Detecting Goal-Oriented vs. Browsing Users Through Behavior Analysis

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Abstract **- Understanding user personas in e-commerce is important for promoting successful online interactions. Two common personas include goal-oriented and browsing users. A goal-oriented user has the intention of completing a specific task as efficiently as possible (e.g., purchasing a product). A browsing user explores for information that will ultimately determine the next objective (e.g., to purchase or look elsewhere). A website that customizes content to a goal-oriented versus browsing user will improve the user experience and ultimately maximize conversion. In this research, we provide a methodology for differentiating between goal-oriented and browsing users by monitoring users' behavior on the website. We conducted a study where participants were randomly assigned to either a goal-oriented task to find a product or told to simply browse the website. Based on the study's results, we discuss suggestions to assist future human-computer interaction (HCI) researchers on how to design behavior-monitoring studies to accurately portray goal-oriented versus browsing users. We also provide insights into the need for considering the motivation of Amazon's Mechanical Turk workers to appropriately utilize them as a sample population in future behavior-monitoring studies.**

Keywords - e-commerce persona, mouse tracking, behavior analysis, goal-oriented users, browsing users, human-computer interaction

I. Introduction

Enabling effective online interactions is essential for business. In the United States, nearly 30% of all business is done online [1]. Consumers frequently expect to be able to interact with companies online. Yet, e-commerce conversion rates (i.e., purchasing) are abysmally small, being less than 3% on average [2]. Businesses spend billions of dollars searching for ways to improve their online sales and better meet consumers' needs [3].

One successful technique to improve conversion is to understand user personas and customize the online experience to match user personas. A persona refers to "archetypical users whose goals and characteristics represent the needs of a larger group of users" [4]. Examples of personas include goal directed users—a user that has the intention of completing a specific task as efficiently as possible—and browsing users—a user who is exploring for information that will ultimately determine the next objective (e.g., to purchase or look elsewhere). Understanding personas can help business build empathy with their users and provide direction on how to optimize the users experience, ultimately increasing user satisfaction and thus conversion.

Despite the importance of understanding user personas, detecting user personas is very difficult. It often requires the use of historical data gained by tracking a user across the web through third-party cookies. However, third party cookies are highly criticized due to privacy concerns, and users and companies alike are beginning to block them [5]. In addition, regulations, such as GDPR, ban the use of third-party cookies without the user's consent [6].

We propose that one way to detect user personas without the negative side effects of third-party cookies is to analyze how a user is browsing a website in real time. This can be done by recording and analyzing the users' mouse-cursor movements and determine if the user is goal-directed or browsing a website. Mouse cursor movements have been shown to provide valuable insight into users' attentional, emotional, and cognitive states online [e.g., 7, 8]. We extend this research to explore whether mouse-cursor movements can differentiate among users' personas. In summary, we address the following research questions:

Can mouse-cursor movements be used to differentiate between goal-directed and browsing users online?

We address this research question by first summarizing relevant previous research. We then draw on attentional selection theory and response activation model to explain how mouse movement speed, x-flips, and y-flips differentiate between goal-directed and browsing users. We summarize a controlled experiment in an e-commerce setting to test our hypotheses. We then end by discussing the observations from our study and suggest implications for future research.

II. Previous Research

Research has shown that monitoring a person's behavior on a website (e.g., the computer mouse, touchscreen, keyboard, etc.) can reveal valuable insights into the user. For example, eye fixations and mouse movements are correlated. Namely, monitoring the computer mouse can show where users' attention is, thus we can better gage what the user is viewing or doing based on the mouse location [9]. Earlier research shows that considering mouse-cursor activity can provide insight into what users find relevant in a search result and predicts where they will click [10].

On a more sophisticated level, mouse cursor tracking can provide valuable information into the cognitive and emotional state of the user. For example, in a credibility setting, mouse-cursor movements have been used to detect fraud [11], compliance [12], and even deception [13]. In an ecommerce setting, monitoring the computer mouse can provide insight into whether a user is frustrated or experiencing heightened cognitive demand [14]. For example, Hibbiln and colleagues [7] examined how negative emotions influence mouse movements via their burden on working memory. They confirmed in three studies in an online shopping context that mouse-cursor movements and emotion are indeed correlated.

Our research builds on extant literature to examine whether monitoring mouse-cursor movements can be used to differentiate between users who are goal-directed and users who are browsing a website. Previous research has shown that there are eye tracking fixation differences between users who are goal-directed and those who are viewing a website for recreation [15]. While valuable for understanding how attention differs for those user personas, the use of eye tracking is limited in normal e-commerce situations. Hence, there is a need to create theoretically sounds indicators of goal-directed and browsing users that can be used in the "wild" – i.e., normal use situations. In the following section, we describe how mouse movement speed, x-flips, and y-flips are theoretically sound candidates of indicators to differentiate between goal-directed versus browsing users in a natural e-commerce environment.

III. Theory and Hypotheses

To develop our hypotheses, we draw on attentional selection theory. Namely, there are three different strategies that derive where someone allocates attention: goal-driven selection, stimulus-driven selection, and history-driven selection [16]. A goal-driven selection strategy suggests that a person is looking for something specifically and filters out other stimuli that are not relevant to finding that target. For example, if someone is searching for a specific pair of pants on a clothing website, the person will not devote attention to or be distracted by shirts on the website.

Conversely, in a stimulus-driven selection strategy, a person is not specifically looking for one target. Rather, the person is observing the environment and various stimuli compete for attention. The most salient stimuli will ultimately capture the attention. Salience is determined both by presentation (e.g., bold items, large items, color, etc.) and also preference (e.g., you like cars more than clothes, so the cars catch your attention).

Finally, the history-driven selection strategy posits that people allocate attention based on their history with the environment. For example, people ignore an item in a room because through past experience, they know it is not relevant to their current situation.

For the context of this study, we focus specifically on the first two selection processes—goal-driven and stimulus-driven strategies—as they are relevant for differentiating between goal-directed users, and users who are browsing information on an unfamiliar website. It is worth noting, however, that the history-driven selection process is very relevant if someone already has experience with a website. Importantly, how one allocates attention will influence how one navigates a website with a computer mouse, touchscreen, or other input device. Namely, when something draws a person's attention, it increases the likelihood of moving to that object.

This phenomenon is explained through the Response Activation Model, which describes how competing movement responses influence hand movements. The theory explains "attention and action are intimately linked" [17]. All targets that capture a user's attention will prime specific movement responses. To prime a behavior refers to subconsciously programming a movement response (transmitting nerve impulses to the hand and arm muscles) to move toward the stimulus (i.e., a link, image, etc.). The biological reason for priming movements is to enable faster reaction times. It also helps the person focus attention on the target element. For example, if various items catch a users' attention on a page as possible destinations (i.e., because they find the stimuli interesting), the brain will subconsciously and simultaneously prime movements to the various items and people will likely move, at least somewhat, toward the items that catch their attention (see Figure 1 for an example).

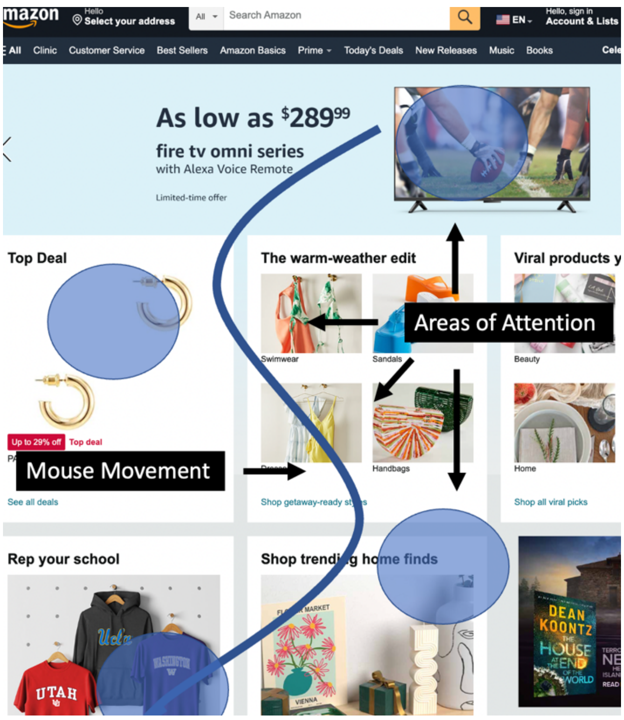

Figure 1. Example of how items that catch a users attention may influence mouse movements.

Combining the stimulus-driven strategy of attentional selection theory and the response activation model, we predict that goal-directed users will have faster mouse movement speed than browsing users. When a user is browsing in a shopping scenario, they are motivated to explore different information and not immediately make a purchase. Browsing is done for two primary reasons: 1) to research a category of items or 2) for leisurely pleasure [18]. Typically, when people are doing something leisurely, they are not in a rush, they move at a somewhat consistent rate taking in the world as they go. In terms of attentional selection theory, they are in a stimulus-driven selection mode. They take time to allow stimuli to catch their attention, and often move towards those stimuli to focus on them. This increase attention to various stimuli results in the user moving slower as it consumes cognitive resources that could otherwise be used to quickly progress through a task [7]. Conversely, in a goal driven setting, the user utilizes a goal-driven selection strategy, ignoring irrelevant items to their task, and devoting more resources to quickly completing the task.

To illustrate the relation between speed, attention, and motivation, imagine two people walking down the street. One is out for pleasure, window shopping as they go. This person tends to look in the windows as they walk, going at a slow to average pace to devote attention to various items. The other person is out shopping for a very specific item. They walk quickly and with purpose looking in the windows only for the item that might meet their needs, and not devoting attention to other items. This allows them to more quickly accomplish their task.

In summary, when a user is browsing and various items capture attention, the user will overall move the mouse slower. However, when a person is goal directed, the user will move the mouse more quickly ignoring other stimuli to more efficiently accomplish the task.

H1. Goal-directed users will have faster speed than browsing users.

We also predict that users who are goal directed will have more deviation in their movements versus those uses who are browsing. When users browse, they are more likely to utilize a stimulus-driven selection strategy to determine where they devote their attention. Various items of potential interest may catch their attention. As previously explained, when these items catch their attention, the response activation model predicts that they are more likely to move their hand (and in a computer context, the computer mouse) towards the items, resulting in a less direct path.

To illustrate this, again consider the two in-person shoppers. This time, imagine them in a store instead of just window shopping. Let's assume that person A has a strict shopping list. Since she has specific goals, she will walk directly towards the items she needs. This means she will most likely take the shortest and quickest path to those items, assuming she knows where the items are. Compare this with shopper B who we assume isn't sure exactly what he is wanting from the store. He will spend more time wandering around the store and taking indirect routes before arriving at an item they think they want.

Translating these shopping habits to a digital world, one way to measure less direct movements is through x- and y-flips. An x-flip refers to a change in direction on the x-axis and a y-flip refers to a change in direction on the y-axis. Goal directed users are not likely to change directions as much, as they are trying to efficiently complete the task without being distracted by other stimuli. However, a browsing user is likely to switch directions more often as the user's attention, and thus movements, move more frequently among items. In summary, we predict:

H2. Goal-directed users will have fewer x-flips than browsing users.

H3. Goal-directed users will have fewer y-flips than browsing users.

IV. Methodology

To test our hypotheses, we designed a between-subject experiment where half of the participants were assigned to a goal-directed task and half of the participants were assigned to a browsing task on the same online store interface.

The study was conducted online. First, a survey was administered that collected basic demographics on participants. Afterwards, participants were randomly assigned to the goal-directed treatment or a browsing treatment on a storefront created by the research team to ensure no one had previous experience with the store (see Figure 2)

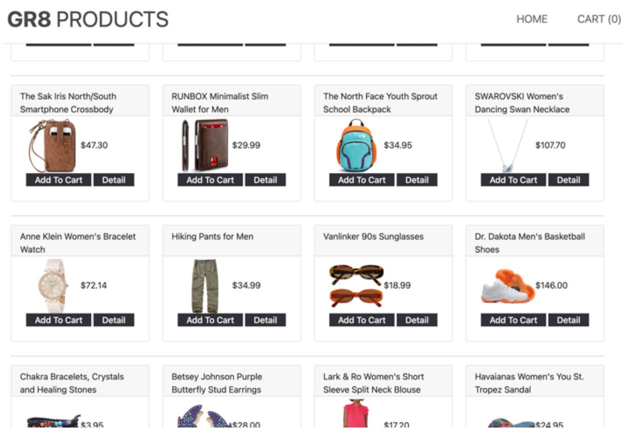

Figure 2. Example of how items that catch a users attention may influence mouse movements.

A. Goal-driven treatment

In the goal driven treatment, participants were told:

> *You are interviewing for a new job. To prepare, you need to find nice business clothes to wear that fit the company's requirements found below:*
>
> *- Navy or black bottoms*
>
> *- A button up top*
>
> *- Dark colored dress shoes*
>
> *Visit the website below and find clothes that meet the requirements. Take a screenshot of your final shopping cart and upload it.*

B. Browsing treatment

In the browsing treatment, participants were told:

Pretend it is your birthday. Hypothetically, someone gives you the option of $50 in cash or you can get 3 items off the website below. Browse the website for a bit and put your decision below.

If you choose three items, take a screenshot of your shopping cart for later.

C. Data capture

Participants then visited the website to complete their task. This website contained embedded JavaScript that captured behavioral data as the user interacted with the website. The library captured the x- and y-location of mouse movements, along with timestamps. It then sends the data to the server to calculate speed, x-flips, and y-flips.

To calculate speed, we first calculated the cursor distance for each participant using the Euclidean distance between two x/y positions a_i and a_{i+1}: $d(a_i, a_{i+1}) = \sqrt{(a_i^{(x)} - a_{i+1}^{(x)})^2 + (a_i^{(y)} - a_{i+1}^{(y)})^2}$, leading to a total distance of $D = \sum_{i=1}^{n-1} d(a_i, a_{i+1})$ between the recorded points $a_1, a_2, \ldots, a_n$. Cursor speed was then calculated as a function of cursor distance D and movement time t during the task, measured in pixels per millisecond: $v = D / t$.

X- and y-flips were calculated through logic that recorded which way the user was moving on the x- and y-axis. Then, if the direction of movement changed, the number of x- or y-flips were incremented depending on whether the change occurred on the x-axis, y-axis, or both. Figure 3 – 6 demonstrates scenarios of no flips, an x-flip, a y-flip, and a combined x- and y-flip.

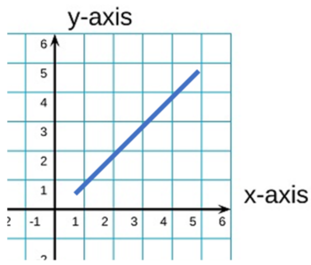

Figure 3. No flip

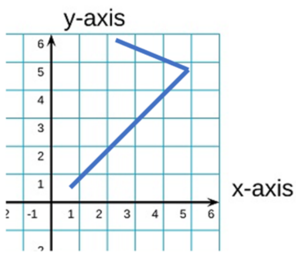

Figure 4. X-flip

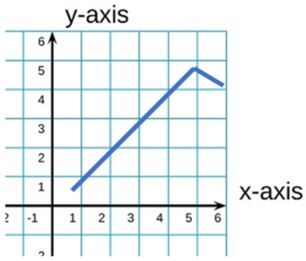

Figure 5. Y-flip

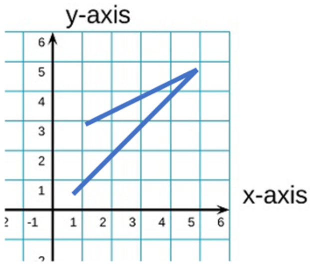

Figure 6. Both x- and y-flip

We also recorded which treatment all participants were in so we could examine differences in speed and x- and y-flips per treatment.

D. Participants

One-hundred-sixty-six participants were recruited from Amazon's Mechanical Turk to participate in the study. They were paid $2 for an approximately 10-minute task, which is equivalent to a $12 hourly rate. Forty-three percent of participants were between the age of 35 – 44; the second most common age group was 25-34 (31%). Sixty-one percent of the participants were male. The most common ethnicities were White (61%), Asian (32%), and African American (6%). Participants were limited to those who had a computer mouse. In some cases, technical difficulties made it impossible to calculate statistics and those participants were therefore excluded as denoted in the analysis.

E. Analysis

We conducted Welch two sample t-tests to test our hypotheses. First, we examined whether speed was different between users in the goal-directed task and the browsing task. The mean speed in the browsing group was 1.99 (sd = 1.59) pixels / ms, and the mean for the goal directed group was 1.36 (sd = 1.36) pixels / ms. The difference was significant: t = 3.30 (104.90), $p < .001$. Hence, the people in the browsing condition moved significantly faster than people in the goal-directed condition. H1 was thus not supported; although it was significant, it was significant in the opposite direction as hypothesized.

Next, we examined whether x- and y-flips were different between users in the goal-directed tasks and the browsing task. The mean x-flips and y-flips in the browsing group was 21.04 (sd = 18.27) and 26.11 (sd = 24.51) respectively, and the means for the goal directed group were 29.98 (sd = 26.50) and 37.32 (sd = 35.73) respectively. Both the differences for x-flips [t (143.79) = -2.52, p < .01] and y-flips [t (143.40) = -2.34, p < .05] were significant. Hence, H2 and H3 were not supported; although they were significant, they were significant in the opposite direction as hypothesized. The results are summarized in Table 1.

TABLE I. SUMMARY OF RESULTS

Hypothesis	***Browsing mean (standard deviation)***	***Goal Driven mean (standard deviation)***	***Result***
H1. Goal-directed users will have faster speed than browsing users	1.99 (1.59) pixels / ms	1.36 (0.64) pixels / ms	Opposite Effect Observed***
H2. Goal-directed users will have fewer x-flips than browsing users	21.04 (18.27)	29.98 (26.50)	Opposite Effect Observed **
H3. Goal-directed users will have fewer y-flips than browsing users	26.11 (24.51)	37.32 (35.73)	Opposite Effect Observed *

* p < .05, ** p < .01, p < .001

V. DISCUSSION AND FUTURE RESEARCH

In our study, we examined the influence of a goal-directed task on movement speed, x-flips, and y-flips compared to a browsing task. We predicted that one who is goal directed would move faster to achieve the goal and deviate less in terms of x- and y- flips. To test our hypotheses, we created an experiment where participants recruited from Amazon Mechanical Turk were randomly assigned to a shopping task where they were asked to find a specific product (goal-directed task) or explore the website to find products that might be interesting to them (browsing task). Contrary to our predictions, participants in the browsing task had less deviation and moved slower (H1, H2, and H3 not supported; significant opposite effect observed).

Upon further evaluation of the experimental design, we are hesitant to conclude that indeed a person in a browsing state would normally move faster and have less deviation than a person in a goal driven state. Rather, we believe the difference is due to the sample population: Amazon Mechanical Turk. Namely, despite our manipulations, it is probable that the majority of Mechanical Turk Workers were driven by a high goal-directed motive: to adequately complete the task as quickly as possible to be paid so they can move on to the next task. Thus, we propose that perhaps both groups could be in a goal-directed state, but the participants who receive the goal-directed manipulation had more requirements to complete the task (find a specific product) that required more careful evaluation, slowing down speed and creating more deviation in their search task. Whereas people in the browsing manipulation did not have requirements to find any product specifically, so they were able to put in much more minimal effort and could complete the task with lesser involvement. This is evident in that participants in the browsing group completed the task in 20 seconds less than people in the goal-directed tasks (71,284 ms compared to 93,702 ms on average).

We believe that our observations potentially have important implications for the use of Amazon Mechanical Turk as research subjects [19-21]. One must consider how the goal-directed motivation of workers to complete tasks efficiently to move onto the next task interacts with the manipulations in the experiment. There are several reasons why an Amazon Mechanical Turk worker's motivation to complete a task efficiently differs from a normal population's motivation as shown in Table II.

TABLE II. POSSIBLE DIFFERENCES BETWEEN AN AMAZON MECHANICAL TURK WORKER AND OTHER POPULATIONS

Category	***Amazon Mechanical Turk Worker***	***Non-Crowd Sourced Worker***
Compensation	Daily compensation is determined by how many tasks can be completed	Daily compensation is limited to this task; there is likely not another immediate task to complete
Task Experience	Has experience in completing tasks efficiently.	Doing an experimental task is novel.
Motivation	More universely motivated to complete task efficiently to earn more money, resulting in a systematic pattern.	A variety of motivations that are randomly distributed across participants, resulting in random noise.

In the case of our experiment, not considering the motivation may have unintentionally changed our manipulations. Instead of having a goal-directed and browsing manipulation, we more likely had a goal-directed with specific requirements manipulation and a goal-directed with minimal requirements manipulation (Figure 7)

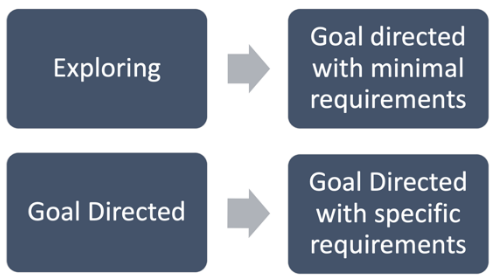

Figure 7. How a Amazon Mechanical Turk sample population influenced the intended manipulations of this study

Hence, we recommend that researchers ask the following question before selecting Amazon Mechanical Turk as the sample population:

Does the motivation of the sample population matter?

In many cases, it does not. For example, it likely matters less when participants are selecting their preference for different products, doing classification tasks, or providing their opinion on a variety of matters. However, it likely does matter when the researchers are trying to manipulate motivation, because the results of the study may not generalize to random populations that do not have a systematically higher motivation to complete the task efficiently to increase their daily compensation. It is also questionable whether Amazon Mechanical Turk workers are appropriate for tasks where the research is attempting to generalize elements of timing to other populations (movement speed, classification time, navigation patterns, etc.).

VI. Conclusion

This paper explores how to analyze mouse-cursor movements to categorize browsing and goal-directed users in an online setting. Drawing on attentional selection theory and response activation model, we predict how mouse-movement speed, x-flips, and y-flips will differentiate between users who are browsing a website versus goal-directed users. We conducted an experiment where participants were randomly assigned to either a goal-oriented task or a browsing task in a mock online store. Our hypotheses were not supported; rather, we found a significant opposite effect. However, we speculate that the results were largely affected by the systematic motivation of our selected sample population – Amazon's Mechanical Turk. We discuss learnings on when it is appropriate to use Amazon's Mechanical Turk, and implications for designing future studies to classify user personas.

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