cognitive engagement-guided design of medical graphics used in physician-patient communication [16].

(inference) and engaging computers (analytics). We also presents some exploratory applications of our research results, enabling more engaging synergized interactions between human users and AI systems as well as non-AI elements in a technology.

ACKNOWLEDGMENTS
This work was partially supported by the HKUST Initiation Grant #IGN15EG02 and by the WeChat-HKUST Joint Laboratory on Artificial Intelligence Technology (WHAT LAB) grant #1516144-0 and #1617170-0.

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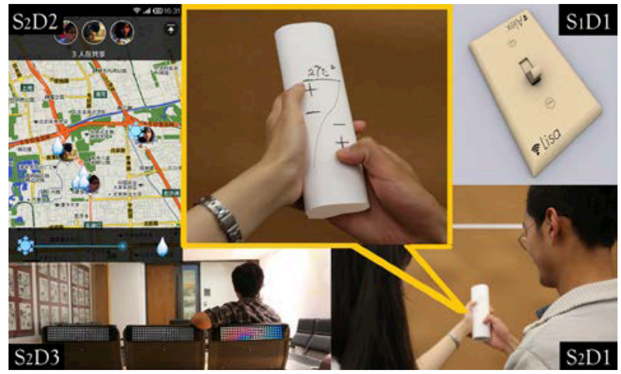

Figure 8: Prototypes of persuasive design for encouraging interpersonal interactions [18]: (S2D2) Cool Map, map sharing user-perceived temperature; (S1D1) WiFi Teeterboard, a WiFi redistribution switch; (S2D3) Sense Me Chat with Me, affective bench; and (S2D1) Remotouch, a collaborative air-conditional remote control.

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