Transactions on Human – Computer Interaction

Original Research

Measuring Actual Behaviors in HCI Research – A call to Action and an Example

Parker A. Williams
University of Arizona
parkerwilliams@email.arizona.edu

Jeffrey L. Jenkins
Brigham Young University
jjenkins@byu.edu

Joseph S. Valacich
University of Arizona
valacich@arizona.edu

Michael D. Byrd
University of Arizona
byrd@email.arizona.edu

Abstract:

There have been repeated calls for studies in behavioral science and human-computer interaction (HCI) research to measure participants' actual behaviors. HCI research studies often use multiple constructs as *perceived* measures of behavior, which are captured using participants' self-reports on surveys. Response biases, however, are a widespread threat to the validity of self-report measures. To mitigate this threat to validity, we propose that studies in HCI measure actual behaviors in appropriate contexts rather than solely perceptions. We report an example of using movements that reflect both actual behavior and behavioral changes measured within a health care IS usage context, specifically the detection and alleviation of neuromuscular degenerative disease. We propose and test a method of monitoring mouse-cursor movements to detect hand tremors in real time when individuals are using websites. Our work suggests that analyzing hand movements as an actual (rather than perceptual) measure of usage could enrich other areas of IS research (e.g., technology acceptance, efficacy, fear, etc.), in which perceptions of states and behavior are measured post hoc to the interaction and subject to the threats of various forms of response bias.

Keywords: Measuring actual behavior, HCI; Neuro-motor system, Neuro-muscular system, Behavioral biometrics, Mouse movements, Digital body language

Dennis F. Galletta was the accepting senior editor for this paper.

Recommended Citation

Williams, Parker A.; Jenkins, Jeffrey; Valacich, Joseph; and Byrd, Michael D. (2017) "Measuring Actual Behaviors in HCI Research – A call to Action and an Example," *AIS Transactions on Human-Computer Interaction* (9) 4, pp. 339-352

DOI: 10.17705/1thci.00101

Available at: http://aisel.aisnet.org/thci/vol9/iss4/4

1 Introduction

Several researchers have emphasized the importance of measuring actual behaviors in the behavioral sciences, including psychology (Baumeister et al. 2007), personality psychology (Furr 2009), and specific areas, such as the study of narcissism (Holtzman et al. 2010). Much like behavioral research, information systems (IS) research is often criticized for not measuring actual behaviors. In fact, IS measures in general have been criticized as lacking in rigor (Burton-Jones and Lee 2017). In response, some specific areas within IS now emphasize the importance of examining actual behavior (e.g., when studying information security), rather than just examining intentions (e.g., Boss et al. 2015; Crossler et al. 2013; Moody and Galletta 2015).

We believe that these criticisms are also particularly relevant to human-computer interaction (HCI) research. Studies in the field of HCI research often use multiple constructs that are operationalized as *perceived* measures of behavior, which are measured by self-reports on surveys completed by participants. However, response biases threaten the validity of surveys. *A response bias* (also known as a survey bias) is the tendency of people to respond to questions on some basis other than the question content (Paulhus 1991). For example, a respondent may misrepresent an answer so that it will be viewed more favorably by others; this is known as *social desirability bias* (Fisher 1993). Likewise, people have the tendency to portray themselves in the best light, particularly when they are asked about personal traits, attitudes, and behaviors; this tendency often causes people to falsify or exaggerate answers (Paulhus 1991). In other situations, a respondent may not be sure how to answer a question because of a lack of knowledge in the area or a lack of understanding of the question. There are many types of response biases, and each type represents a greater or lesser validity threat depending on the research context (see Table 1 for examples of several response biases).

Table 1. Examples of Response Biases

Type of Bias	Description
Acquiescence bias	The tendency of respondents to agree with all the questions in a measure
Extreme responding	The tendency of respondents to always choose the most extreme options or answers available
Prestige bias	The tendency of respondents to overestimate personal qualities
Social desirability bias	The tendency of respondents to misrepresent an answer in such a manner that it will be viewed more favorably by others
Survey fatigue	The tendency of respondents to give less thoughtful answers due to being tired of answering questions
Unfamiliar content	The tendency of respondents to randomly choose an answer because they do not understand the question or do not have knowledge to answer the question
Completion / Incentive bias	The tendency of respondents to randomly or systematically choose an answer because their primary incentive when answering questions or completing a task is to receive an external reward (e.g., payment, extra course credit, etc.)

1.1 Mouse Cursor Tracking as a Measure of Behavior

The construct of ease of use (EOU), which is typically operationalized as *perceived ease-of-use* (PEOU), is an example of how perception-based measures are typically collected in HCI and technology acceptance literature. PEOU reflects the extent to which a person *believes* that using a technology will be free of effort (Davis 1989; Venkatesh 2000). PEOU is widely validated and cited, and, as noted, is typically measured through surveys or other self-report instruments (Venkatesh 2000). In some situations, PEOU provides an ideal measure of a system's EOU. However, in other situations, soliciting self-report measures can be challenging. For example, in 'live' websites, surveys that ask for self-report measures can be perceived as interruptive, annoying, cumbersome, or time-consuming. As a result, asking survey questions during use of a live system can yield low response rates, and these responses are often biased toward those who had highly positive (or negative) experiences (Leighton-Boyce 2012). Even in some non-live research settings, self-report measures may be influenced by various biases (e.g., Chapman 1967; Fisher 1993; Schuman and Presser 1981). Jenkins and Valacich (2015) proposed a behavior-based measure of EOU based on the analysis of users' mouse-cursor movements. Specifically, they theorize how differences in system usability would influence various movement characteristics (i.e., movement precision). Such a technique would allow

EOU to be unobtrusively measured in live environments and at Internet-scale deployment (e.g., large commercial websites).

In addition to various response biases, other validity threats can result from item effects, including scale format and context effects, such as priming and timing (Podsakoff et al. 2003; Schuman and Presser 1981). In addition, the implementation of self-report mechanisms can be disruptive to the realism of experimental scenarios. If a participant is interrupted to respond to a questionnaire, he/she is removed from immersion in the experience, and his/her actions will no longer be the same as if they had remained undisturbed. By measuring actual behaviors instead of perceptions and self-reports, many of these issues can be mitigated or avoided entirely. Additionally, the incorporation of measurements of actual behaviors helps facilitate mixed methods research by providing an alternative data source that can be continuously and unobtrusively captured without disrupting task-related activities (i.e., increasing realism of the study – Dennis and Valacich (2001)). Likewise, the results reported from mixed method studies are more robust to validity threats and other potential issues (Venkatesh et al. 2013).

An example of when mouse-cursor tracking was used to infer specific behavior was reported in Hibbeln et al. (2014). Specifically, they used mouse-cursor movements to detect possible fraudulent insurance claims and found that users who entered fraudulent claims had predictable changes in their movement characteristics (i.e., longer and slower movements). In another more recent example, Hibbeln et al. (2017) used actual participant behavior to infer emotion, valence, and variations. In this work, three studies are reported in which mouse-cursor movements were used as a potential real-time indicator of emotion. In the first study, an experiment with 65 participants from Amazon's Mechanical Turk, negative emotion was manipulated by having participants complete a fair or unfair intelligence test (i.e., the unfair test was designed to induce negative emotion). Immediately after completing the test, mouse-cursor movements were monitored while participants completed a number-ordering task. The results showed that negative emotion increased the distance and reduced the speed of mouse cursor movements during the task.

In the second study, an experiment with 126 participants, negative emotion was manipulated by having participants complete the same shopping task while utilizing an e-commerce website with high or low usability (i.e., low usability was designed to induce negative emotion). Mouse-cursor movements were monitored while participants interacted with the mock e-commerce site. The results showed that mouse-cursor distance and speed could be used to infer the presence of negative emotion with an overall accuracy rate of 81.7 percent.

In the third study, an observational study with 80 participants, mouse-cursor movements were monitored while participants interacted with an online product configurator. Negative emotion was induced by changing the relative difficulty of the configuration tasks. After completing each of the configuration tasks, participants self-reported their level of emotion. The results showed that mouse-cursor distance and speed could be used to infer the level of negative emotion with an out-of-sample R^2 of 0.17. The mouse-cursor tracking methodology can enable the tracking of emotional reactions during use of live systems. Thus, mouse-cursor tracking enables the near real-time measurement of system usability, emotional reactions, fraudulent interactions, and a host of other behaviors that were previously difficult to analyze in an unobtrusive or unbiased way. We have found that mouse-cursor tracking can be deployed in broad research and operational contexts; this allows for better understanding the user without disrupting natural interaction through invasive data collection approaches (Grimes et al. 2013; Hibbeln et al. 2014; Hibbeln et al. 2017; Jenkins and Valacich 2015; Jenkins et al. 2017; Williams et al. 2016).

In this paper, we present an example of measuring actual behaviors in HCI research. Our chosen context is health care, specifically the detection and mitigation of neuromuscular degenerative disease. We propose and test a method of monitoring mouse-cursor movements to detect hand tremors in real time when individuals are using websites. Health care is an emerging and important area of research within IS and HCI in particular (Wilson and Djamasbi 2015). Recent work in this area spans from the use of wearables for e-Health monitoring (Castillejo et al. 2013) to more extensive, systematic smart health monitoring systems (Baig and Gholamhosseini 2013). Past research has identified various interventions to make computers more enjoyable for people with hand tremors, such as filtering out mis-clicks, smoothing algorithms for mouse movements, and accentuating intelligent design (Riviere and Thakor 1996). However, an understudied area in this research is the ability to first detect if hand tremors are present so that websites can offer or deploy the use of such interaction improvement techniques. We address this need by exploring how analyzing users' mouse-cursor movements can be an effective method for detecting hand tremors in users. In summary, this research example explores the following research question: *what characteristics of users' mouse-cursor movements detect if a user has hand tremors?*

Using participants from the International Essential Tremor Foundation and Mechanical Turk, we conducted an exploratory study that monitored and analyzed mouse-cursor movements on a website. We found five characteristics of users' mouse-cursor movements that were influenced by hand tremors. The results of our research will not only help make websites more accessible for users with hand tremors, but also improve health monitoring as well as advance mouse-cursor research.

2 Literature Review

Neuromuscular degenerative diseases, such as Parkinson's disease and diseases with related neurocognitive impairment symptoms, such as Alzheimer's disease, are an area of great interest for HCI research. Researchers have used accelerometers to detect and classify movement disorders (Garcia et al. 2016), proprietary robotic systems to assess Alzheimer's patients (Bartoli et al. 2017), immersive VR systems to screen for cognitive impairment using kinematic movement analysis (Seo et al. 2017), and signal analysis from multiple body attached sensors for the evaluation of Parkinson's (Dinesh et al. 2016) and Alzheimer's (Cheng and Zhuang 2010) symptoms.

A challenge with this type of research is the use of proprietary sensor technology. A recent work required subjects to be connected to EEG and a proprietary accelerometer to differentiate tremor types (Panyakaew et al. 2017). These proprietary systems can be highly effective, but they are problematic for wide-scale deployment in both research and practice due to their limited availability and cost. Some researchers have begun to use more widely available and inexpensive HCI devices, such as smartphones and mice. O'Reilly and Plamondon (2012), for example, used computer mice to diagnose neuromuscular disorders and separately evaluate the suitability of standard mice for movement analysis against other, less common HCI devices, such as digitizer tablets (O'Reilly and Plamondon 2011). In addition, smartphones have been evaluated for the detection of tremors in unconstrained environments (García-Magariño et al. 2016).

2.1 Mouse Tracking

Mouse-cursor tracking as a scientific methodology that was originally explored as a cost-effective alternative to eye tracking to denote where people devote their attention in a human-computer interaction context (Byrne et al. 1999; Pappas et al. 2014; Tarafdar et al. 2007). For example, research has shown that eye gaze and mouse-cursor movement patterns are highly correlated with each other (Liljander and Strandvik 1997; Pappas et al. 2014; Tarafdar et al. 2007). When scanning search results, the mouse often follows the eye and marks promising search hits (i.e., the mouse pointer stops or lingers near information), and this suggests where people devote their attention (Rodden et al. 2008). Likewise, people often move their mouse while viewing web pages, suggesting that the mouse may indicate where people focus their attention (Lu and Yu-Jen Su 2009). In selecting menu items, the mouse often tags potential targets (i.e., hovers over a link) before selecting an item (Unsworth and Spillers 2010).

As the abilities to collect fine-grained measurements and perform analyses of mouse-cursor movements have improved, research has expanded the use of mouse-cursor tracking to explore a more diverse set of neuromotor and psychological responses. In a concise review of mouse tracking literature, Freeman and Ambady (2011, p. 1) suggest that the "movements of the hand…offer continuous streams of output that can reveal ongoing dynamics of processing, potentially capturing the mind in motion with fine-grained temporal sensitivity." Accordingly, hundreds of recent studies have chosen mouse tracking as a methodology for studying various cognitive and emotional processes.

We extend this research to explore how mouse-cursor movement can be used to detect the physiological characteristics of users (e.g., hand tremors) in addition to the psychological characteristics. We identify and develop mouse-cursor movement measures when the starting position of the mouse-cursor may vary (the mouse-cursor may be anywhere on the screen as opposed to always on the lower middle of the screen), and the desired final goal of the individual is unknown. We next introduce two theories that we will leverage to explain how users' mouse-cursor movements demonstrate their hand tremors.

2.2 Hand Tremors

Hand tremors pose a challenge for effective human-computer interaction. A hand tremor is a rhythmic oscillation of the fingers, hand, or arm (Deuschl et al. 2001). Hand tremors are very common. It is estimated that 10 million people have essential hand tremors (a common neurological disorder) in the United States (Stephens 2011), and the most common movement disorder, "pathological tremor", increases its prevalence with aging (Rocon et al. 2004). In addition to this, millions of people are affected by various other neurological diseases and disorders (e.g., Parkinson's) that cause hand tremors. People with hand tremors typically often have a very difficult time using the computer, specifically with navigating websites. These tremors can cause shaking that makes it difficult to navigate a website, select links on a webpage, and perform various other everyday computing activities. Such deleterious effects occur because it is difficult to click on small targets (e.g., links), difficult to hover over targets, and difficult to select options in web applications (Rotondi et al. 2007). Sixty-five percent of people suffering from upper limb tremor report serious difficulties in performing their activities related to daily living (Rocon et al. 2004).

Given the prevalence of hand tremors and their adverse influence on human-computer interactions, research has identified ways to make computers more accessible and usable to users. This research is split up into two categories: physical tools to reduce hand tremors and digital compensations.

Physical tools include mechanisms that a) apply friction to the hand to reduce shaking and b) find other ways for users to interact with the computer without using the hand (Rocon et al. 2004). In this realm, companies have developed specialized arm rests that stop the arm from shaking and input devices (e.g., key boards and mice) that require more friction to operate (and thus are not influenced by shaking)[1]. Sample products include the MIT damped joystick, the Controlled Energy Dissipation Orthosis, CEDO, and the Modulated Energy Dissipation (MED) Arm. Most HCI futurists envision a future where users with or without motor control deficiencies interact using multiple methods that include voice, gestures, and eye movements in addition to current approaches (Mannes 2016).

Digital compensations include software and design layouts that can compensate for hand tremors. Software includes digital filters that differentiate between hand tremors and actual movements. Such filtering software can be installed on a users' computer or be deployed dynamically in a website. Features of such systems include anti-tremor mouse filtering and removal of accidental mouse clicks, to name a few[2]. In addition, websites can be designed such that they can dynamically adjust to become more usable for people with hand tremors. Such systems provide interventions that include larger links, magnetic links (links that grab the mouse cursor when it gets close to them), and websites that are compatible with alternative input devices made for hand tremors (Riviere and Thakor 1996; Rotondi et al. 2007).

Our research is particularly relevant to the "digital compensations" area of research. Namely, we investigate whether the analysis of users' mouse cursor movements can be used to detect hand tremors. Using this method, websites would be capable of digitally adapting to the user to create a more enjoyable and accessible user experience.

3 Methodology

To answer our research question, we developed a study in which two groups of participants—those with hand tremors and those without hand tremors—navigated a website while mouse-cursor movements were monitored.

3.1 Participants

Participants were recruited from two sources. In order to find a large enough population of participants with hand tremors, we first recruited participants through the International Essential Tremor Foundation (IETF), a 501(c)3 non-profit organization that promotes and funds essential tremor (ET) research. These participants were pulled from a group of over 1,700 individuals. Second, to find additional participants with *and* without hand tremor, participants were recruited through Amazon's Mechanical Turk (MTurk). According to Berinsky et al. (2012), MTurk has been shown to be an appropriate participant recruitment tool for random sampling of populations.

A total of 200 individuals participated in this study. The average age of participants was 43.6 years, with 56% being male and 44% being female. Of this sample, 86.9% reported being White/Caucasian, 5.1% reported being Hispanic, 4.3% reported being Asian, 2.5% reported being African American, and 1.2% reported being other. Of those who participated, 35% stated that they currently have hand tremors. Seventy-

[1] http://ndipat.org/blog/computer-access-and-parkinsons-3-great-products-and-a-freebie/

[2] https://www.steadymouse.com/

five percent of those who identified as currently experiencing ET stated that they had experienced ET for longer than 10 years.

3.2 Study Design

Participants recruited through the IETF were provided a link to an online survey. Individuals recruited through MTurk were also provided the same link via MTurk's HIT system. This survey displayed IRB consent forms and informed participants that they could decline or stop participating in the study at any time. The survey also asked several questions, including a) whether they had hand tremors, b) if they were currently using software or a device to compensate for the tremors while participating in the study, and c) the severity of their tremors. Upon completion of this initial survey, a link was provided to a website for participants to interact with a fictitious online retailer. When leaving the survey system, a unique ID was passed with the link to the website in order to associate participants' interactions with the website with their survey responses.

At the website, participants were asked to complete one task. The mock e-commerce website had various interaction features typical of such sites (i.e., drop-down menus, buttons, links, forms, radio buttons, etc.). A sample screenshot from the mock e-commerce website is shown in Figure 1. While participants were navigating the website to complete the task, which included finding a specific product, adding the product to the cart, and simulating a checkout, mouse-cursor movements were captured. Upon completion of the task, participants were redirected to a short follow-up survey. The same unique ID that was passed from the initial survey to the mock e-commerce website was also passed from the website to the follow-up survey in order to link participants' interaction and self-report data. In this follow-up survey, participants answered questions regarding the website's ease of use and responded to several demographic-related questions.

3.3 Measuring Mouse Movement

In order to track participants' movements on the website, a JavaScript script was embedded into each page of the website. X, Y coordinates and timestamps were captured and stored to calculate various statistics such as velocity, acceleration, and distance throughout the interaction. Collecting the coordinates also allowed us to visualize the movements. A sample movement from a participant with tremors is shown in Figure 2. This method of capturing and storing mouse movement data and timestamps using a JavaScript script allowed participants to be tracked unobtrusively and allowed us to record the movements to a secure server for later analysis.

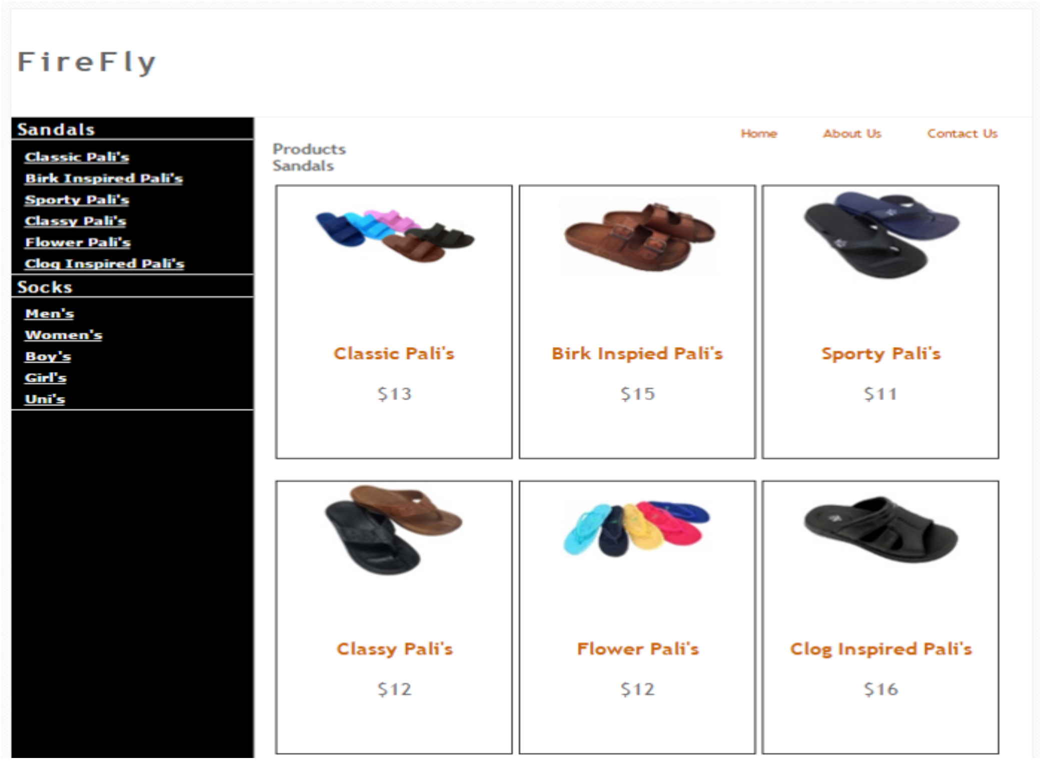

Figure 1. Screenshot from Website

Figure 2. A Sample Mouse Trail from a Participant with Tremors

4 Analysis

To explore how hand tremors influence mouse-cursor movements, we first calculated several statistics (see Tables 2 and 3). We then specified a multivariate general linear model that explored whether people who self-reported hand tremors had significantly different mouse cursor movement statistics than people who did not report having hand tremors. We removed any participants who reported that they were currently using a tremor mitigation technique during the study (special hardware or software). As displayed in Table 2, we found that tremors statistically influenced five different variables. We also found that tremors do not statistically influence the remaining five variables, as seen in Table 3.

Table 2. Variables Statistically Influenced by Tremors

Variable Name / Description	Z-Score	P-Value
Overall area under the curve3 normalized (divided) by speed	15.35	< .001
The total number of flips on the x axis	6.53	< .001
The total number of flips on the y axis	10.34	< .001
The average distance between destinations (clicks)	8.799	< .001
The average distance between destinations (clicks) normalized (divided) by speed	15.35	< .001

Table 3. Variables Not Statistically Influenced by Tremors

Variable Name / Description	Z-Score	P-Value
Overall area under the curve	0.757	> .05
The average area under the curve between destinations (clicks)	0.007	> .05
Overall distance	0.007	> .05
Overall distance minus the minimum distance required to perform a movement	1.395	> .05
Total time	0.007	> .05

5 Discussion

This research answered the following research question: *what characteristics of users' mouse-cursor movements detect if a user has hand tremors?* We found that five variables were significantly correlated with hand tremors, and therefore could be used as measures of actual behavior of hand tremors in this context rather than collecting self-report measures. Below, we discuss the implications of these findings for research and practice.

5.1 Implications for Research

We report a practical example of the use of movements that reflect both actual behavior and behavioral changes measured within an information technology usage context. Our work suggests that analyzing hand movements as an actual (rather than perceptual) measure of usage could enrich other areas of IS research (e.g., technology acceptance, efficacy, fear, etc.), in which perceptions of states and behavior are measured post hoc to the interaction and subject to the threats of various forms of response bias. Clearly, this approach suggests there are numerous research opportunities.

Within its specific health care IS context, this paper contributes to research by extending literature on hand tremor mitigation and mouse cursor tracking in several ways. First, past research has examined software and design principles for creating websites that are more accessible to people with hand tremors. However, very little research has explored how to detect if someone has hand tremors, which can be used to trigger these interventions. We contribute to this research by conducting exploratory research that will result in an easy-to-deploy and unobtrusive method for detecting hand tremors: the analysis of mouse-cursor movements.

Moreover, we contribute to literature on mouse-cursor tracking. In recent years, there has been increasing interest in studying mouse movements within the IS domain; for example, Hibbeln et al. (2017) examined the effects of negative emotion on mouse movements, Grimes et al. (2013) examined the effects of valence and arousal, and Jenkins and Valacich (2015) employed mouse movements to examine a system's ease of use.

[3] The total area bounded by the most direct path between two points (i.e., clicks) and users' actual path of movement.

Past mouse-cursor tracking research has focused on using mouse-cursor tracking as a substitute methodology for eye tracking or to infer psychological states (e.g., emotion, cognitive conflict, etc.). We extend this research to also explore how mouse cursor movement can be used not only to reliably infer emotional states (see Hibbeln et al. 2017), but also as a methodology for detecting other psychological states that are relevant to human-computer interaction. In sum, our work adds to the accumulating evidence of linking hand movements captured through mouse movements to various emotional and cognitive processes (Freeman et al. 2011; Grimes et al. 2013; Hibbeln et al. 2017).

5.2 Implications for Practice

Hand tremors can severely deter human-computer interactions, resulting in websites that are difficult to use or not accessible to users. Our research can be used to create adaptive websites that are more accessible to people with hand tremors. Namely, by unobtrusively monitoring mouse-cursor movement through imbedded JavaScript in the webpage, websites can potentially detect mouse-cursor movements and dynamically adjust to create a more accessible and enjoyable experience for users. For example, when tremors are detected, a website could make selecting regions larger and thus easier to click. Additionally, a plug-in could be added to a user's browser to intercept shaking motion, smoothing the movements on the screen, blocking unintentional mouse clicks, and snapping clicks to icons and links when the cursor is within a likely selection region (see www.steadymouse.com). Such improvements will not only improve the experience for users with hand tremors, but may also lead to increased use and revenue for the website. In a broader sense, our work serves to indicate that by measuring mouse movements, businesses and other organizations can gain a better understanding of the intent and feelings of their customers and users. This is a form of "digital body-language" and will increasingly serve to enhance interactions in an online setting, where traditional cues such as eye contact and body posture are not available. Digital body-language can be utilized for both risk mitigation in detecting potentially malicious actors and for prioritizing resources and enhancing service offerings for particular categories of customers, as we have demonstrated here.

6 Conclusion

There have been repeated calls to reemphasize the measurement of actual behaviors in behavioral sciences. We believe that these criticisms are also particularly relevant to HCI research. In this paper, we report a practical example of the use of movements that reflect both actual behavior and behavioral changes measured within an information technology usage context. Our work suggests that analyzing hand movements as an actual (rather than perceptual) measure of usage could enrich other areas of IS research (e.g., technology acceptance, efficacy, fear, etc.), in which perceptions of states and behavior are measured post hoc to the interaction and subject to the threats of various forms of response bias. Clearly, there is great potential for the further measurement of actual behaviors in the IS domain.

References

Baig, M. M., and Gholamhosseini, H. 2013. "Smart Health Monitoring Systems: An Overview of Design and Modeling," *Journal of Medical Systems* (37:2), p. 9898.

Bartoli, E., Caso, F., Magnani, G., and Baud-Bovy, G. 2017. "Low-Cost Robotic Assessment of Visuo-Motor Deficits in Alzheimer's Disease," *IEEE Transactions on Neural Systems and Rehabilitation Engineering* (25:7), pp. 852-860.

Baumeister, R. F., Vohs, K. D., and Funder, D. C. 2007. "Psychology as the Science of Self-Reports and Finger Movements: Whatever Happened to Actual Behavior?," *Perspectives on Psychological Science* (2:4), pp. 396-403.

Berinsky, A. J., Huber, G. A., and Lenz, G. S. 2012. "Evaluating Online Labor Markets for Experimental Research: Amazon. Com's Mechanical Turk," *Political Analysis* (20:3), pp. 351-368.

Boss, S., Galletta, D. F., Lowry, P. B., Moody, G., and Polak, P. 2015. "What Do Systems Users Have to Fear? Using Fear Appeals to Engender Threats and Fear That Motivate Protective Security Behaviors in Users," *MIS Quarterly* (December), pp. 837-864.

Burton-Jones, A., and Lee, A. S. 2017. "Thinking About Measures and Measurement in Positivist Research: A Proposal for Refocusing on Fundamentals," *Information Systems Research* (28:3), pp. 451-467.

Byrne, M. D., Anderson, J. R., Douglass, S., and Matessa, M. 1999. "Eye Tracking the Visual Search of Click-Down Menus," in: *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*. Pittsburgh, Pennsylvania, USA: ACM, pp. 402-409.

Castillejo, P., Martinez, J. F., Rodriguez-Molina, J., and Cuerva, A. 2013. "Integration of Wearable Devices in a Wireless Sensor Network for an E-Health Application," *IEEE Wireless Communications* (20:4), pp. 38-49.

Chapman, L. J. 1967. "Illusory Correlation in Observational Report," *Journal of Verbal Learning and Verbal Behavior* (6:1), pp. 151-155.

Cheng, H. T., and Zhuang, W. 2010. "Bluetooth-Enabled in-Home Patient Monitoring System: Early Detection of Alzheimer's Disease," *IEEE Wireless Communications* (17:1), pp. 74-79.

Crossler, R. E., Johnston, A. C., Lowry, P. B., Hu, Q., Warkentin, M., and Baskerville, R. 2013. "Future Directions for Behavioral Information Security Research," *Computers & Security* (32:Supplement C), pp. 90-101.

Davis, F. D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly* (13:3), pp. 319-340.

Dennis, A. R., and Valacich, J. S. 2001. "Conducting Experimental Research in Information Systems," *Communications of the AIS* (7(5):July).

Deuschl, G., Raethjen, J., Lindemann, M., and Krack, P. 2001. "The Pathophysiology of Tremor," *Muscle & Nerve* (24:6), pp. 716-735.

Dinesh, K., Xiong, M., Adams, J., Dorsey, R., and Sharma, G. 2016. "Signal Analysis for Detecting Motor Symptoms in Parkinson's and Huntington's Disease Using Multiple Body-Affixed Sensors: A Pilot Study," *2016 IEEE Western New York Image and Signal Processing Workshop (WNYISPW)*, pp. 1-5.

Fisher, R. J. 1993. "Social Desirability Bias and the Validity of Indirect Questioning," *Journal of Consumer Research* (20:2), pp. 303-315.

Freeman, J. B., and Ambady, N. 2011. "When Two Ecome One: Temporally Dynamic Integration of the Face and Voice," *Journal of Experimental Social Psychology* (47:1), pp. 259-263.

Freeman, J. B., Dale, R., and Farmer, T. A. 2011. "Hand in Motion Reveals Mind in Motion," *Frontiers in Psychology* (2:59).

Furr, R. M. 2009. "Personality Psychology as a Truly Behavioural Science," *European Journal of Personality* (23:5), pp. 369-401.

Garcia, R. G., Ballado, A. H., Paglinawan, A. C., Paglinawan, C. C., Gavino, R. B., Magcamit, B. A. J., Miranda, J. C. S., and Tiongson, M. F. 2016. "Hand Tremor Analyzer Using Accelerometry for Preliminary Diagnosis, Classification and Monitoring of Selected Movement Disorders," *2016 6th IEEE International Conference on Control System, Computing and Engineering (ICCSCE)*, pp. 392-396.

García-Magariño, I., Medrano, C., Plaza, I., and Oliván, B. 2016. "A Smartphone-Based System for Detecting Hand Tremors in Unconstrained Environments," *Personal and Ubiquitous Computing* (20:6), pp. 959-971.

Grimes, M., Jenkins, J., and Valacich, J. 2013. "Exploring the Effect of Arousal and Valence on Mouse Interaction," *International Conference on Information Systems*, Milan, Italy.

Hibbeln, M., Jenkins, J., Schneider, C., Valacich, J., and Weinmann, M. 2014. "Investigating the Effect of Insurance Fraud on Mouse Usage in Human-Computer Interactions," in: *International Conference on Information Systems*. Auckland, New Zealand.

Hibbeln, M., Jenkins, J. L., Schneider, C., Valacich, J. S., and Weinmann, M. 2017. "How Is Your User Feeling? Inferring Emotion through Human-Computer Interaction Devices," *MIS Quarterly* (41:1), pp. 1-21.

Holtzman, N. S., Vazire, S., and Mehl, M. R. 2010. "Sounds Like a Narcissist: Behavioral Manifestations of Narcissism in Everyday Life," *Journal of Research in Personality* (44:4), pp. 478-484.

Jenkins, J., and Valacich, J. 2015. "Behaviorally Measuring Ease-of-Use by Analyzing Users' Mouse Cursor Movements," *Special Interest Group on Human-Computer Interaction*, Fort Worth, TX.

Jenkins, J. L., Valacich, J. S., and Williams, P. A. 2017. "Mouse-Cursor Movement Indicators of Response Biases in Online Surveys," *International Conference on Information Systems*, Seoul, South Kore.

Leighton-Boyce, T. 2012. "Let Your Customers Tell You How to Make Your Site Better." Retrieved 8/1, 2013, from http://www.cxfocus.com/index.php/ecommerce-usability/customers-site/#sthash.XBxdP2cg.dpbs

Liljander, V., and Strandvik, T. 1997. "Emotions in Service Satisfaction," *International Journal of Service Industry Management* (8:2), pp. 148-169.

Lu, H.-P., and Yu-Jen Su, P. 2009. "Factors Affecting Purchase Intention on Mobile Shopping Web Sites," *Internet Research* (19:4), pp. 442-458.

Mannes, J. 2016. "Augmented Reality Computer Mouse Touchscreen Iphone Software: The Future of Human Computer Interaction Will Be Multimodal." Retrieved December 16, 2017, from https://techcrunch.com/2016/09/14/the-future-of-human-computer-interaction-will-be-multimodal/

Moody, G., and Galletta, D. F. 2015. "Lost in Cyberspace: The Impact of Information Scent and Time Constraints on Stress, Performance, and Attitudes," *Journal of Management Information Systems* (32:1), pp. 192-224.

O'Reilly, C., and Plamondon, R. 2012. "Design of a Neuromuscular Disorders Diagnostic System Using Human Movement Analysis," *2012 11th International Conference on Information Science, Signal Processing and their Applications (ISSPA)*, pp. 787-792.

O'Reilly, C., and Plamondon, R. 2011. "Can Computer Mice Be Used as Low-Cost Devices for the Acquisition of Planar Human Movement Velocity Signals?," *Behavior Research Methods* (43:1), pp. 229-238.

Panyakaew, P., Lavenstein, B., and Hallett, M. 2017. "Childhood Tremor: Electophysiological Evaluation and Clinical Correlates (P3.011)," *Neurology* (88:16 Supplement), p. P3.011.

Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., and Chrissikopoulos, V. 2014. "Shiny Happy People Buying: The Role of Emotions on Personalized E-Shopping," *Electronic Markets* (24:3), pp. 193-206.

Paulhus, D. L. 1991. "Measurement and Control of Response Bias," in *Measures of Personality and Social Psychological Attitudes,* J.P. Robinson, P.R. Shaver and L.S. Wrightsman (eds.). San Diego, CA: Academic Press, pp. 17-59.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., and Podsakoff, N. P. 2003. "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies," *Journal of Applied Psychology* (88:5), pp. 879-903.

Riviere, C. N., and Thakor, N. V. 1996. "Modeling and Canceling Tremor in Human-Machine Interfaces," *IEEE engineering in medicine and biology magazine* (15:3), pp. 29-36.

Rocon, E., Belda-Lois, J., Sanchez-Lacuesta, J., and Pons, J. 2004. "Pathological Tremor Management: Modelling, Compensatory Technology and Evaluation," *Technology and Disability* (16:1), pp. 3-18.

Rodden, K., Fu, X., Aula, A., and Spiro, I. 2008. "Eye-Mouse Coordination Patterns on Web Search Results Pages," in: *CHI '08 Extended Abstracts on Human Factors in Computing Systems*. Florence, Italy: ACM, pp. 2997-3002.

Rotondi, A. J., Sinkule, J., Haas, G. L., Spring, M. B., Litschge, C. M., Newhill, C. E., Ganguli, R., and Anderson, C. M. 2007. "Designing Websites for Persons with Cognitive Deficits: Design and Usability of a Psychoeducational Intervention for Persons with Severe Mental Illness," *Psychological Services* (4:3), p. 202.

Schuman, H., and Presser, S. 1981. *Questions and Answers in Attitude Surveys: Experiments on Question Form, Wording, and Context*. Thousand Oaks, California: Sage.

Seo, K., Kim, J.-k., Oh, D. H., Ryu, H., and Choi, H. 2017. "Virtual Daily Living Test to Screen for Mild Cognitive Impairment Using Kinematic Movement Analysis," *PLOS ONE* (12:7), p. e0181883.

Stephens, S. 2011. "Essential Facts About Essential Tremor: This “Quiet” Disease, Which Affects 10 Million Americans, Is Anything but Benign," *Neurology Now* (7:1), pp. 21-23.

Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., and Ragu-Nathan, T. 2007. "The Impact of Technostress on Role Stress and Productivity," *Journal of Management Information Systems* (24:1), pp. 301-328.

Unsworth, N., and Spillers, G. J. 2010. "Working Memory Capacity: Attention Control, Secondary Memory, or Both? A Direct Test of the Dual-Component Model," *Journal of Memory and Language* (62:4), pp. 392-406.

Venkatesh, V. 2000. "Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model," *Information Systems Research* (11:4), pp. 342-365.

Venkatesh, V., Brown, S. A., and Bala, H. 2013. "Bridging the Qualitative-Quantitative Divide: Guidelines for Conducting Mixed Methods Research in Information Systems," *MIS Quarterly* (37:1), pp. 21-54.

Williams, P. A., Jenkins, J. L., and Valacich, J. S. 2016. "Real-Time Hand Tremor Detection Via Mouse Cursor Movements for Improved Human-Computer Interactions: An Exploratory Study," *Workshop on the SIG HCI*, Fort Worth, TX.

Wilson, V., and Djamasbi, S. 2015. "Human-Computer Interaction in Health and Wellness: Research and Publication Opportunities," *AIS Transactions on Human-Computer Interaction* (7:3), pp. 97-108.

About the Authors

Parker Williams is a doctoral student in Management Information Systems at the University of Arizona. His research focuses on human-computer interaction in the context of the detection of deception, physical impairments, and emotional arousal. He also studies how human-computer interaction movement indicators influence survey research and form optimization. Parker has previous experience as a software engineer and web developer.

Jeffrey Jenkins. Jeff is an assistant professor of Information Systems at Brigham Young University and is an expert in detecting human states using computer input devices. He has developed and extensively validated algorithms to detect deception, cognitive conflict, uncertainty, and emotional reactions while people are using electronic devices. Jeff's research also explores methodologies for detecting and mitigating insider security threats—i.e., a trusted member of an organization who poses an information security risk because of ignorance, negligence, or malicious intent. His research has been published in top academic journals and conference proceedings, including *MIS Quarterly*, *Information Systems Research*, *Journal of Management Information Systems*, and *ACM CHI Conference on Human Factors in Computing Systems* (CHI). Jeff earned his Master's degree in Management Information Systems from Brigham Young University and his PhD in Information Systems Management from the University of Arizona. Prior to his career in academia, he was a software engineer.

Joseph (Joe) Valacich is the *Eller Professor of Management Information Systems* within the Eller College of Management at the University of Arizona, a Fellow of the Association for Information Systems (2009), and the Chief Science Officer (CSO) of Neuro-ID, Inc. Dr. Valacich is a prolific scholar, publishing more than 100 scholarly articles in numerous prestigious journals. His work has had a tremendous impact on several disciplines, including information systems, computer science, psychology, marketing, and management. In December 2017, Google Scholar lists his citation counts over 21,500, with an H-index of 66. He has several pending patents related to identifying emotional state changes and indecision using human-computer interaction data. He has also coauthored several leading textbooks.

Michael Byrd. Michael is a doctoral student in Management Information Systems at the University of Arizona. His research focuses on human-computer interaction in the context of the detection of deception, emotional arousal, and other mental states. He also studies the use of computational linguistics in deception detection, fraud detection, and judgment and decision making. Michael is a Certified Public Accountant and a Certified Fraud Examiner and has extensive previous experience as a forensic accountant, fraud investigator, forensic data analyst, and software engineer.

Transactions on Human – Computer Interaction