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Understanding Product Interest through Mouse-Cursor Tracking Analysis

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ABSTRACT

With third-party cookies being banned, alternative methods to assess users' interests online are necessary. We propose that analyzing mouse cursor movements can help address this need. Based on the response activation model, we hypothesize that interest in a product will decrease the user's movement speed and increase the number of submovements. We conducted an online study that monitored users' mouse movements while they were presented with several products and navigated to a button to indicate purchase intention (yes/no). Following this, participants ranked their interest in each product. Contrary to our prediction, we found that product interest increased speed and decreased the submovement count. This suggests that current theories and metrics for mouse cursor tracking are insufficient for predicting product interest. Further research is needed to develop reliable measures for gauging user interest in products.

Keywords

Product interest, advertisements, mouse cursor movement, movement speed, submovement count, response activation model.

INTRODUCTION

In today's digital age, understanding users' product interests is critical for e-commerce success. Third-party cookies have long been used to track users' online activity for targeted advertising and analytics. However, due to increasing concerns about user privacy and data security, third-party cookies are now facing a ban in various browsers and regulations. This ban poses challenges for businesses and marketers, as they will need to find alternative ways to understand user interests and deliver personalized advertisements.

We propose that the analysis of users' mouse-cursor movements can provide insights into users' product interests. Every click, hover, or drag uncovers hidden trends, reflecting the cognitive processes that guide decision-making (Pieters & Wedel, 2004). Online environments, especially in e-commerce, have become central arenas where consumers engage, deliberate, and decide (Manchanda et al., 2006). These digital footprints offer us unique insights into the underlying cognitive processes of users. Understanding how these digital interactions correlate with product interest and preferences is not just an academic question but holds immense commercial value.

To explore the potential of analyzing mouse movement behavior to understand product interest, we draw on the response activation model (Welsh & Elliott, 2004). We hypothesize that users will move more slowly and experience a greater number of submovements when they encounter a product of interest. However, the results of a controlled study revealed the opposite effect: product interest drove significantly faster movements and fewer submovements. We discuss how the response activation model, despite its popularity, may not be sufficient alone to explain product interest and suggest future research and feature generation to better gauge users' interest in products.

RELATED WORK

Research on assessing users' product interests has expanded significantly over the past few decades, especially within an advertising context. A central theme of this area of research is what influences and captures users' attention in online product advertising scenarios. For example, Goldfarb and Tucker (2011) analyzed the influence of different ads on users, finding that attention is allocated differently depending on the advertisement type. Pieters and Wedel (2004) employed eye-tracking methodologies to outline how various visual elements within online advertisements command consumer attention. In a video context, Teixeira et al. (2019) analyzed the temporal dynamics of attention, highlighting how the initial few seconds of video advertisements are crucial in capturing viewer interest.

In this paper, we explore how users' attention influences mouse cursor movements. Mouse movements have been shown to be influenced by different cognitive and emotional states (Hibbeln et al., 2017; Banholzer et al., 2021; Valacich et al., 2013; Weinmann et al., 2021). Of particular interest, mouse-cursor tracking has emerged as a valuable tool in understanding human attention allocation. Through the simple motion of a computer mouse, researchers can gain insights into users' attention patterns and behaviors. By monitoring the movement and positioning of the mouse cursor on a computer screen, it becomes possible to infer what captures users' attention and where their focus lies.

As real-world visual environments are far more complex than the typical lab test interface, attention researchers integrate complementary theories to more accurately model human behavior (Schneider et al., 2013). One of the most commonly utilized theories is the response activation model (RAM) (Welsh & Elliott, 2004). RAM explains how hand movement originates, explaining that "attention and action are intimately linked" (Welsh & Elliott, 2004, p. 1054). RAM has been used to explain how people answer questions about compliance (Jenkins et al., 2021), deception (Jenkins et al., 2019), real-time decision processes (Freeman & Ambady, 2010), decision conflict (Dale & Duran, 2011), and emotion (Hibbeln et al., 2017), to name a few examples. In this paper, we incorporate the RAM to explain the relationship between product interest and mouse-cursor behavior.

THEORY & HYPOTHESES

RAM explains the relationship between attention and hand movements. Specifically, when an item with actionable potential (e.g., something you could click on, read, explore more, etc.) captures a user's attention, the body's nervous system automatically and subconsciously primes movements toward the item (Welsh & Elliott, 2004). For instance, if an advertisement on the side of a webpage captures a user's attention because of personal interest, the user is more inclined to move towards the item.

This natural reaction to items that catch one's attention allows the body to optimize movements. It takes time for the brain to perceive an item, intentionally decide how to respond to the item, and then send actions through the nervous system to perform the action. To optimize this process, the brain primes movement toward the item before intentionally deciding to move, allowing the body's reaction time to be substantially faster (Welsh & Elliott, 2004). People often see the aftermath of this process. For example, if you are driving on the road and see something that attracts your attention, you may have noticed yourself swaying the steering wheel towards the target.

Through top-down processing, you may ultimately choose not to move towards the object. When this happens, nervous system stimulation priming the movement halts, overcoming the subconscious attraction to the object (Welsh & Elliott, 2004). The brain programs corrections, known as submovements, that ultimately move the hand away from the stimulus and toward the intended destination (Meyer et al., 1988). As will be explained in our methods section, these submovements can be measured by analyzing the computer mouse data. If a product captures a user's attention, we expect to see an increase in the number of submovements as more corrections are needed to ultimately reach the intended destination. In summary, we predict:

H1: Interest in a product displayed on a webpage will increase the number of submovements for a user.

Aside from creating more submovements, attention-grabbing stimuli on a webpage consume cognitive resources and thereby slow down mouse movements due to the limited capacity of the human brain to process information. When individuals encounter multiple stimuli simultaneously, their attention is divided, and cognitive resources are distributed among the various stimuli. This divided attention leads to slower processing and response times. In the context of a webpage, distracting stimuli, such as advertisements or products that capture attention, can divert cognitive resources away from the task at hand, which is typically navigating the page or moving the mouse. As a result, the brain's ability to process and execute quick, precise movements with the mouse is hindered, leading to slower mouse movements. In summary, we predict:

H2: Interest in a product displayed on a webpage will decrease the movement speed of a user.

ONLINE STUDY

To test our hypothesis, we conducted an online study in which participants completed two tasks. In the first task, we showed the participants 30 different products in a random order and asked them if they would buy the product (yes/no). Participants could only see the product once after they clicked the "show picture" button (see Figure 1). While making their decision (yes/no), we tracked their mouse cursor movements. Note that the "yes" and "no" buttons were also randomized per participant, so differences in the location of buttons cancel out.

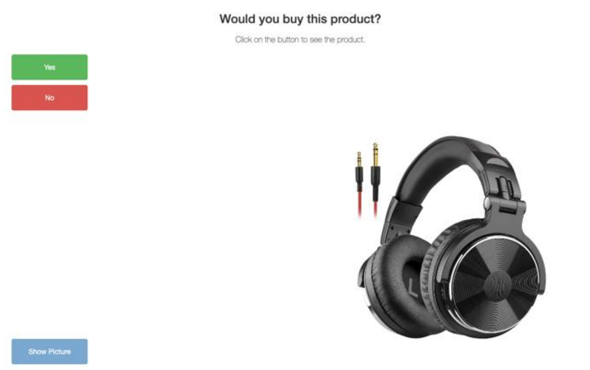

Figure 1. Part 1 of the study: Tracking participants' mouse movements while they made a decision.

In the second part of the study, we showed the participants the same products and asked for their preferences regarding the respective product on a Likert scale from 1 to 5 ('Not interesting at all' – 'Extremely interesting'; see Figure 2). Finally, we gathered demographic variables and debriefed the participants.

Figure 2. Part two of the study: Asking participants about their preferences regarding the products from task 1.

Participants

We recruited 100 participants between the ages of 18 to 75 from the United States via Prolific. The mean age was 35.5 years, and 46% of the participants were female. The study was only accessible for desktop users. We removed two participants for whom we had no mouse movement data. Given that 98 participants completed 30 tasks, we had a total of 2,940 observations to analyze. Each participant received £1 for completing the 6-minute study.

Measurements

Using JavaScript, we collected raw mouse cursor movement data (e.g., x-y coordinates, timestamp, etc.) and related behavioral data (e.g., clicks, etc.) while the user was responding to whether or not they would buy the product. This data was sent to a custom webservice and stored on a server for subsequent analysis. For every participant, we calculated the mouse cursor speed by dividing the actual distance traveled by the movement time. We also calculated the count of submovements, defined as uninterrupted cursor movement without a meaningful pause. A click or a meaningful pause, defined as a time stop greater than 200ms (Weinmann et al., 2021), denoted the end of a submovement and incremented our submovement count.

Model Specification

We specified a linear multilevel regression model to estimate the product interest on two outcome variables: movement speed and submovement count. Multilevel models allow us to account for repeated observations for each individual. The model is shown below:

$$y_{ij} = \alpha + \beta * product\ interest_{ij} + u_i + \varepsilon_{ij},$$

where y_{ij} denotes the i-th observation of y (i.e., mouse submovement or mouse movement speed) for the j-th participant. Further, α represents the fixed intercept and β the effect of preference on either speed or submovement. u_i is the subject-specific effect and ε_{ij} the residual error. According to our hypotheses, we expect β to be positive for the submovement model (H2) and negative for the speed model (H1).

Results

The regression results did not support our hypotheses (see Table 1). In fact, we observed a significant opposite effect to what was hypothesized. Increased interest leads to a significant increase in speed (β = 0.03, p < 0.05) and a significant decrease in the number of submovements (β = −0.04, p < 0.01). To facilitate interpretation, we transformed the results into percentages. For each additional rating score on the preference scale (measured from 1-5), mouse movement speed increases by about 9 percentage points, and the submovement decreases by 10 percentage points.

	Dependent Variable	
	Submovement count (H1)	Speed (H2)
Interest	-0.041*** (0.016)	0.030** (0.014)
Constant	0.436*** (0.042)	0.365*** (0.038)
Observations	2,940	2,940

Participants	98	98
Notes: standardized betas; * p<0.1, **p<0.05, ***p<0.01		

Table 1. Results from a multilevel regression model with user-specific effects

DISCUSSION

In this paper, we examined how a person's interest in a product would influence their mouse cursor movements. Based on the response activation model (RAM), we postulated that heightened interest in a product would increase submovement count and decrease speed. To test these predictions, we designed and executed a controlled study. Contrary to our initial expectations, the data did not support our hypothesis; instead, we found a significant opposite effect for both hypotheses.

Contributions to Research

Much research has used the RAM to explain the relationship between cognitive processes and mouse cursor movements. However, in our context, we found the RAM alone is not adequate to explain the relationship between product interest and movement speed/submovement count. This suggests that new theoretical perspectives are needed to explain the relationship between product interest and mouse cursor movements.

One theory that could potentially improve our understanding is Capacity Theory (Kahneman, 1973). In understanding consumer interactions and behaviors, the allocation and management of attentional resources play a crucial role. Rooted in cognitive psychology, the capacity theory posits that individuals possess a finite set of attentional resources, which they allocate differently based on task demands and personal interests.

Within the context of Capacity Theory, when a product resonates more with an individual, it commands a larger share of their attentional resources. This may manifest itself in direct and rapid movements towards the product, indicating heightened interest (Pieters & Warlop, 1999). On the other hand, less attention to the product may result in more exploratory and less directed movements, symbolizing lower engagement or interest (Orquin & Loose, 2013). Based on this theory, one explanation for the opposite effect observed in our study is that when individuals view a product that resonates with their preferences, there is an instinctive surge in the allocation of their finite cognitive resources, leading to quicker mouse movements and more direct movements (fewer submovements). We recommend future research to explore this potential explanation in more detail.

We also recommend more sophisticated measures of users' behavior that more robustly and accurately indicate a user's cognitive and emotional states. In our study, we relied on two aggregate statistics that described the movement: movement speed and the number of submovements. However, these statistics do not explain how a movement changed throughout the interaction. We anticipate that there is a decisioning component to the movement (a period deciding how to respond) and a reaction part of the movement (moving to click yes or no after the decision). Developing more fine-grained temporal measures describing the movement (e.g., changes in acceleration, velocity, and accelerator) during the period of the movement may provide insight into a user's interest in the product.

Finally, analyzing users' mouse-cursor movement to understand product interest contributes to marketing literature on advertising. Much research has examined advertisement effectiveness based on self-report measures or using eye tracking (e.g., Goldfarb & Tucker, 2011; Pieters & Wedel, 2004; Teixeira et al., 2019). However, self-reporting and eye-tracking detract from the flow of the interaction and are not easily scalable to the wild – i.e., uninterrupted use of a website in the real world. Mouse-cursor tracking can be analyzed covertly without interrupting or distracting from a natural interaction. Hence, our research creates a foundation for advertising research to collect even more realistic data and thereby make more ecologically valid conclusions.

Managerial Implications

The inability to rely on third-party cookies to understand users' preferences creates a significant challenge for business owners. Traditionally, these cookies have played a crucial role in collecting data about users' online activities, allowing businesses to analyze and understand their customers' interests and behaviors. However, with growing concerns about privacy and increased regulations, such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), the use of third-party cookies is becoming increasingly limited.

Our research endeavors to address this pressing need. By utilizing mouse-cursor tracking, we can potentially gain valuable insights into users' interests and preferences within a single session without requiring any prior knowledge of the user or storing sensitive data across websites. While our initial hypotheses were not supported, we did uncover significant results that point in the opposite direction. This suggests that behavior tracking has the potential to offer meaningful insights into users' interests. Conducting further research to better understand this relationship and develop more robust and accurate mouse-cursor movement measures will benefit business owners and consumers alike, enabling them to enjoy customized experiences without sacrificing privacy.

Limitations

In our study, we conducted a controlled experiment that involved individuals moving vertically on a webpage while viewing a product image on the side. The purpose of this was to simulate an advertisement on the side of a webpage. However, the overall design lacked the realism of a real e-commerce webpage with advertisements on the side. We recommend future research to address this limitation.

Additionally, our initial metrics, focusing on mouse movement speed and submovements counts, could be expanded. Future studies should also explore new metrics, such as mouse acceleration, which could provide deeper insights into individuals' attraction to products.

CONCLUSION

In this paper, we explore the dynamics of mouse movements as a metric for assessing product interest in online environments and understanding the decision processes. Based on the response activation model, we predict that a person's interest in a product would decrease their movement speed and increase the submovement count. We created an online study to test our hypotheses, where people navigated a task in the presence of a product while we collected mouse-cursor behavior and later reported their interest in the product. Contrary to our prediction, we found that product interest increased speed and decreased submovement count. Our results suggest that the response activation model – despite its common use in mouse-tracking literature – alone is not adequate to explain the relationship between mouse-cursor speed, submovement count, and product interest. We discuss possible other theoretical lenses to understand the relationship and propose more sophisticated movement measures to gauge product interest through mouse-cursor movements.

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