Association for Information Systems
AIS Electronic Library (AISeL)

SIGHCI 2015 Proceedings

Special Interest Group on Human-Computer Interaction

12-13-2015

Behaviorally Measuring Ease-of-Use by Analyzing Users' Mouse Cursor Movements

Jeffrey Jenkins
Brigham Young University, jjenkins@byu.edu

Joseph Valacich
University of Arizona, valacich@arizona.edu

Behaviorally Measuring Ease-of-Use by Analyzing Users' Mouse Cursor Movements

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

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

ABSTRACT

Ease-of-use—the extent to which a technology is free of effort—is a hallmark of many successful websites and is a predictor of important user outcomes including intentions to use a system and a system's perceived usefulness. We propose a behavior-based measure of ease-of-use based on the analysis of users' mouse cursor movements. As a basis for this measure, we explain how ease-of-use influences the precision of users' mouse cursor movements, extending Attentional Control Theory and the Response Activation Model. We propose two mousing statistics—Normalized Area under the Curve and Normalized Additional Distance—and predict that they are correlated with PEOU and can be used to differentiate ease-of-use among different tasks. We end by describing next steps to test our hypotheses and highlight potential implications.

Keywords

Ease-of-use, normalized area under the curve, normalized additional distance, response activation model, attentional control theory, mouse cursor movements

INTRODUCTION

Ease-of-use—the extent to which a technology is free of effort (Davis, 1989)—is a hallmark of many successful systems and websites. In an era of instant information and online services, ease-of-use (EOU) is particularly salient and important. If users cannot quickly accomplish their goal with minimal effort, they will often leave a website. A study of 205,873 webpages, each with over 10,000 visits, found that users are most likely to abandon a webpage within the first 10 seconds; notably, with low EOU being a key contributor to abandonment (Nielsen Norman Group, 2011). Studies have shown that minimizing effort is generally more important to users than maximizing the quality of information they find (e.g., Griffiths and Brophy, 2005). Further, websites that lack EOU often discourage continued use (Venkatesh, 2000). Given its importance, billions of dollars are spent annually on usability testing to make user interfaces easier to use.

To understand system acceptance and improve interface usability, researchers and practitioners use various measures to assess EOU. One common measure of EOU is *perceived ease-of-use* (PEOU)—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 is typically measured through surveys or other self-report instruments (Venkatesh, 2000). It 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 asking self-report measures can be perceived as being an interruption, annoying, cumbersome, or time-consuming. As a result, asking survey questions on live websites can yield low response rates and are often biased toward those who had highly positive (or negative) experiences (Leighton-Boyce, 2012).

To help address these challenges of self-report instruments, research has stressed the importance of obtaining measures of actual behaviors (e.g., Baumeister, Vohs and Funder, 2007). This paper proposes that EOU can be behaviorally measured by analyzing users' mouse cursor movements[1], providing an unbiased, non-invasive, continuous, mass-deployable EOU measure. Mouse cursor movements have been suggested to provide "high-fidelity, real-time motor traces of the mind [and] can reveal 'hidden' cognitive states that are otherwise not availed by traditional measures" (Freeman and Ambady, 2011). Extending *Attentional Control Theory* (Coombes, Higgins, Gamble, Cauraugh and Janelle, 2009) and the *Response Activation Model* (Welsh and Elliott, 2004), we explain how lower EOU causes users' mouse movement precision to decrease. We define, and then empirically test, indicators of movement precision that can be

[1] Cursor movements may be captured via a computer mouse, touchpad, touchscreen, or other computer input devices controlled by the hand. For parsimony, the paper's scope focuses primarily on indicators of ease-of-use that can be captured by the computer mouse, although evidence exists that other input devices (e.g., touchscreens, touchpads, in-air sensors such as the Microsoft Kinect, game controllers, accelerometers and gyros in smart phones) may also provide rich information about cognitive and emotional stats.

automatically analyzed from users' mouse cursor movements using JavaScript embedded in webpages.

In summary, we explore the following research question: 1) how does EOU influence users' mouse cursor movements.

LITERATURE REVIEW

PEOU (Davis, 1989) is one of the most common and validated perceptual measures of effort when examining technology acceptance. Since its inception, PEOU has been examined or referenced in thousands of studies, and shown to influence a wide variety of important user outcomes, such as initial user acceptance and continued system use (Venkatesh, 2000). A meta-analysis conducted on the technology acceptance model (TAM) concluded that the influence of PEOU on behavioral intentions can vary depending on a system's characteristics. Based on the 67 papers examined, 30 (~45%) reported a non-significant relationship ($p > 0.05$ level) between PEOU and behavioral intentions (King and He, 2006). In this analysis, PEOU was found to primarily influence behavioral intentions through the mediator of perceived usefulness (average $\beta = 0.479$, $z = 12.821$, $p < .001$, $n = 12{,}263$). However, when accounting for the type of system usage (e.g., job-office applications, general, and ecommerce / internet applications), PEOU was found to be "very important…in internet applications" (pg. 751), almost always significant when predicting behavioral intentions. Additionally, when system use is an internet application, the effect size is nearly double that of other system use-types (average $\beta = 0.258$, $z = 5.646$, $p < .001$, $n = 4{,}472$) (King and He, 2006). Clearly, EOU is a critical aspect of internet / e-commerce adoption.

In many situations, PEOU provides an ideal measure of EOU. However, as with *all* instruments, self-report measures present some challenges in certain scenarios, and particularly when evaluating the EOU of systems in real-world, non-controlled settings. For example, some commercial websites solicit visitors to complete an online survey at the end of an interaction to capture usability measures. Typically, response rates are low (often only 2-5%) and are frequently biased toward extremely positive or negative experiences (Leighton-Boyce, 2012). Further, if surveys are solicited too often, they may be perceived as annoying, possibly discouraging future use of the system. In some situations, such self-report measures may also be influenced by social-desirability bias , priming / wording bias (having the question prime thoughts that would normally not have been primed otherwise, Schuman and Presser, 1981), or availability bias (having one thought—e.g., a single hard to use system component—unproportionately bias one's overall evaluation because it is brought to mind easier, Chapman, 1967).

To help address these challenges, research has repeatedly stressed the need to corroborate self-report measures with behavior-based measures (e.g., Baumeister et al., 2007). This paper proposes that users' mouse cursor movements can be used to behaviorally measure EOU and can be collected unobtrusively in users' natural settings. Previous research in neuroscience and psychology has unequivocally demonstrated that linkages exist between cognitive processing and hand movements. Of interest to this study, monitoring mouse cursor movements can give insight into how users devote their attention during system use. For example, research has suggested that "attention and action are intimately linked" (Welsh and Elliott, 2004), mouse cursor movements giving insight into where users' devote their attention (Guo and Agichtein, 2010) and where the eye is gazing (Chen, Anderson and Sohn, 2001; Guo and Agichtein, 2010).

Our research extends this past literature by drawing on *Attentional Control Theory* to explain how EOU influences users' attention and thereby mouse cursor movements. Attentional Control Theory (ACT) (Eysenck, Derakshan, Santos and Calvo, 2007) was initially used to explain how anxiety influences attentional control and thereby cognitive performance. *Attentional control* refers to peoples' ability to choose what they pay attention to and what they ignore. As people experience anxiety, their attention shifts from being goal-directed to being stimulus-driven in search for threat-stimuli in the environment. This results in a greater "distribution of attentional resources toward threat-related stimuli at the expense of attention allocated to the task" (Hwang, Hong, Cheng, Peng and Wu, 2013). In neurological terms, anxiety decreases the efficiency of the brain's attentional inhibition and shifting functions, which decreases attentional control. *Inhibition* refers to the function of the brain that prevents stimuli unrelated to a task from capturing a person's attention. *Shifting* is used to allocate attention to the stimuli that are most relevant to a task. The theory further posits that processing more stimuli in the environment reduces the processing and storage capacity of the center processing unit of working memory, which may therefore decrease cognitive performance (Eysenck et al., 2007).

HYPOTHESES

We extend literature on mouse cursor tracking and ACT by hypothesizing how EOU influences attentional control and thereby decreases the precision of mouse cursor movements. We then define two behavioral measures of mouse-movement precision, hypothesizing how EOU influences each measure.

Ease-of-Use and Attentional Control

We propose that lower EOU elicits a shift in attention from being goal-directed to being stimulus-driven, which decreases attentional control. ACT suggests that "stimuli may produce anxiety in participants who perceive them as interfering with performance or as signaling a difficult task" (Eysenck et al., 2007). Lower EOU is one such barrier that may interfere with performance or signal that a task is more difficult than desired, and thereby induce anxiety. As such, consistent with ACT, lower EOU may result in anxiety, which will decrease attentional control (Eysenck et al., 2007).

Furthermore, per the principle of least effort, people have a natural tendency to divert their attention from high-effort tasks [2]. The principle of least effort suggests that people naturally prefer and choose the path of least resistance or effort (Zipf, 1949). The principle is based on the premise that humans have limited resources (e.g., time, cognitive effort, and abilities), and choose alternatives that will minimize effort and thereby free resources for other tasks (Case, 2012). This tendency to free resources is almost always present (Zipf, 1949). Even if other tasks are not currently competing for resources, humans will naturally free resources so that they are available for future use, such as responding to unanticipated events (Case, 2012). People's desire to minimize effort is shown to be often greater than their desire to achieve an optimal solution (e.g., Griffiths and Brophy, 2005).

One's tendency to avoid a behavior increases as the effort associated with that behavior increases (Zipf, 1949). As effort increases, more cognitive resources are consumed and the brain is less capable of responding to other, sometimes important, stimuli. Hence, as effort increases, people are more motivated to find ways to accomplish the goal with less effort and are more easily diverted by less effortful tasks (Zipf, 1949). To search for a path of less resistance, people distribute their attentional resources toward stimuli in the environment, decreasing the brain's attentional inhibition and shifting functions. This is often described as the information search stage in the ill-structured problem solving process, which involves exploring the problem space and task environment for possible solutions. While allowing people to discover less resistant paths of goal attainment, the decreased inhibition and shifting functions also decrease attentional control. People are less able to focus their attention on the task at hand, and are more likely to give attention to other stimuli in the environment.

[2] Effort resulting from lower ease-of-use should not be confused with challenge. Challenge is defined as an efficacy motivation that leads an individual to develop competence and feelings of self-efficacy in dealing with one's environment. Effort is defined as strenuous physical or mental exertion. Whereas challenge may increase attention to a stimulus, effort decreases attention to a stimulus (Eysenck et al., 2007). Furthermore, effort and challenge are not mutually exclusive; challenge may include motivation to find a less-effortful way to accomplish a task.

Attentional Control and Movement Precision

A decrease in attentional control leads to a decrease in movement precision. The Response Activation Model (RAM) (Welsh and Elliott, 2004) explains that all stimuli (e.g., a link, image, etc.) with actionable potential that capture a user's attention will prime movement responses (Song and Nakayama, 2008). To *prime* a movement response refers to subconsciously programming an action (transmitting nerve impulses to the hand and arm muscles) toward or away from the stimulus. This priming causes the hand to deviate from its intended movement (i.e., decreases the precision of movement), as the observed hand movement is a product of all primed responses, both intended and non-intended (Welsh and Elliott, 2004). For example, if one is intending to move the mouse cursor to a destination on the page, and other stimuli on the page catch the user's attention, the hand will prime movements toward these other stimuli. Together, this priming will cause the trajectory of movement to deviate from the path leading directly to the intended destination. Throughout the movement, the brain will compensate for these departures by automatically programming corrections to the trajectory based on continuous visual feedback, ultimately reaching the destination (Welsh and Elliott, 2004). In summary, decreased attentional control caused by lower EOU will result in less precise movements.

Measuring Precision

To measure precision while a user interacts with a live website requires several adaptations to existing mousing statistics used in past literature. Much of the extant mouse tracking literature has been conducted in highly-controlled studies that examine psychological phenomenon. For example, in one experiment (Freeman and Ambady, 2011), participants were asked to classify faces as male or female. They would click a button at the bottom center of the screen to see the face, then move the mouse to the upper left or right corners of the screen to select the correct sex. The studies then measure how various manipulations (e.g., typical and atypical voices that accompany the face) influence mouse movement trajectories.

In such studies, precision can be measured by drawing a straight line from the bottom button (where each trial starts) to the correct answer in one of the upper-corners of the screen. This straight line is often referred to as the *idealized response trajectory*, representing the shortest line between the beginning and ending point. The amount of deviation between the idealized response trajectory and one's actual trajectory is calculated to assess precision. Two common measures of deviation include the A*rea Under the Curve (AUC)* and *Additional Distance (AD).* AUC refers to the geometric area between the actual mouse trajectory and the idealized response trajectory; it is a measure of total deviation from the idealized response trajectory. AD refers to the distance a user's mouse cursor travels on the screen minus the distance that it would have required along the idealized response trajectory. Figure 1 graphically depicts AUC and AD.

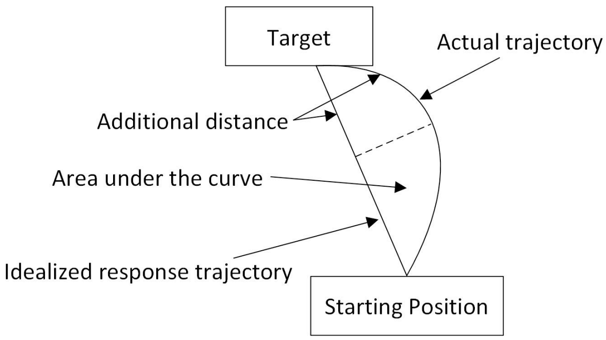

Figure 1. AUC and AD for an example movement

Measuring precision in a webpage, however, is considerably different than measuring precision in these highly controlled experiments. Namely, users may freely browse a webpage to accomplish a task. As such, they may have several destinations on a page they intend to move towards (rather than just one in an upper corner of the page). Furthermore, the starting position of the mouse is not limited to the bottom center of the screen. To accommodate for these differences, we propose two modifications to the measures used in prior highly controlled studies.

First, we used two heuristics (described below) to automatically generate a personalized idealized response trajectory for each person that may include multiple endpoints on a page. When people navigate a webpage, they may intend to move the mouse toward multiple destinations on a page (rather than just one as in the controlled experiments). For example, a person may move the mouse to enter information in an input box, click on a button, examine a piece of information, or interact with a variety of other webpage components before leaving the page. To measure precision of one's movements, the idealized response trajectory should include lines between all points a user intends to visit on a page, and this may be different for every user.

While automatically computing this complex idealized response trajectory with complete accuracy is likely impossible, we used two heuristics to determine the different endpoints on a page for each user. First, if a person *clicks* on a target, we assumed that the location of the click is likely a location the user intended to reach, treating this as an endpoint. Second, if a person stops moving the mouse, we assume this point likely denotes the end of a continuous movement. Again, while no heuristic can be perfect, we propose that these will generate a more accurate estimation of the idealized response trajectory than only using where the person entered and exited the page. In the methodology section, we evaluate the utility of these heuristics in calculating mouse movement precision.

Second, we normalize AUC and AD by the distance of the idealized response trajectory for each person (e.g., total area under the curve divided by the idealized response trajectory distance). Even under optimal circumstances, all hand movements naturally will vary somewhat from a person's idealized response trajectory due to neuromotor noise—i.e., natural variability in the neuromotor channel that prevents someone from making perfectly precise intended movements. As AUC and AD are additive, they will therefore naturally be larger for movements that have longer idealized response trajectories. For example, if people hypothetically have an additional distance of 10 pixels for every 100 pixels due to normal neuromotor noise, traveling a distance of 1000 pixels may have an additional distance of 100 pixels, whereas traveling a distance of 500 pixels may have an additional distance of 50 pixels, without one being more or less precise than the other. To account for this, we divide a person's AUC and AD by the distance of the idealized response trajectory for that person. This results in a ratio of the amount of deviation. Because our AUC and AD are normalized, we name them Normalized Area Under the Curve (NAUC) and Normalized Additional Distance (NAD) to differentiate them from the past literature.

Combining these three adapted measures with our prior argument that lower EOU will decrease the precision of movement, we predict that lower EOU will cause an increase in NAUC and NAD. In summary, we predict:

> H1: NAUC is negatively correlated with EOU.
>
> H2: NAD is negatively correlated with EOU.

NEXT STEPS

We will test these hypotheses using a field test of a commercial software. We will have participants complete several tasks using different features of the software. After each task, we will have people report the perceived ease-of-use of the software feature. We will then explore if perceived ease-of-use, NAUC, and NAD are correlated. We will also explore the degree to which NAUC and NAD can predict which tasks had the lowest ease-of-use.

CONTRIBUTION

This research reports a novel methodology for conducting multi-method research and cost-effective usability testing using NAUC and NAD, and thereby provides an approach for improving the study and design of systems. We contribute to mouse cursor movement literature by defining two different measures of movement precision that can be analyzed to infer EOU. Traditional measures of area under the curve and additional distance are often used to indicate deviation from the idealized response trajectory in highly controlled experiments—e.g., moving the mouse from the bottom of the screen to choose between two competing responses located in the upper corners of the screen. We adapt these measures to a new context: measuring mouse cursor movement precision during free navigation of a system. To do this, we made several computational adjustments to the statistics that represent methodological contributions. First, instead of comprising the idealized response trajectory from only one pair of points (the starting and ending point), we comprise it of potentially multiple point pairs (determine through heuristics) because people may intentionally navigate to multiple areas of a page. Second, we normalize area under the curve and additional distance by the distance of the idealized response trajectory.

CONTRIBUTION

In this paper, we proposed a behavior-based measure of ease-of-use based on the analysis of users' mouse cursor movements. Based on Attentional Control Theory and the Response Activation Model, we explain how ease-of-use influences the Normalized Area under the Curve and Normalized Additional Distance of users' mouse cursor movements. We propose that these mouse movement indicators of ease-of-use can be used to conduct objective, multi-method, and continuous-measurement research and benefit practice through enabling mass-deployable usability testing.

REFERENCES

1. 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, 396-403.
2. Case, D. (2012) *Looking for Information: A Survey of Research on Information Seeking, Needs and Behavior. 3rd ed*. Bingley, UK: Emerald Group Publishing.
3. Chapman, L.J. (1967) Illusory Correlation in Observational Report, *Journal of Verbal Learning and Verbal Behavior*, 6, 1, 151-155.
4. Chen, M.C., Anderson, J.R., and Sohn, M.H. (2001) What Can a Mouse Cursor Tell Us More?: Correlation of Eye/Mouse Movements on Web Browsing, in: *CHI '01 Extended Abstracts on Human Factors in Computing Systems*. Seattle, Washington: ACM, 281-282.
5. Coombes, S.A., Higgins, T., Gamble, K.M., Cauraugh, J.H., and Janelle, C.M. (2009) Attentional Control Theory: Anxiety, Emotion, and Motor Planning, *Journal of Anxiety Disorders*, 23, 8, 1072-1079.
6. Davis, F.D. (1989) Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, *MIS Quarterly*, 13, 3, 319-340.
7. Eysenck, M.W., Derakshan, N., Santos, R., and Calvo, M.G. (2007) Anxiety and Cognitive Performance: Attentional Control Theory, *Emotion*, 7, 2, 336-353.
8. Freeman, J.B., and Ambady, N. (2011) When Two Become One: Temporally Dynamic Integration of the Face and Voice, *Journal of Experimental Social Psychology*, 47, 1, 259-263.
9. Griffiths, J.R., and Brophy, P. (2005) Student Searching Behavior and the Web: Use of Academic Resources and Google, *Library Trends*, 53, 4, 539-554.
10. Guo, Q., and Agichtein, E. (2010) "Towards Predicting Web Searcher Gaze Position from Mouse Movements," *CHI'10 Extended Abstracts on Human Factors in Computing Systems*, Austin, TX: ACM, 3601-3606.
11. Hwang, M.-Y., Hong, J.-C., Cheng, H.-Y., Peng, Y.-C., and Wu, N.-C. (2013) Gender Differences in Cognitive Load and Competition Anxiety Affect 6th Grade Students' Attitude Toward Playing and Intention to Play at a Sequential or Synchronous Game, *Computers & Education*, 60, 1, 254-263.
12. King, W.R., and He, J. (2006) A Meta-Analysis of the Technology Acceptance Model, *Information & Management*, 43, 6, Sep, 740-755.
13. 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
14. Nielsen Norman Group. (2011) How Long Do Users Stay on Web Pages? Retrieved August 14, 2013, from http://www.nngroup.com/articles/how-long-do-users-stay-on-web-pages/
15. Schuman, H., and Presser, S. (1981) *Questions and Answers in Attitude Aurveys: Experiments on Question Form, Wording, and Context*. Thousand Oaks, California: Sage.
16. Song, J.H., and Nakayama, K. (2008) Target Selection in Visual Search as Revealed by Movement Trajectories, *Vision Research*, 48, 7, 853-861.
17. 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, 342-365.
18. Welsh, T.N., and Elliott, D. (2004) Movement Trajectories in the Presence of a Distracting Stimulus: Evidence for a Response Activation Model of Selective Reaching, *The Quarterly Journal of Experimental Psychology*, 57, 6, 1031-1057.
19. Zipf, G.K. (1949) *Human Behavior and the Principle of Least Effort*. Oxford, England: Addison-Wesley Press.