Exploring the Effect of Arousal and Valence on Mouse Interaction

Completed Research Paper

G. Mark Grimes
University of Arizona
1130 East Helen Street
Tucson, AZ 85721
mgrimes@cmi.arizona.edu

Jeffrey L. Jenkins
Brigham Young University
783 TNRB
Provo, UT 84602
jjenkins@byu.edu

Joseph S. Valacich
University of Arizona
1130 East Helen Street
Tucson, AZ 85721
jvalacich@cmi.arizona.edu

Abstract

Determining a user's affective state can be an important element when trying to understand human-computer interactions. Accurately assessing affect during system use, however, can be very difficult, especially in a non-laboratory setting. Extensive previous research in neuroscience has shown that arousal and valence influence motor control. In this research, the prior relevant neuroscience findings inform the investigation of mouse movement behavior under conditions of low and high arousal as well as positive and negative valence. A controlled laboratory experiment was conducted, providing support for hypotheses predicting that arousal and valence may be inferred by monitoring for differences in the distance, speed, and trajectory of mouse movement. Implications of these results for future research and practice are explored.

Keywords: Human-Computer Interaction, Mouse Dynamics, Affective Computing

Introduction

Affect, often defined as the interaction of arousal and valence, plays an important role in understanding human-computer interactions. Positive affect can increase information system (IS) use (e.g., Beaudry and Pinsonneault 2010; Bhattacherjee 2001) as well as important IS outcomes, such as purchase intentions (Bai et al. 2008), information disclosure (Anderson and Agarwal 2011), IT evaluations and success (Briggs et al. 2008; Zhang 2007), and technology acceptance (Zhang et al. 2006). One way to encourage positive affect is through strategic system design—e.g., proper design of user interfaces (Deng and Poole 2010) and human-computer interactions (Derrick et al. 2011). As such, there is need to develop instruments that aid designers in understanding how design decisions influence users' affective responses.

Determining a user's affective state can be an important element of system interactions. Accurately assessing users' affect during system use, however, can be very difficult, especially in a non-laboratory setting. In face-to-face interactions, behavioral observers can watch users interact with a system and identify affective responses (e.g., frustration, excitement, etc.) at specific points during the interaction (Rubin and Chisnell 2008). Alternatively, studies conducted in laboratories may utilize neuroscience tools to infer affective responses during system use, such as functional magnetic resonance imaging (fMRI), Electroencephalography (see Dimoka et al. 2012), or eye tracking devices (e.g., Cyr et al. 2009). However, these tools are of limited applicability if tests are to be completed remotely—i.e., usability testing of web sites in the 'wild' (Waterson et al. 2002)—or if budgets prohibit the use of expensive NeuroIS tools. Hence, in these situations, researchers must often rely on self-report measures that can be susceptible to biases such as social desirability, subjectivity, and common method bias, assuming that users are even aware of their affect (Dimoka et al. 2011; Lopatovska and Arapakis 2011).

To address these limitations, a cost-effective method for inferring affect through analysis of users' mouse movements is explored. Specifically, this research examines whether it is possible to infer both valence and arousal—two common dimensions of affect (Russell and Barrett 1999) operationally defined in this study as feelings of happiness or sadness and activation from excited to calm—through analyzing mouse movements. Past neuroscience research has unequivocally demonstrated that cognitive and emotional responses continuously influence hand movements (e.g., see Freeman et al. 2011 for review). Preliminary research on mouse movements has also suggested that changes in valence and/or arousal may lead to changes in mouse movements, although these results are inconclusive (e.g., Maehr 2008; Zimmermann et al. 2006; Zimmermann et al. 2003). This study builds on the prior research by answering the following research question:

> *RQ: How does high vs. low arousal and positive vs. negative valence influence mouse movements?*

Next, an overview of the extensive literature in neuroscience that suggests valence and arousal influence fine motor control (e.g., movement of the hand), which should be reflected in one's mouse movements, is explored. This is followed by a description of a controlled experiment in which arousal and valence are manipulated while precise mouse movement and timing data are recorded. Next, the analysis and results of the study are presented; the paper concludes by exploring the implications of the results, potential applications of this technology, and directions for future research.

Literature Review

Affect has long been described as an interaction of valence and arousal (Wundt 1896). Research in the area of affect has evolved over the years to incorporate measures of hedonic valence ranging from unpleasant to pleasant, and measures of arousal ranging from unaroused/calm to highly aroused/excited (Osgood et al. 1957). Previous research has indicated these measures of affect are strongly linked to the appetitive and defensive systems in the brain (Lang and Bradley 2007; Lang 1995). As will be described below, this suggests that valence and arousal may also manifest as changes in motor control and thereby mouse movement behavior. If so, this will provide a powerful tool for inferring affect during system use. The current study leverages extensive literature in neuroscience, physiological responses, and motor skill activation as a theoretical base for how arousal and valence influence mouse movement.

Motor movements were once thought to be the end-result of cognitive processing. Recent research, however, is finding that cognitive and affective processing influence motor movement on an ongoing and continuous basis, even as mental processes are still unfolding (Figure 1). According to Freeman et al. (2011 p. 1), the "movements of the hand, however, offer continuous streams of output that can reveal ongoing dynamics of processing, potentially capturing the mind in motion with fine-grained temporal sensitivity."

Figure 1. Relationship Between Affective System and Motor Movements
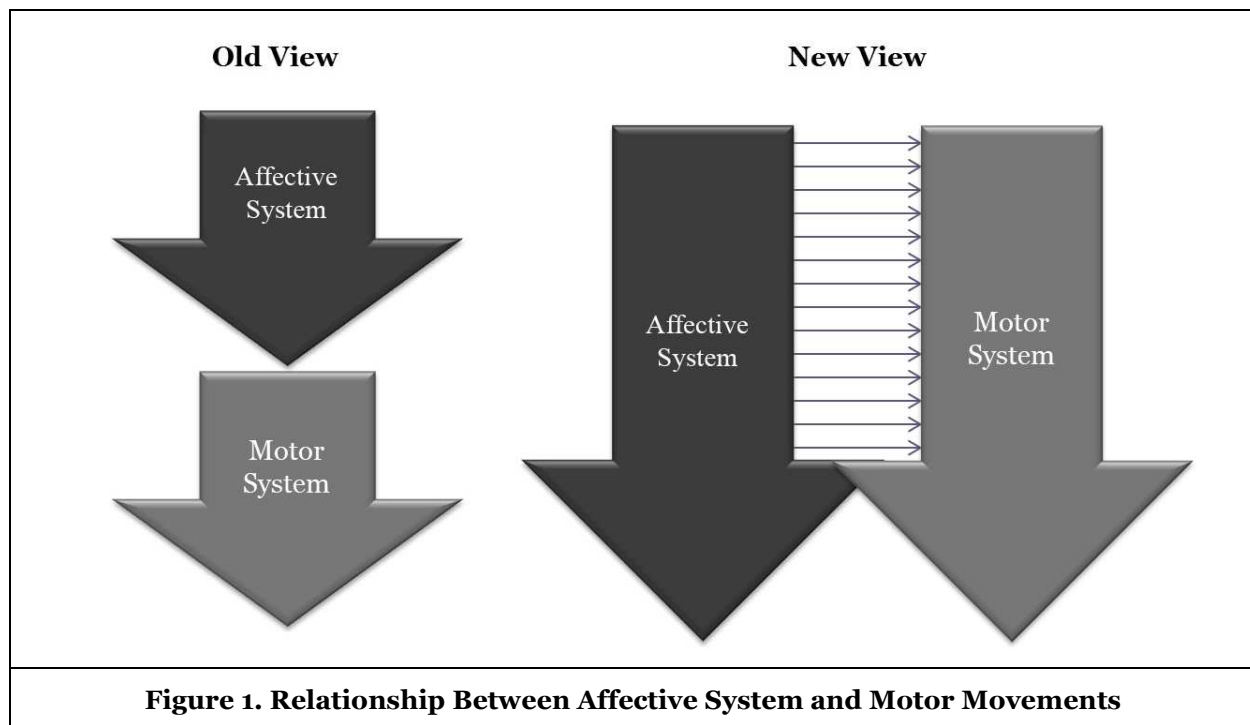
Research in neuroscience and psychophysiology has shown that affect can have a significant impact on motor movements of individuals—e.g., hand movements. Several studies have demonstrated that when an individual experiences an affective reaction, this reaction will immediately influence the parts of the brain and spinal cord that are responsible for motor movements (see Table 1). Similarly, changes in valence and arousal have been shown to increase excitability in the motor track, leading to stimulation that is indicative of potential movement (e.g., Tanaka et al. 2012; van Loon et al. 2010). Valence and arousal can also lead to motor evoked potentials (MEP) - electrical signals measured on the muscles - that indicate potential movement (e.g., Coelho et al. 2010; Coombes et al. 2009). Finally, both force production and reaction time have been found to be influenced by the valence and arousal of an experience (Coombes et al. 2008; Coombes et al. 2009; Naugle et al. 2012), impacting the performance of both fine and gross motor control (Yoshie et al. 2009).

| Table 1. Sample of Recent Articles Demonstrating that Affect Influences Motor Behavior			
Citation	**Dependent Variable**	**Influence on Motor Movement / Potential Motor Movement**	
		Increased Arousal	**Negative Valence**
(Smith and Kornelsen 2011)	Ventral cervical spinal cord activity		Increase
(Hajcak et al. 2007)	Cortex Excitability	Increase (regardless of valence)	Unaffected
(Coombes et al. 2008)	Force production		Increase (the same as positive valence though)
(Yoshie et al. 2009)	Fine motor skill performance	Decrease	Decrease
(Coombes et al. 2009)	Reaction time Force amplitude Motor evoked potential		Decrease Increase Increase
(Sharma 2011)	Fine motor control	Decrease	
(van Loon et al. 2010)	Corticospinal excitability		Increase (more so than positive images)
(Pereira et al. 2010)	Midcingulate cortex influence on motor movements (interaction between emotion and movements)		Increase
(Sagaspe et al. 2011)	Voluntary inhibition Reaction times (suppression of current or planned actions to afford adapted behavioral responses)	Unaffected Increased	Unaffected Increased
(Coelho et al. 2010)	Corticomotor excitability [action readiness] Motor evoked potentials		Increase Increase
(Franken et al. 2008)	Cognitive processing		The same as positive valence
(Oathes et al. 2008)	Corticospinal motor responses	Increased	Increase
(Naugle et al. 2012)	Force production		Increase
(Coombes et al. 2011)	Force production		Increase
(Tanaka et al. 2012)	Motor tract (CST) excitability Fine motor skill performance	Increase Decrease	Increase Decrease
(McIver et al.)	Cervical spinal cord activity		Increase

A small amount of previous research has examined how valence and arousal directly influence mouse movements (e.g., Maehr 2008; Zimmermann et al. 2006; Zimmermann et al. 2003). For example, in an experiment that manipulated valence through videos (which has been questioned as an effective affect manipulation as videos contain additional elements that may complicate and confound the manipulation (Lang and Bradley 2007)), Maehr (2008) found that arousal, but not valence, influenced mouse movements. This research seeks to better understand the interaction and relationship between how high and low arousal, and positive and negative valence, influence mouse movements through both theory development and empirical Investigation.

Theoretical Development

This research proposes a theoretical foundation for inferring high vs. low arousal and positive vs. negative valence from mouse movements by building on the Stochastic Optimized Submovement (SOS) model (Meyer et al. 1988; Meyer et al. 1990). The SOS model explains that fine motor skill movements (i.e., hand and mouse movements) are composed of multiple applications of force and direction. Initially the application of force is directed at the center of the intended target and is referred to as the primary submovement. As the hand (or in this case cursor) moves closer to the target, adjustments to force and direction are made in order to ultimately reach the target. These automatic, subconscious adjustments are

typically guided through visual input and are referred to as secondary submovements (Meyer et al. 1990; van Beers et al. 2004). When moving the cursor across a computer screen toward a target, a primary submovement (force and direction) toward the target is first applied to the mouse. As the mouse cursor moves closer to the target, the force is decreased causing the speed to become slower and directional changes are made to the movement to fine tune the trajectory to reach the target (e.g., Figure 2).

Figure 2. Primary and Secondary Submovements
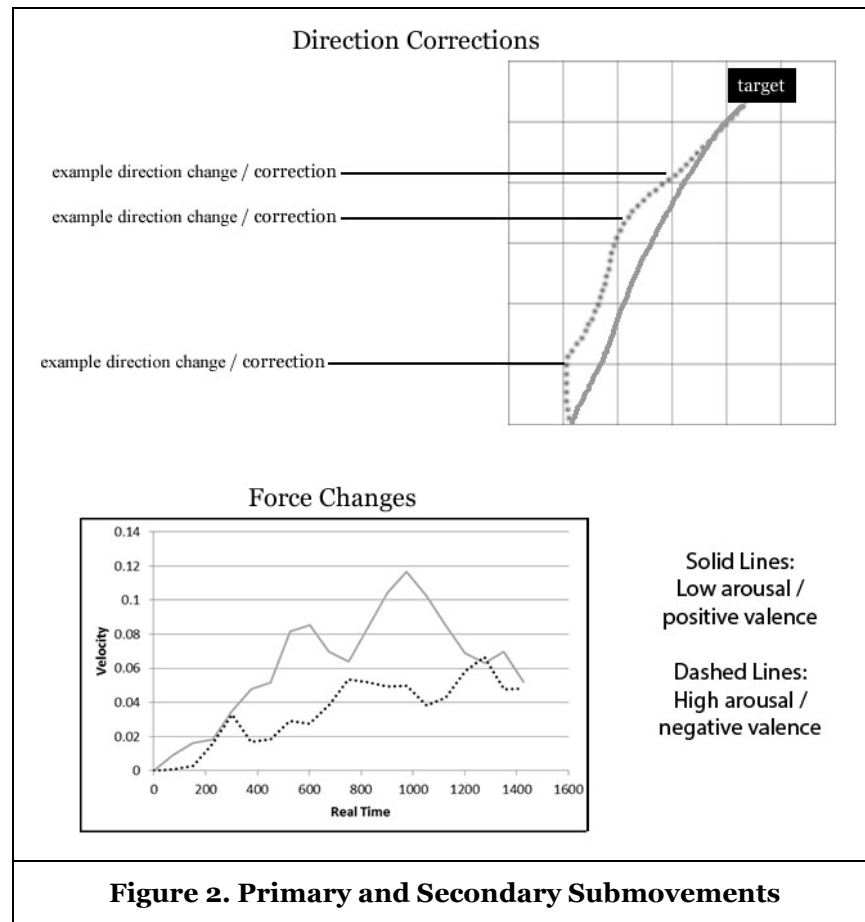
The precision of the primary submovement – how close the initial movement gets to the target – and the secondary submovements thereafter are influenced by *neuromotor noise* (van Beers et al. 2004). Neuromotor noise is the variability in the neuromotor channels that inhibits the ability to move in exactly the intended way (Fitts 1954; Meyer et al. 1988). As neuromotor noise increases, the degree to which the endpoints of primary submovements deviate from the target also increases (Meyer et al. 1988). Although the source of much neuromotor noise is unknown (Meyer et al. 1990), it is likely that both valence and arousal will cause neuromotor noise which will be reflected in deviations in mouse movements as described below.

High arousal leads to greater motor track excitability (Oathes et al. 2008; Tanaka et al. 2012) or stimulation in the motor cortex that may result in movement. Thus, high arousal will ultimately decrease fine motor control (Sharma 2011; Tanaka et al. 2012) and increase neuromotor noise. According to the SOS model, the mind automatically compensates for this increased neuromotor noise through two mechanisms. First, the mind can compensate by decreasing the velocity of submovements. Second, the mind can compensate by creating more secondary submovements (Meyer et al. 1988; Meyer et al. 1990), which ultimately results in a greater overall distance traveled. These subconscious, automatic adjustments help ensure that the target is reached.

The first process decreases the velocity of submovements, thereby increasing their precision (Fitts 1954; Meyer et al. 1988). Stated more formally, variations in submovements increase proportionally with velocity, such that the standard deviation of submovement endpoints S can be described as $S = VK$, where V represents the velocity, and K a positive constant. Thus, when velocity decreases, the endpoint will be closer to the target, and less extensive corrections (secondary submovements) are needed. In the second process, the mind may compensate for increased neuromotor noise by increasing the number and magnitude of secondary submovements—i.e., corrections or changes in direction (Meyer et al. 1988; Meyer et al. 1990). Although the submovements may be less precise because of neuromotor noise, the hand will eventually reach the target as more frequent and extensive corrections to the trajectory are made based on continuous perceptual and visual input (Crossman and Goodeve 1983). Less precision and more extensive secondary submovements also result in greater total distance as larger corrections are needed to reach the target. The SOS model explains that the mind automatically and subconsciously tries to minimize average total movement time by optimizing both the number of submovements and velocity (Meyer et al. 1988; Meyer et al. 1990). Thus, the following hypotheses are proposed:

H1a. Exposure to stimuli with high-arousal will result in a greater number of corrections to the movement trajectory (i.e., direction changes) than exposure to stimuli with low-arousal.

H1b. Exposure to stimuli with high-arousal will result in more mouse movement (i.e., greater distance traveled) than exposure to stimuli with low-arousal.

H1c. Exposure to stimuli with high-arousal will result in slower speed than exposure to stimuli with low-arousal.

Previous research also suggests that experiencing negative valence will result in more neuromotor noise than positive valence. Although some research has suggested that positive and negative valence create similar outcomes in terms of motor track excitability (Hajcak et al. 2007) or force production (Coombes et al. 2008), other research suggests that experiences with negative valence cause greater neuromotor effects and noise than experiences with positive valence (van Loon et al. 2010). Studies have shown that experience with negative valence increases activity in the ventral cervical spinal cord (Smith and Kornelsen 2011), motor evoked potential (electrical stimulation to muscles) (Coombes et al. 2009; McIver et al. 2012), and corticomotor excitability or action readiness (Coelho et al. 2010; Oathes et al. 2008). This stimulation may cause greater variability in fine motor skills (Tanaka et al. 2012). Furthermore, negative valence may cause an increase in force production (Coombes et al. 2011; Coombes et al. 2009; Naugle et al. 2012). While this may increase performance of gross motor skills (lifting weights, running, etc.), it will disrupt fine motor skills (Yoshie et al. 2009). Finally, negative valence has been shown to also influence reaction times (Sagaspe et al. 2011), inhibiting the ability to make corrective actions, resulting in greater deviations in trajectory when moving toward the target.

Per the SOS model described previously, the mind will automatically compensate for the increased neuromotor noise caused by negative valence by decreasing velocity or by creating more secondary submovements, resulting in more corrections to the mouse trajectory and greater distance traveled (Meyer et al. 1988; Meyer et al. 1990). As the mind optimizes the movements and submovements, the resulting path is likely to be slower, longer, and consist of a greater number of direction changes. In summary:

H2a. Exposure to stimuli with negative valence will result in a greater number of corrections to the movement trajectory (i.e., direction changes) than exposure to stimuli with positive valence.

H2b. Exposure to stimuli with negative valence will result in more mouse movement (i.e., greater distance traveled) than exposure to stimuli with positive valence.

H2c. Exposure to stimuli with negative valence will result in slower speed than exposure to stimuli with positive valence.

Methodology

To test the hypotheses, arousal and valence were manipulated in a controlled environment by using images designed to elicit specific states of arousal and valence. Images have been shown to be excellent cues for eliciting specific affective responses as they are static and unchanging, thereby introducing little variability. Additionally, images provide contextual cues similar to live experience (visualization of danger, proximity, proportional size, etc.), which may not be readily available using other modalities such as text or audio based descriptions (Lang and Bradley 2007). To this end, images from the International Affective Picture System (IAPS) were used. IAPS is a collection of over 1,000 images covering a wide range of settings and activities that have been validated across hundreds of studies to elicit specific affective states (Lang and Bradley 2007; Lang et al. 2008) .

A laboratory experiment was conducted at a large university in the Southwestern United States. Ninety four students (sixty male) from a junior level MIS class participated in exchange for class credit. The average age was 21 years (min: 19, max: 32, SD: 1.79), and the ethnic makeup was 65% Caucasian, 15% Chinese, 11% Hispanic, and 9% other. The experiment was conducted in a computer lab equipped with privacy screens and noise isolating headphones to minimize distractions and preclude participants from seeing images on other computer screens. Images were presented in a full screen web browser on 22" LCD monitors with a screen resolution of 1920x1080.
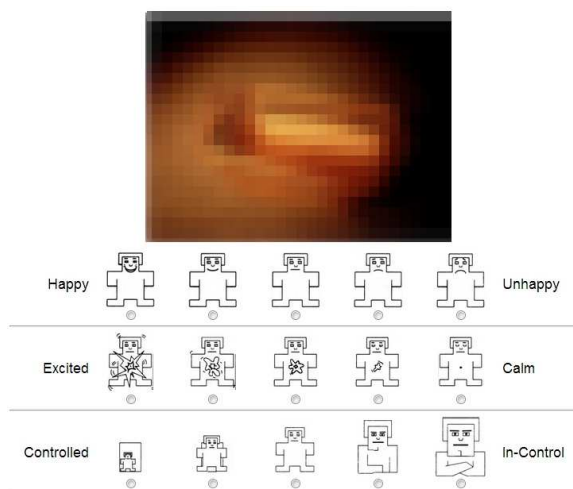
Upon arrival, participants were briefed on the experiment (per IRB protocol) and assigned an ID number to log into the system. After completing a brief survey, participants were shown a three minute instructional video which described the flow of the experiment and provided instructions for describing and rating the images. After watching the video, participants were shown a series of sixteen images with the following workflow:

- Blank screen (10 seconds)
- View the image (10 seconds)
- Type a description of the image (60 seconds)
- Rate the image (20 seconds)

The ten second blank screen was intended to give a buffer between images to reduce the influence of a previous image on the next. Having participants type a description of the image ensured they were indeed viewing and comprehending the images.

* This image is blurred to comply with IAPS terms of use

Figure 3: Rating the Images

As a manipulation check (described in the next section) and to solicit mouse movements, images were rated on three dimensions as defined in the IAPS technical manual: valence (happy/sad), arousal (excited/calm) and dominance (controlled/in-control) using a five point Likert scale (Lang et al. 2008). The measure was administered using the Self-Assessment Mannequin (SAM). The SAM measurement tool is commonly used in studies such as this because it provides an easy to understand and language agnostic way of describing emotional states (Lang and Bradley 2007; Lang et al. 2008).

To rate the images, participants used the mouse to move the cursor to the radio button corresponding to their desired rating (Figure 3), which served as a precise target for the motor movement. Just before rating each image, the participant was required to click a button at the top center of the screen, which served as an anchoring point so each participant's mouse cursor started at the same point on the screen (i.e. the distance from the starting point to each rating was the same for each user). Once the participant began moving the mouse, x and y coordinates of the mouse cursor were collected in increments of approximately every 8 milliseconds using a small JavaScript application embedded in the web page. After each image was rated, the ratings and the raw mouse movement data were stored in a SQL database for analysis. It should be noted that some rating combinations require a greater amount of mouse movement

– for example, rating an image as "happy" and "calm" (elements at opposite ends of the scale) would require more mouse movement that "happy" and "excited" (elements at the same end of the scale). To correct for this, the minimum distance required to provide the rating is calculated and stored as a baseline. Using this baseline, it can then be determined how far the user moved the mouse beyond the minimum distance required to make the provided rating.

Participants were presented with a series of sixteen images one at a time following the procedure previously described. Eight of the images were low arousal, neutral valence images of common items (IAPS image reference number noted in parentheses): rolling pin (7000), towel (7002), spoon (7004), mug (7009), basket (7010), rubber bands (7012), stool (7025), and baskets (7041). Four of the images were high arousal, positive valence images of skydivers (5621), skier (8030), white water rafting (8370), and bungee jumping (8179) and four of the images were high arousal, negative valence images of attack (6350), attack (6563), hurt dog (9183), and vomit (9325). These images were chosen because they provided unambiguous and easy to describe scenarios, however, it is expected that any images with similar levels of valence and arousal would elicit similar responses, as suggested by previous IAPS studies (Lang et al. 2008). Images were presented in four different orders in an effort to remove order effects. In each ordering, sets of four images were constructed in the following configurations: [neutral, positive, positive, neutral], [neutral, positive, negative, neutral], [neutral, negative, positive, neutral], [neutral, negative, negative, neutral]. In total the image description and rating portion of the experiment lasted approximately 30 minutes.
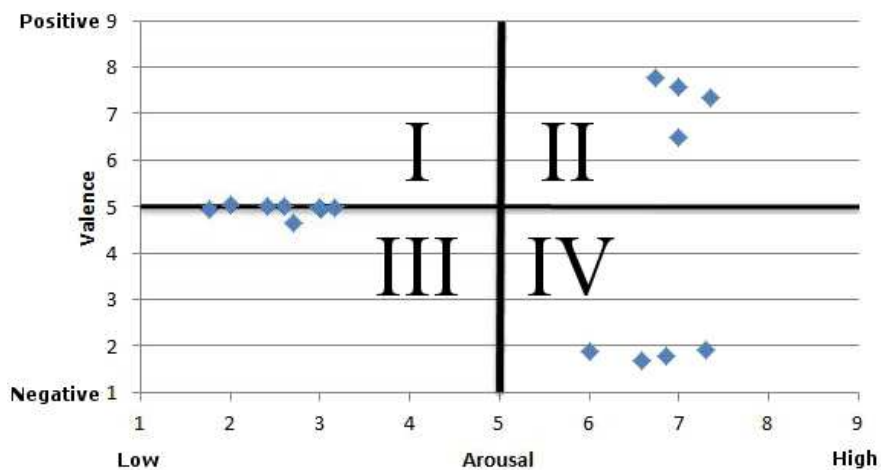

Figure 4: Arousal and Valence of Target Images

When considering the relationship between valence and arousal, the activation typically follows a trajectory such that images with neutral valence have low arousal and images with high arousal have either a negative or positive valence (Lang et al. 2008) - i.e. there are few images that are high arousal with neutral valence, or low arousal with positive or negative valence. It has been suggested that eliciting a high level of negative affect may require a high level of arousal (Tellegen et al. 1988). Figure 4 graphically represents the relationship between valence and arousal for the sixteen images used in this study. Hypotheses H1a-c focus on arousal, irrespective of valence. To test H1a-c, responses elicited by the images located collectively in quadrants I/III (low arousal) and quadrants II/IV (high arousal) were used, with eight images/responses in each set. Hypotheses H2a-c focus exclusively on valence. Since the low arousal images found in quadrants I/III have a neutral valence, they were excluded from the analysis. Responses elicited from the images in quadrants II (positive valence) and IV (negative valence) were used for this analysis with four images/responses in each set.

Analysis

To extract meaningful features from the raw data, observations were aggregated into time periods (e.g., Freeman et al. 2011). Several time divisions between 100 and 1,500 milliseconds were explored with 500 millisecond divisions being found to provide the most appropriate level of detail from the data. Using these chunks, features related to the distance, speed, and direction changes (i.e., reversal of the direction of movement on the x- or y-axis) were extracted from the raw mouse data. As previously mentioned, items that are rated at opposite ends of the scale (e.g., unhappy/excited) will naturally cause longer distance than items are rated at the same end of the scale (e.g., unhappy/calm or happy/excited). To adjust for this, the minimum distance required to make the observed rating was calculated, and was subtracted from the total distance traveled, resulting in a measure of distance traveled beyond the minimum required distance. This provides an equitable measurement for all observations.

Manipulation Check

Prior to testing the hypotheses, a manipulation check was performed to examine whether the images used elicited the expected states of arousal and valence. After viewing each image, participants were asked to rate the image on a 5-point pictorial scale measuring valence, arousal, and dominance (Figure 3). Ratings provided by the participants were validated against ratings and standard deviations for valence, arousal, and dominance provided in the IAPS technical manual (Lang and Bradley 2007; Lang et al. 2008). The dominance rating was collected to match the methodology typically used for studies using IAPS, however, dominance was not an item of interest for this study and will not be discussed in any further detail. Table 2 shows the IAPS provided ratings for valence, arousal, and dominance along with the ratings from participants in this study for each image. The current data was collected using a five point instrument scaled to nine points to match the IAPS provided ratings. The ratings in the current study closely match the previously validated IAPS ratings, falling within 1 standard deviation for each item. While not shown here, the neutral items elicited responses that were similarly consistent with the IAPS provided measures.

Table 2: Valence, Arousal, and Dominance for High Arousal Items								
Picture #	5621 (Positive)	8179 (Positive)	8030 (Positive)	8370 (Positive)	6350 (Negative)	6563 (Negative)	9183 (Negative)	9325 (Negative)
IAPS Valence	7.57 (1.42)	6.48 (2.18)	7.33 (1.76)	7.77 (1.29)	1.90 (1.29)	1.77 (1.23)	1.69 (1.10)	1.89 (1.23)
IAPS Arousal	6.99 (1.95)	6.99 (2.35)	7.35 (2.02)	6.73 (2.24)	7.29 (1.87)	6.85 (2.18)	6.58 (2.12)	6.01 (2.54)
IAPS Dominance	5.81 (2.38)	4.73 (2.68)	4.70 (2.66)	5.37 (2.02)	2.73 (2.16)	2.93 (2.12)	2.96 (1.85)	3.22 (1.96)
Current Valence	7.26 (1.70)	5.87 (2.18)	6.83 (1.66)	7.45 (1.47)	1.87 (1.30)	2.04 (1.16)	1.27 (0.91)	2.18 (1.43)
Current Arousal	6.04 (2.63)	6.30 (2.68)	6.13 (2.56)	6.18 (2.74)	6.30 (2.47)	5.43 (2.28)	5.91 (2.68)	4.09 (2.87)
Current Dominance	5.56 (2.28)	4.78 (2.93)	5.04 (2.03)	5.50 (2.76)	3.04 (2.94)	3.30 (2.80)	2.82 (2.60)	3.81 (3.41)

As a second method of analysis, the ratings were also clustered on arousal and valence using a k-means clustering algorithm. The appropriate items clustered together with an accuracy of about 80%. Upon inspection of the clustering results, it appears that some items intended to have a positive valence – specifically the images of skydiving and bungee jumping – may have elicited a negative response from a subset of participants. Despite this misclassification for some participants, the manipulations worked as intended for the majority of participants.

H1a - H1c: Arousal

Mouse movement data from each participant were grouped by arousal level and aggregated to determine number of direction changes, distance traveled, and average speed for high (quadrants I/III) and low (quadrants II/IV) arousal images. Paired-samples t-tests were conducted for each hypothesis to identify differences in high and low arousal levels. In line with the SOS model, which would predict a higher

number of correcting adjustments in cases of high arousal, the number of direction changes (H1a) was found to be significantly higher in the high arousal condition (t(93)=6.039, p < .001), with an average of 30.4 direction changes in the high arousal condition and 26.3 direction changes in the low arousal condition.

Distance (H1b) was also found to be significantly greater in the high arousal condition than in the low arousal condition (t(93)=4.317, p < .001). Supporting H1b, it was found that on average participants traversed 2,856 pixels above the minimum distance required to provide their ratings in the high arousal condition, while traversing only 2,432 extra pixels in the low arousal condition.

Speed was not found to be significantly different between conditions (t(93)=1.327, p > .05), and thus H1c was not supported.

H2a - H2c: Valence

Mouse movement data from each participant were next grouped by positive (quadrant II) or negative (quadrant IV) valence and aggregated to determine number of direction changes, distance traveled, and average speed. Since items in quadrants I and III were of neutral valence, they were excluded from this analysis. Paired-samples t-tests were conducted for each hypothesis to compare responses elicited by images with positive or negative valence.

Neither number of direction changes (H2a, t(93)=1.573, p > .05) nor speed (H2c, t(93)=.205, p > .05) alone were found to be statistically significant indicators of valence. Distance (H2b), however, was found to be significantly greater in the negative valence condition than in the positive valence (t(93)=2.106, p < .05). On average, the mouse movements covered 3,006 pixels above the minimum number require to make their ratings in the negative valence condition, while traversing only 2,711 extra pixels in the positive valence condition.

To more fully understand the data, exploratory machine learning analysis was conducted, which resulted in the discovery of additional interactions between valence, direction changes, distance, and speed. The results of the machine learning analysis indicated that speed and direction changes might be useful as a second level of classification after distance. Therefore, participants were filtered based on whether H2b held for their interaction (i.e. distance was longer in the negative valence condition) and analysis on speed and direction changes was conducted a second time.

For the 66 participants conforming to H2b, number of direction changes was found to be significantly higher for negative valence (t(65)=5.446, p < .001). On average, those exposed to negative valence images exhibited 32.2 direction changes vs. 27.8 direction changes for those exposed to positive images, thus providing partial support for H2a. For this group, speed was found to be significantly faster for negative valence at 411.6 pixels per second as compared to positive valence at 381.1 pixels per second (t(65)=2.755, p < .01) – the opposite of what is predicted by H2c.

For the 28 participants not conforming to H2b (i.e. distance was longer in the positive valence condition), number of direction changes was found to be significantly higher for positive valence, 35.1 direction changes, compared to 29.4 direction changes for negative valence (t(27)=-3.338, p < .01) – the opposite of what is predicted by H2a. However, speed was found to be significantly slower for negative arousal with this group at 372.6 pixels per second vs. 436.5 for the positive condition (t(27)=-2.561, p < .05), thus providing partial support for H2c.

While only H2b was fully supported, the partial support of H2a and H2c provides additional insight into the interactions between features of mouse movement and should be explored in future research to develop more sophisticated classification techniques to identify valence. Based on the results, a basic decision tree based on the significant findings describing the interaction of distance, speed, and direction changes with valence is presented in Figure 5.
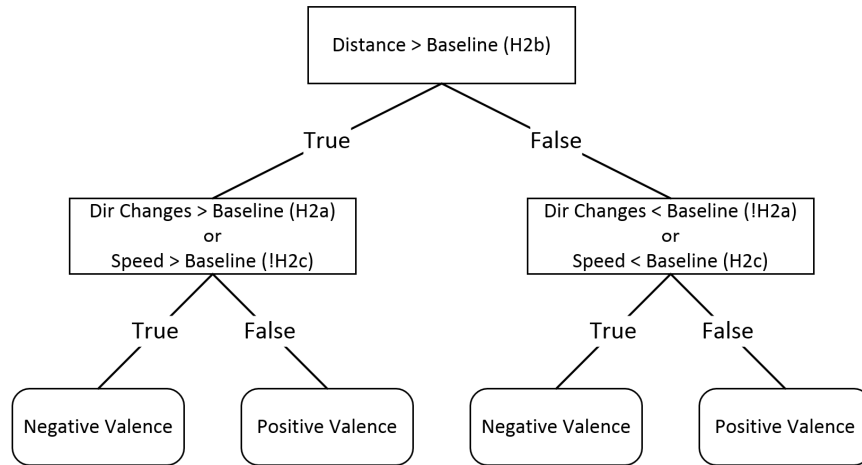
Figure 5: Decision Tree for Determining Valence

Discussion

This paper addressed the following research question: *How does high vs. low arousal and positive vs. negative valence influence mouse movements?* It hypothesized that high arousal would result in a greater number of direction changes (H1a), more mouse movements (H1b), and slower speed than low arousal (H1c). The results indicated that direction changes and distance were significantly greater in the high-arousal condition than in the low-arousal condition. Thus, H1a and H1b were supported. It was also hypothesized that negative valence would result in a greater number of direction changes (H2a), more mouse movements (H2b), and slower speed than positive valence (H2c). The results showed that distance was significantly higher in the negative valence condition than in the positive valence condition. When accounting for those participants who conformed to H2b (distance), direction changes and speed also significantly differentiated between high and low arousal. Thus, H2b was supported and H2a and H2c were partially supported. Table 3 summarizes the results. Theoretical and practical contributions of this research will now be discussed.

Table 3. Summary of Results	
Hypothesis	**Supported**
H1a. Exposure to stimuli with high-arousal will result in more corrections to the movement trajectory (i.e., direction changes) than exposure to stimuli with low-arousal.	Supported
H1b. Exposure to stimuli with high-arousal will result in more mouse movement (i.e., greater distance traveled) than exposure to stimuli with low-arousal.	Supported
H1c. Exposure to stimuli with high-arousal will result in slower speed than exposure to stimuli with low-arousal.	Not Supported
H2a. Exposure to stimuli with negative valence will result in more corrections to the movement trajectory (i.e., direction changes) than exposure to stimuli with positive valence.	Partially Supported after filtering participants conforming to H2b
H2b. Exposure to stimuli with negative valence will result in more mouse movement (i.e., greater distance traveled) than exposure to stimuli with positive valence.	Supported
H2c. Exposure to stimuli with negative valence will result in slower speed than exposure to stimuli with positive valence.	Partially Supported after filtering participants conforming to H2b

Implications for Research

First, this research introduces an objective methodology for inferring affect in information systems research. It found that both arousal and valence influence mouse movements in measureable and predictable ways. This can aid future research in conducting multi-method studies through monitoring mouse movements to examine how system design choices influence users' affective reactions in a human-computer interaction context. This will result in more valid and rigorous data collections that can complement self-report measures to help overcome self-report biases. The approach to inferring affect outlined in this paper can also be used as an alternative to more expensive neuroscience techniques that cannot always be used because of costs or deployability issues (i.e., they cannot be easily deployed to measure users' affective responses in the 'wild' or a non-laboratory setting).

Second, this research extends the Stochastic Optimized Submovement (SOS) model to explain how arousal and valence influence mouse movements. The SOS model was originally developed to explain the well-validated logarithmic trade-off between speed and accuracy in hand movements described in Fitts's law (Fitts 1954). The SOS model predicts that primary submovements do not always reach their intended target because of neuromotor noise. This model is extended by explaining how arousal and valence may be a source of neuromotor noise, as they create motor track excitability (Oathes et al. 2008; Tanaka et al. 2012), influence reaction times (Sagaspe et al. 2011), and influence force production (Coombes et al. 2011; Coombes et al. 2009; Naugle et al. 2012). It is likely that neuromotor noise results in longer distances (along with direction changes as corrections are made), slower speeds or both. The extension of the SOS model to this context provides a novel theoretical foundation for explaining how arousal and valence influence mouse movements.

Implications for Practice

Detecting affective reactions to systems can be challenging in the 'wild'—i.e., while monitoring user interactions with a system in a non-laboratory setting. In such situations, established Neuroscience tools are not always viable options, and thus the only feedback regarding affective responses is through self-reported information. This research provides practitioners with an alternative or complementary method for inferring users' affect through analyzing mouse movements. For example, in this experiment, mouse movements were measured using a JavaScript application that is compatible with most web browsers. This method facilitates remote usability testing of systems as well as cost-effective usability testing in laboratory environments. Furthermore, the methodology for monitoring mouse movements presented in this paper can be applied to identify 'break points' during actual system use - instances of system interaction that cause frustration or other affective responses that may ultimately result in discontinued use of the system. This may be used to enable just in time service interventions or may be used to inform future development to create more positive experiences with the system.

Second, the techniques used in this paper for inferring affect through analyzing mouse movements has potential for creating more interactive, intelligent systems. This may be applied to research in the area of 'affective computing', which focuses on recognizing human emotions using various technologies to improve the end-user experience (e.g., Picard 2000; Picard 2003). This would facilitate the creation of systems that can recognize and respond to user affect and may lead to more life-like and interactive human-computer interactions (Derrick et al. 2011). Furthermore, detecting affective responses can have novel applications for revealing hidden cognitive states in users, such as detecting when people are lying during online credibility assessments or engaging in threatening security practices (Jenkins et al. 2013). Future research can be conducted to apply the presented methodology to these contexts, and examine its efficacy.

Limitations and Future Research

The current experiment manipulated arousal and valence using a library of images designed specifically to elicit these responses. While the manipulations were effective, future research should consider more fluid and realistic scenarios to elicit these types of responses – for example, having users interact with applications that appear normal, but are specifically designed to induce frustration, anger, or other affective states. Future research should also consider leveraging subject pools beyond the student

population. While students provide a nice representative sample of technologically savvy users, detecting changes in affect could be particularly useful for individuals with lower levels of computer skill.

These findings, perhaps in conjunction with other measures of computer interaction, personality traits, and computer efficacy, should also be used to create a robust classification mechanism for real time detection of affect. There are many features that may be derived from raw mouse data. The present study just scrapes the surface of the data that is available and the analysis that can be conducted. Previous literature suggests that certain personality traits – specifically neuroticism – may moderate the effect of arousal on motor control (Wassermann et al. 2001). Additionally, elements such as computer self-efficacy, handedness, and other environmental factors may come in to play. Continued work using machine learning techniques to analyze these features and beyond would be useful in creating systems to effectively identify affect and emotional state.

Conclusion

As online systems continue to play an ever increasing role in business and personal interactions, increasing the efficacy of interaction between humans and computers is of paramount importance. While sophisticated technological solutions such as fMRI can provide computer systems with some insight into the affective process, expensive and invasive solutions such as this are not practical for widespread application. By leveraging hardware and software that is already pervasive, this research presents a method for inferring affective state based on changes in mouse movement behavior. Systems such as the one described in this study are cost effective, non-intrusive, and have great potential to provide value in many areas of human computer interaction.

References

Anderson, C.L., and Agarwal, R. 2011. "The Digitization of Healthcare: Boundary Risks, Emotion, and Consumer Willingness to Disclose Personal Health Information," *Information Systems Research* (22:3), pp. 469-490.

Bai, B., Law, R., and Wen, I. 2008. "The Impact of Website Quality on Customer Satisfaction and Purchase Intentions: Evidence from Chinese Online Visitors," *International Journal of Hospitality Management* (27:3), pp. 391-402.

Beaudry, A., and Pinsonneault, A. 2010. "The Other Side of Acceptance: Studying the Direct and Indirect Effects of Emotions on Information Technology Use," *MIS Quarterly* (34:4), pp. 689-710.

Bhattacherjee, A. 2001. "Understanding Information Systems Continuance: An Expectation-Confirmation Model," *MIS Quarterly* (25:3), pp. 351-370.

Briggs, R.O., Reinig, B.A., and Vreede, G.-J.d. 2008. "The Yield Shift Theory of Satisfaction and Its Application to the Is/It Domain*," *Journal of the Association for Information Systems* (9:5), p. 267.

Coelho, C.M., Lipp, O.V., Marinovic, W., Wallis, G., and Riek, S. 2010. "Increased Corticospinal Excitability Induced by Unpleasant Visual Stimuli," *Neuroscience Letters* (481:3), pp. 135-138.

Coombes, S.A., Gamble, K.M., Cauraugh, J.H., and Janelle, C.M. 2008. "Emotional States Alter Force Control During a Feedback Occluded Motor Task," *Emotion* (8:1), pp. 104-113.

Coombes, S.A., Naugle, K.M., Barnes, R.T., Cauraugh, J.H., and Janelle, C.M. 2011. "Emotional Reactivity and Force Control: The Influence of Behavioral Inhibition," *Human Movement Science* (30:6), pp. 1052-1061.

Coombes, S.A., Tandonnet, C., Fujiyama, H., Janelle, C.M., Cauraugh, J.H., and Summers, J.J. 2009. "Emotion and Motor Preparation: A Transcranial Magnetic Stimulation Study of Corticospinal Motor Tract Excitability," *Cognitive, Affective, & Behavioral Neuroscience* (9:4), pp. 380-388.

Crossman, E., and Goodeve, P. 1983. "Feedback Control of Hand-Movement and Fitts' Law," *The Quarterly Journal of Experimental Psychology* (35:2), pp. 251-278.

Cyr, D., Head, M., Larios, H., and Pan, B. 2009. "Exploring Human Images in Website Design: A Multi-Method Approach," *MIS Quarterly* (33:3), Sep, pp. 539-566.

Deng, L., and Poole, M.S. 2010. "Affect in Web Interfaces: A Study of the Impacts of Web Page Visual Complexity and Order," *MIS Quarterly* (34:4), p. 711.

Derrick, D.C., Jenkins, J.L., and Nunamaker Jr, J.F. 2011. "Design Principles for Special Purpose, Embodied, Conversational Intelligence with Environmental Sensors (Species) Agents," *AIS Transactions on Human-Computer Interaction* (3:2), pp. 62-81.

Dimoka, A., Banker, R.D., Benbasat, I., Davis, F.D., Dennis, A.R., Gefen, D., Gupta, A., Lschebeck, A., Kenning, P.H., Pavlou, P.A., Muller-Putz, G., Riedl, R., vom Brocke, J., and Weber, B. 2012. "On the Use of Neurophysiological Tools in Is Research: Developing a Research Agenda for Neurois," *MIS Quarterly* (36:3), Sep, pp. 679-702.

Dimoka, A., Pavlou, P.A., and Davis, F.D. 2011. "Research Commentary—Neurois: The Potential of Cognitive Neuroscience for Information Systems Research," *Information Systems Research* (22:4), pp. 687-702.

Fitts, P.M. 1954. "The Information Capacity of the Human Motor System in Controlling the Amplitude of Movement," *Journal of Experimental Psychology* (47:6), pp. 381-391.

Franken, I.H., Muris, P., Nijs, I., and van Strien, J.W. 2008. "Processing of Pleasant Information Can Be as Fast and Strong as Unpleasant Information: Implications for the Negativity Bias," *Netherlands Journal of Psychology* (64:4), pp. 168-176.

Freeman, J.B., Dale, R., and Farmer, T.A. 2011. "Hand in Motion Reveals Mind in Motion," *Frontiers in Psychology* (2:59), pp. 1-6.

Hajcak, G., Molnar, C., George, M.S., Bolger, K., Koola, J., and Nahas, Z. 2007. "Emotion Facilitates Action: A Transcranial Magnetic Stimulation Study of Motor Cortex Excitability During Picture Viewing," *Psychophysiology* (44:1), pp. 91-97.

Jenkins, J.L., Grimes, M., Proudfoot, J.G., and Lowry, P.B. 2013. "Improving Password Cybersecurity through Inexpensive and Minimally Invasive Means: Detecting and Deterring Password Reuse through Keystroke-Dynamics Monitoring and Just-in-Time Fear Appeals," *Information Technology for Development*:ahead-of-print), pp. 1-18.

Lang, P., and Bradley, M.M. 2007. "The International Affective Picture System (Iaps) in the Study of Emotion and Attention," *Handbook of emotion elicitation and assessment*), p. 29.

Lang, P.J. 1995. "The Emotion Probe," *American psychologist* (50:5), pp. 372-385.

Lang, P.J., Bradley, M.M., and Cuthbert, B.N. 2008. "International Affective Picture System (Iaps): Affective Ratings of Pictures and Instruction Manual," *Technical Report A-8*).

Lopatovska, I., and Arapakis, I. 2011. "Theories, Methods and Current Research on Emotions in Library and Information Science, Information Retrieval and Human–Computer Interaction," *Information Processing & Management* (47:4), pp. 575-592.

Maehr, W. 2008. *Emotion: Estimation of User's Emotional State by Mouse Motions*. VDM Verlag.

McIver, T., Kornelsen, J., Smith, S.D., Summers, R., and Tomanek, B. "The Neural Correlates of Limb-Specific Emotionally Charged Images: A Spinal Fmri Study,").

McIver, T., Kornelsen, J., Smith, S.D., Summers, R., and Tomanek, B. 2012. "The Neural Correlates of Limb-Specific Emotionally Charged Images: A Spinal Fmri Study,").

Meyer, D.E., Abrams, R.A., Kornblum, S., Wright, C.E., and Keith Smith, J. 1988. "Optimality in Human Motor Performance: Ideal Control of Rapid Aimed Movements," *Psychological Review* (95:3), pp. 340-370.

Meyer, D.E., Smith, J.E.K., Kornblum, S., Abrams, R.A., and Wright, C.E. 1990. "Speed-Accuracy Tradeoffs in Rapid Aimed Movements: Toward a Theory of Rapid Voluntary Action," in *Attention and Performance Xiv* M. Jeannerod (ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, pp. 173-226.

Naugle, K.M., Coombes, S.A., Cauraugh, J.H., and Janelle, C.M. 2012. "Influence of Emotion on the Control of Low-Level Force Production," *Research Quarterly for Exercise and Sport* (83:2), pp. 353-358.

Oathes, D.J., Bruce, J.M., and Nitschke, J.B. 2008. "Worry Facilitates Corticospinal Motor Response to Transcranial Magnetic Stimulation," *Depression and Anxiety* (25:11), pp. 969-976.

Osgood, C.E., Suci, G.J., and Tannenbaum, P.H. 1957. *The Measurement of Meaning*. Urbana: University of Illinois Press.

Pereira, M.G., de Oliveira, L., Erthal, F.S., Joffily, M., Mocaiber, I.F., Volchan, E., and Pessoa, L. 2010. "Emotion Affects Action: Midcingulate Cortex as a Pivotal Node of Interaction between Negative Emotion and Motor Signals," *Cognitive, Affective, & Behavioral Neuroscience* (10:1), pp. 94-106.

Picard, R.W. 2000. *Affective Computing*. Cambridge, MA: MIT Press.

Picard, R.W. 2003. "Affective Computing: Challenges," *International Journal of Human-Computer Studies* (59:1-2), Jul, pp. 55-64.

Rubin, J., and Chisnell, D. 2008. *Handbook of Usability Testing: Howto Plan, Design, and Conduct Effective Tests*. Wiley.

Russell, J.A., and Barrett, L.F. 1999. "Core Affect, Prototypical Emotional Episodes, and Other Things Called Emotion: Dissecting the Elephant," *Journal of Personality and Social Psychology* (76:5), pp. 805-819.

Sagaspe, P., Schwartz, S., and Vuilleumier, P. 2011. "Fear and Stop: A Role for the Amygdala in Motor Inhibition by Emotional Signals," *NeuroImage* (55:4), pp. 1825-1835.

Sharma, R. 2011. "Stress and Anxiety in Sport," *International Referred Research Journal* (2:18), pp. 32-34.

Smith, S.D., and Kornelsen, J. 2011. "Emotion-Dependent Responses in Spinal Cord Neurons: A Spinal Fmri Study," *NeuroImage* (58:1), pp. 269-274.

Tanaka, Y., Funase, K., Sekiya, H., and Murayama, T. 2012. "Modulation of Corticospinal Motor Tract Excitability During a Fine Finger Movement under Psychological Pressure: A Tms Study," *International Journal of Sport and Health Science* (10:0), pp. 39-49.

Tellegen, A., Watson, D., and Clark, L. 1988. "Development and Validation of Brief Measures of Positive and Negative Affect: The Panas Scales," *Journal of Personality and Social Psychology* (54:6), pp. 1063-1070.

van Beers, R.J., Haggard, P., and Wolpert, D.M. 2004. "The Role of Execution Noise in Movement Variability," *Journal of Neurophysiology* (91:2), pp. 1050-1063.

van Loon, A.M., van den Wildenberg, W.P., van Stegeren, A.H., Ridderinkhof, K.R., and Hajcak, G. 2010. "Emotional Stimuli Modulate Readiness for Action: A Transcranial Magnetic Stimulation Study," *Cognitive, Affective, & Behavioral Neuroscience* (10:2), pp. 174-181.

Wassermann, E.M., Greenberg, B.D., Nguyen, M.B., and Murphy, D.L. 2001. "Motor Cortex Excitability Correlates with an Anxiety-Related Personality Trait," *Biological Psychiatry* (50:5), pp. 377-382.

Waterson, S., Landay, J.A., and Matthews, T. 2002. "In the Lab and out in the Wild: Remote Web Usability Testing for Mobile Devices," *CHI'02 Extended Abstracts on Human Factors in Computing Systems*: ACM, pp. 796-797.

Wundt, W. 1896. *Lectures on Human and Animal Psychology*. New York: Macmillan.

Yoshie, M., Kudo, K., Murakoshi, T., and Ohtsuki, T. 2009. "Music Performance Anxiety in Silled Panists: Efects of Scial-Ealuative Performance Situation on Subjective, Autonomic, and Electromyographic Reactions," *Experimental Brain Research* (199:2), pp. 117-126.

Zhang, P. 2007. "Positive and Negative Affect in It Evaluation: A Longitudinal Study," in: *SIGHCI*. p. 4.

Zhang, P., Li, N., and Sun, H. 2006. "Affective Quality and Cognitive Absorption: Extending Technology Acceptance Research," *Hawaii International Conference on System Sciences*.

Zimmermann, P., Gomez, P., Danuser, B., and Schär, S. 2006. "Extending Usability: Putting Affect into the User-Experience," *Proceedings of NordiCHI'06*, pp. 27-32.

Zimmermann, P., Guttormsen, S., Danuser, B., and Gomez, P. 2003. "Affective Computing-a Rationale for Measuring Mood with Mouse and Keyboard," *International Jjournal of Ooccupational Ssafety and Eergonomics* (9:4), pp. 539-551.