Summer 2016

Effect of timing and source of online product recommendations: An eye-tracking study

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EFFECT OF TIMING AND SOURCE OF ONLINE PRODUCT
RECOMMENDATIONS: AN EYE-TRACKING STUDY

by

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A THESIS

Presented to the Faculty of the Graduate School of the

MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE IN INFORMATION SCIENCE AND TECHNOLOGY

2016

Approved by

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ABSTRACT

Online retail business has become an emerging market for almost all business owners. Online recommender systems provide better services to the consumers as well as assist consumers with their decision making processes. In this study, a controlled lab experiment was conducted to assess the effect of recommendation timing (early, mid, and late) and recommendation source (expert reviews vs. consumer reviews) on e-commerce users' interest and attention. Eye-tracking data was extracted from the experiment and analyzed. The results suggest that users show more interest in recommendation based on consumer reviews than recommendation based on expert reviews. Earlier recommendations do not receive greater user attention than later recommendations.

ACKNOWLEDGMENTS

First, I want to thank Dr. Fiona Nah from Missouri University of Science and Technology for mentoring me on various research projects including this research. I would also like to thank my committee members, Dr. Keng Siau and Dr. Richard Hall, for your advice and suggestions on this thesis.

Next, I want to thank Dr. Amy Shi, Dr. Chuan-Hoo Tan, and Dr. Choon Lin Sia from City University of Hong Kong for giving me the opportunity to collaborate with them on this experimental research study. I would also like to thank Samuel Smith for helping to proofread the thesis.

Last but not least, I want to thank all members from the Laboratory for Information Technology Evaluation for helping to coordinate and conduct these experiments.

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1. INTRODUCTION

Based on data from the U.S. Census Bureau, U.S. retail e-commerce sales for the first quarter of 2016 has reached $92.8 billion, which accounts for 7.8 percent of total retail sales (DeNale & Weidenhamer, 2016). Over the past decade, sales of retail e-commerce have a yearly growth of more than 15%. In order to boost sales, more and more retailers are implementing online recommender systems, or, recommendation agents (RAs) which can provide better services and help customers with the decision making process. The algorithms underlying online recommender systems (Hostler et al., 2012) as well as the effects of online recommender systems (Adomavicius et al., 2013) have been studied in the past decade but there is little research to assess its efficacy and user interest.

Although online product recommender systems have been influential in boosting sales as well as user satisfaction, there are still some recommender systems that are poorly designed or ineffectively implemented. The goal of this research is to study some of the key characteristics of online product recommender systems and their effects on users.

In this research, the researcher is interested to examine the effects of an online product recommender system on users' attention and interest in terms of the display timing (i.e., early, mid, and late) of the recommendation and the sources of recommendation content (i.e., expert vs. consumer).

We expect the outcome of this research to be helpful to online retailers in improving their online recommender systems.

2. LITERATURE REVIEW

2.1. ONLINE PRODUCT RECOMMENDER SYSTEMS

Online product recommender systems are widely used to provide consumers with alternatives that they might be interested in. Current product recommender systems are using various filtering systems including content-based filtering, collaborative filtering, and hybrid methods to provide consumers with the right products (Aciar et al., 2007). Online retailers rely on recommender systems as a decision aid to the customers in order to provide better service and to boost sales. According to research conducted by Forrester Research, product recommender systems accounted for 10 to 30 percent of total sales by a retailer (Schonfeld, 2007).

Prior studies on product recommender systems are mainly focused on the optimization of algorithms to provide more accurate predictions and suggestions to the customers (Hostler et al., 2012). According to Adomavicius et al. (2013), most recommender systems take into account consumers' ratings of the products experienced and used them to calculate ratings for the products and to predict customer preferences. One type of recommender systems that is widely used is called the collaborative recommendation system. Such type of systems does not recommend items based on similarities with the users' past preferences, but on what similar users like. Another popular type of recommender systems is called content-based recommendation system. It provides recommendations by comparing products to users' profiles. Based on the match of product features and user preferences, the item with the highest rating will be recommended to the user. Some recommender systems implement a hybrid approach to combine both content-based and collaborative systems to avoid the weaknesses of either systems (Balabanovic, 1997). Although most recommender systems have limitations such as the requirement to have a large amount of prior customer data (Ansari, Essegaier, & Kohli, 2000), the impact of recommendation systems on consumers' decision making process has been effective. Lu et al. (2015) evaluated recommender systems in different business settings to provide suggestions on building an effective recommender system.

In general, online user reviews can influence consumers through awareness effects or persuasive effects (Duan et al., 2008). Awareness effects can create exposure of the product to the customer so that he or she is more likely to include the recommended product in his or her choice set. Persuasive effects can improve customers' attitudes during the evaluation process, which in turn affects their decision making. Online reviews can also affect customers' decision making through word of mouth.

Table 2.1 provides a summary of research studies on online recommender systems.

Table 2.1: Summary of literature review on online recommender systems

Author(s)	**Focus**	**Key findings**
Adomavicius et al., 2013	Influence	People's preference ratings can be significantly influenced by recommendations. Recommender systems have an anchoring effect that is continuous and linear.
Ansari et al., 2000	Algorithm	Simple and flexible models are described to incorporate revealed preferences on the basis of explicit and implicit data. Procedure for ratings data were also developed.
Balabanović & Shoham, 1997	Algorithm	A hybrid online recommender system called Fab was tested against other sources which resulted in higher performance.
Cosley et al., 2003	Influence	In movie ratings, a recommender's prediction can influence users' opinion.
Hostler et al., 2012	Influence	Recommendation systems can increase consumers' perceived attractiveness of products
Guan et al., 2014	Algorithm	A recommender system was proposed that takes into account the item quality and user rating preferences that decreases the computing complexity was proposed. A significant higher accuracy was observed compared to three other benchmark systems.

Table 2.1: Summary of literature review on online recommender systems (cont.)

Iacobucci et al., 2000	Algorithm	Based on an extensive review process and cluster analysis, simple Jaccard coefficient was found to be a reliable index of similarity. Content-based similarity among products and the affirmative customer network should be taken into account in forming the recommendations.
Kim et al., 2005	Algorithm	A recommender system using consumer navigational and behavioral pattern to estimate the consumer preference levels was examined to outperform benchmarking systems.
Lee & Kwon, 2008	Algorithm, Influence	Casual maps based recommendation mechanism was recommended to enhance consumers' decision satisfaction, attitude towards the recommended products, positive purchase intentions, and actual purchase.
Senecal & Nantel, 2004	Features, Influence	Product recommendations result in higher purchase rate than without recommendations. Recommendation systems labeled "recommender system" were more influential than labeled as "human experts" and "other consumers".
Shi et al., 2013	Features, Influence	The timing and basis of the recommendations resulted in significant differences in consumers' decision satisfaction and decision difficulty.
Wang & Benbasat, 2007	Algorithm, Influence	The study found that the use of explanation facilities enhanced consumers' initial trusting beliefs. Furthermore, different explanation types could influence different trusting beliefs.

2.2. EYE-TRACKING

The use of eye-tracking devices on information processing tasks has been around for more than a century. In order to track the location of eye fixations, invasive methods were first implemented involving direct mechanical contact with participants’ cornea. As research on eye-tracking evolves, non-invasive methods such as using light on the cornea and recording the reflection to obtain fixation data became more common (Jacob & Karn, 2003). Eye-tracking studies became more popular as equipment became more accurate and psychological theories became more advanced. Researchers were able to use eye-tracking data to study cognitive processes. However, using eye-tracking to study usability issues was more scarce due to issues regarding data collection and data analysis methods (Jacob & Karn, 2003). In the 1980s, as personal computers became more popular, researchers started using eye-tracking devices to study and solve problems in human-computer interaction.

Klin et al. (2002) utilized eye-tracking and discovered that reduced eye region fixation durations can predict autism. Also, increased fixation duration on mouths indicates improved social adjustment from autism. By studying the gaze shift data from eye-tracking devices, Mason et al. (2013) found that illustrations with text result in higher participants’ effort to integrate verbal and pictorial information. Tsai et al. (2012) used eye-tracking devices to track participants’ eye movement during problem-solving tasks to study their ability to find relevant information and problem-solving outcomes. They found that successful problem solvers focused more on relevant factors.

People’s attention will only focus on the things they need and will ignore others that are presumed to be irrelevant (Triesch et al., 2003). The results from the study by Orquin & Loose (2013) also indicate that decision makers direct their attention to goal-related stimuli. According to Rayner (1978), cognitive processing during a fixation affects the fixation duration. In other words, a longer fixation duration on a certain piece of information implies a higher intensity of cognitive processing.

Based on a study by Shimojo et al. (2003), longer fixation durations reflect higher preference upon choices. As shown in their research, fixations increased exposure to the stimuli which transitioned into preferences. Preferences can reinforce people’s fixations and enhance their perceptions of attractiveness which in turn influence decision making.

The study by Krajbich et al. (2010) indicates that visual fixation process could have a causal effect on people's value comparison process. People's perceived value on choices influences fixations. Also, fixation durations increase as the difficulty of choices increases.

Based on the eye-mind assumption highlighted by Just & Carpenter (1980), people's eyes will remain fixated as long as information is being processed. Rayner (1998) states that although people can move their attention without moving their eyes, it is more efficient to move the eyes than to move attention while fixated on complex stimuli. During an online shopping process, there are many stimuli on the screen. Eye fixation is a well-developed predictor of attention.

Human pupils react not only to change of environmental luminance, but also to change in cognitive processing (Brisson et al., 2013). Pupil dilation was found to be a consequence of attentional effort (Hoeks & Levelt, 1993). According to Laeng et al. (2012), pupil diameter, which is also called "pupillometry", has been used to estimate the intensity of mental activities, change of emotions, change of mental states, and change of attention for more than 50 years. Pupil dilation not only reflects emotional stimuli but also indicates some cognitive mechanisms. In standard light conditions, the diameter of human pupils averages at about 3 mm while the size can reach an average of 7 mm in dim light condition (MacLachlan & Howland, 2002). Pupil diameter is very difficult to control voluntarily. It has been shown that pupil diameter can only be controlled indirectly by mentally imaging a stimuli (Laeng et al., 2012). This characteristic of pupil dilation makes it a good objective measure. In the study by Einhäuser et al (2010), pupil response was defined as the consolidation of mental states related to arousal and mental activities. Pupil dilation was also found to indicate interest to tasks such that an increase in pupil diameter reflects increased interest in the stimuli (Hess & Polt, 1960). Positive pupil dilation indicates an increased task engagement. Negative pupil dilation indicates disengagement from the task.

Greater pupil dilation indicates higher decision threshold in difficult decision making (Cavanagh et al., 2014). The dilation of pupils can represent the need to increase cognitive control when conflicts exist during decision making. Pupil dilation can represents both the mental activity involved as well as the difficulty of the task (Hess & Polt, 1964).

An aggregated review of select prior studies using the eye-tracking technique is listed in table 2.2.

Table 2.2: Summary of literature review on eye-tracking research

Author(s)	Metrics	Key Findings
Brisson et al., 2013	Pupil diameter	Eye-tracking systems have some systematic error estimating pupil size. When reading language such as English, subjects were most aroused when started and became least aroused when reaching the end.
Cavanagh et al., 2014	Gaze dwell time, Pupil dilation	Higher gaze dwell time predicted higher drift rate toward the fixation option. Higher pupil dilation predicted higher decision threshold during difficult decisions.
Einhäuser et al., 2010	Pupil dilation	Pupil dilation reflects post-decisional consolidation of the choice but not the pre-decisional consolidation of the choice.
Gilzenrat et al., 2010	Pupil dilation	Pupil diameter can be measured to reflect locus coeruleus activities. Increases in pupil diameter baseline indicated decrease in task utility and disengagement from the task. Decreases in pupil diameter baseline but increases in task-related dilations indicated higher task engagement.
Hess & Polt, 1964	Pupil diameter	Pupil diameter reflected the total mental activity.
Hoeks & Levelt, 1993	Pupil dilation	Pupil dilation is a consequence of attentional effort. Attentional input and pupil responses are found to have a linear relationship.

Table 2.2: Summary of literature review on eye-tracking research (cont.)

Jacob & Karn, 2003	Fixation, gaze duration, scan path	In HCI, the most widely used eye-tracking metrics are number of fixations, proportion of gaze on each area of interest, fixation duration mean, number of fixations, gaze duration mean, and fixations per second.
Johnson & Mayer, 2012	Area of interest, Scan path	Spatial contiguity resulted in more attempts to integrate words and pictures and had more successful integration of words and pictures during learning which resulted in more meaningful learning outcomes.
Just & Carpenter, 1980	Gaze duration, fixation duration	Readers pause longer on the last word in a sentence when reading. Readers also pause longer when processing loads are greater like accessing infrequent word etc.
Kang & Wheatley, 2015	Pupil diameter	Real-time changes in stimulus salience motivate pupil dilation. Fluctuations of pupil size reflect what is being attended.
Kliegl et al., 2006	Fixation duration	Most of the time, people’s mind processes several words in parallel at different cognitive levels.
Klin et al., 2002	Fixation duration	People with autism exhibit abnormal pattern of social visual pursuit with reduced eye fixations and increased fixations on mouths, bodies, and objects.
Krajbich et al., 2010	Fixation duration	The visual fixation process has a causal effect on the value comparison process. People’s choice can be biased by manipulated relative fixation durations.

Table 2.2: Summary of literature review on eye-tracking research (cont.)

Laeng et al., 2012	Pupil diameter	By reviewing prior studies in pupillometry, pupil response was found to be helpful in studying preverbal or nonverbal participants.
Mason et al., 2013	Fixation count, fixation duration, first-pass fixation time on an Area of Interest, look-back fixation time	Eye-tracking revealed that abstract illustration was more efficient than text alone. Readers made greater effort to integrate verbal and pictorial information when the information was presented with text and illustrations.
Naber et al., 2013	Pupil dilation, pupil oscillation	Pupil dilations and constrictions are both enhanced by available attentional resources.
O'Regan, 1980	Fixation duration, saccade size	When processing linguistic information within six letters distance from current fixation point, the duration of current fixation and the size of the next saccade to be made would be affected. Beyond six words, the linguistic processing became very slow and the current fixation duration and size of next saccade would not be affected.
Orquin & Loose, 2013	Fixation location	Attention processes plays a significant role in making decisions. When making decisions, people make trade-offs between working memories and fixations.
Rayner, 1978	Fixation duration, saccade length, scan path	Eye-tracking data can tell us the processing activities involved in a task. Using eye-tracking data as the dependent variable is a valid approach when studying information processing tasks.

Table 2.2: Summary of literature review on eye-tracking research (cont.)

Shimojo et al., 2003	Gaze location, gaze duration	Manipulated gaze duration results in significant preference biases. People's own gaze bias can be interpreted as a subconscious level preference.
Triesch et al., 2003	Gaze direction	Human vision has a highly task specific nature that people only focus on the information that lead to the solution of a certain task.
Tsai et al., 2012	Fixation duration, fixation heat map, scan path	Participants pay more attention to chosen options rather than to rejected options when making a decision. Successful problem solvers and unsuccessful problem solvers have significantly difference in the scan sequences.
Wierda et al., 2012	Pupil dilation	Pupil dilation provides important information regarding the occurrence of attentional processes.
Hess & Polt, 1960	Pupil dilation	Pupil dilation reflected people's increased interest in visual stimuli.
Krugman, 1964	Pupil dilation	Pupil dilation indicated usefulness on interpreting user interest on visual stimuli.
Stass & Willis, 1967	Pupil dilation	By measuring the pupil dilation, the study found out both women and men were attracted by others who appear to be interested in them.

3. THEORETICAL BACKGROUND AND HYPOTHESES

Jacobs et al. (2015) examined participants' involvement in, and evaluation of motion pictures. The results indicate that consumer reviews significantly influence participants' evaluation while expert reviews do not. However, expert reviews have no effect on participants' involvement with the content compared to consumer reviews. In the context of online shopping, Purnawirawan et al. (2014) found that for positive reviews, expert review did not result in higher purchase intention compared to consumer reviews. However, according to Senecal and Nantel (2004) , consumer recommendations were found to be significantly more trustworthy than expert recommendations. The results from the study by Utz et al. (2012) also indicated that consumer reviews were the key factor to judge the online store trustworthiness. Chiou et al. (2014) found out that in the context of culture offerings, online expert culture reviews have a significantly higher credibility than consumer reviews.

Despite the contradicted findings from previous studies, consumer reviews, in many cases, were found to be more trustworthy than expert reviews in e-commerce. Trustworthiness can lead to higher user attention on the reviews. Bettman et al. (1998) also explained that due to the limited processing capability of consumers, they generally cannot process all available information and they would only direct their interest on information that are perceived to be relevant to their current goals.

Although expert opinions have higher authority in certain contexts, as a shopping aid, recommender systems can be more useful if consumers can be attracted to the content. The similarity-attraction paradigm (Byrne, 1971) can be used to explain the reason consumer reviews won over expert reviews in a number of prior studies in the context of online retailing. The similarity-attraction paradigm posits that people like and are attracted to people who are similar to them (Byrne, 1971). Byrne and Griffitt (1973) found that attraction was found to be positively affected by people with similarities. Also, economic status, simple behavioral acts, and task performance were also found to positively influence perceived attraction among people.

Consumer reviews were written by former consumers who were previously likely to be in or who were facing similar situations as the current customer or shopper. Hence, customers can empathize and relate well with consumers who likely had more similarity in goals, experiences, and/or attitudes. Experts, On the other hand, though considered to be a higher authority in certain fields, may not share similarities with current customer or shopper. Consequently, consumer recommendations are expected to attract greater interest than expert recommendations.

Therefore, based on the similarity-attraction paradigm, the following hypothesis is proposed:

H1: Consumer recommendations will attract greater user interest than expert recommendations.

According to Bettman et al. (1998), people often have no well-defined preferences until they start to build the “preference pool” when they need to make a choice. As indicated from the study by Shi et al. (2013), in the initial phase of online shopping, people tend to increase the “preference pool” in order to not miss any potentially good alternatives. When the “preference pool” reaches saturation, people tend to narrow down the alternatives by rejecting new products and reduce the size of the “preference pool” in order to reach the task goals.

Galinsky and Mussweiler (2001) found that the first offers served as anchors and were a strong predictor of the final deal in a seller-buyer context. During the buyer’s decision making process, his or her judgements rely heavily on the initial anchor. People’s judgement are severely biased by uncertainty and anchoring bias can occur (Tversky & Kahneman, 1974). As consumers work on shopping tasks, their uncertainty about the outcome will be lower as they carry out the evaluation process. Hence, the initial anchors on specific products that have gone through the evaluation process can deter attention on subsequent product recommendations offered by the online recommender system.

Based on the anchoring effect and bias, decision makers tend to make decisions toward the initial anchor (Adomavicius et al., 2013). In an e-commerce context, after a decision maker has anchored on specific products of interest to them, they are less likely to attend to other recommendations offered by online recommender systems. Hence, the following hypothesis is proposed:

H2: The earlier a recommendation is offered by online recommender systems, the greater the user attention toward the recommendation.

4. METHODOLOGY

A 2 X 3 X 2 mixed experimental design was used for his research and the experiment was conducted in the Laboratory for Information Evaluation on the Missouri University of Science and Technology campus. The first factor refers to the source of recommendations provided by an e-commerce website: expert vs. consumer recommendations. The second factor refers to timing of recommendations, i.e., when the recommendations are offered, i.e., early, middle, or late in the e-commerce shopping process. The third factor refers to two product types, laptop and cell phone, used in this experiment. The first and second factors are between-subject factors whereas the third factor is a within-subject factor. Hence, there are 6 (i.e., 2 X 3) experimental conditions in this study. Subjects were randomly assigned to one of the 6 conditions, and the two products or levels associated with the within-subjects factor were counterbalanced to address any potential ordering effect.

76 subjects were recruited from Missouri University of Science and Technology. All subjects were pursuing their bachelor's degree. All subjects have normal eye-sight before or after adjustment. The average size in each experimental condition is 12. A consent form was provided to each subject upon arrival. Subjects were asked to go through a training session on the shopping website that was designed for the experiment. They were then asked to carry out two shopping tasks including two types of products: cell phones and laptops. As mentioned earlier, the sequence of these two tasks involving two different products was counterbalanced. Each subject was given extra credit for their class and was provided with a souvenir after the experiment.

Three Tobii T60 eye-trackers, i.e., one of them in each of three separate lab rooms, were used as the computer monitor displays for the experiment. The resolution of the display is 1280 * 1024. The use of three eye-trackers allowed us to conduct three concurrent experimental sessions with the subjects. The moderator (or experimenter) at each of the three stations was given a standardized moderator script to following in conducting the experiment to avoid moderator biases. The luminance of all lab rooms were controlled to be at the same level.

The recommendation source was manipulated in two categories: expert vs. consumer. In the experiment, the recommendation source was highlighted on the recommendation pages. The heading used for the recommendation page was either “Other consumers recommend this product to you” or “Experts recommend this product to you”. Several product reviews were provided on each product recommendation page and they were extracted from existing e-commerce websites. On each recommendation page, an image of the recommended product along with specifications of the recommended product were displayed.

The recommendation timing was manipulated in three categories: right after entering the website (i.e., early recommendation), after clicking “Add to shopping cart” for the first chosen product (i.e., mid recommendation), and after clicking “Purchase” button (i.e., late recommendation). Early recommendation appeared when the subject first entered the shopping website and before any other activities were conducted, i.e., no alternatives were gathered by this time. Mid recommendation popped up right after the subject has added the first item into the shopping cart as alternatives were being collected. Late recommendation appeared when the subject clicked on the purchase button as preliminary purchase decision has been made.

The subjects were asked to complete two shopping tasks: (i) purchase a laptop, and (ii) purchase a cell phone. Both products were chosen because of their popularity among the pilot test subjects. The laptops had higher average prices than the cell phones. The task sequence was counterbalanced such that some subjects shopped for a cell phone first while others shopped for a laptop first.

The shopping website allowed subjects to search using various combination of search criteria to browse product details from the search results. The subjects were allowed to conduct search activities within the product database until decisions were made. Single criteria searches and multiple criteria searches were both supported. There was no time limit given to complete each task.

5. DATA ANALYSIS AND RESULTS

Due to eye-tracking recording failure, 5 out of the 76 data points were excluded from the data set. All data were recorded by Tobii Studio software on Tobii T60 eye-trackers. The corneal reflection based devices computed and recorded the data including time, coordinates of eye movement activities, eye movement activities, and pupil diameter at a sample rate of 60 per second. Several variables were computed by using the video recordings of all subjects.

A data reduction procedure was conducted to convert raw data into cleansed fixation data on the recommendation pages. All data were exported from Tobii Studio in the format of xlsx. Five Excel VBAs were implemented to achieve the following goals: calculating pupil diameter baseline, cleansing data by time, cleansing data by gaze type, removing duplicate fixation entries, and calculating targeted pupil diameters. The pupil diameter baseline was calculated based on the first 100 seconds of recording during which all subjects were going through the instructions for the experiment.

Fixation durations on the recommendation pages for each subject were calculated. As the total browsing time varied across subjects, we calculated fixation duration per second by dividing total fixation duration by total recommendation browsing time. Pupil dilation was calculated as the percentage of pupil diameter change when browsing the product recommendation page versus the baseline condition (i.e., when reading instructions). By reviewing the recording footages, we observed that all subjects fixated on the recommendation title which indicated their awareness of the recommendation source.

Outlier tests were conducted to detect and remove potential outliers for both dependent variables. 4 outliers were detected and removed for data analysis on pupil dilation. 10 outliers were detected and removed for data analysis on fixation duration per second.

Order effects were tested for both dependent variables and no order effects for tasks (i.e., order of product types) were found for pupil dilation or fixation duration per second as dependent variables.

Statistical analysis were performed using SPSS 21 to conduct three-way ANOVA for each of the dependent variables for the two between-subjects factors: recommendation source and recommendation timing, and one within-subjects factor: product type.

5.1. DATA ANALYSIS ON PUPIL DILATION

The pupil diameter for each task was calculated by averaging the left and right pupil diameters. The average of the pupil diameters was then calculated based on the time stamp of product recommendation page to reveal the target pupil diameter (target PD): diameter of the pupil when looking at the product recommendation page. Pupil dilation was then computed relative to the pupil diameter baseline (PDBL) using following equation.

$$Pupil\ dilation = (target\ PD - PDBL) \div PDBL$$

Pupil dilation reveals the percentage of change on pupil diameter at a given period of time as compared to the baseline.

Excluding the outliers, 67 sets of data for both tasks were used for the analysis. We have an average sample size of 11 for each of the experimental conditions. The descriptive statistics for pupil dilation was shown in table 5.1.

Table 5.1: Descriptive statistics for pupil dilation

	Timing	Source	Mean	# of Subjects
Pupil dilation _cell phone	Early	Expert	-4.04%	12
		Consumer	-0.76%	10
		Total	-2.57%	22
	Mid	Expert	-3.68%	12
		Consumer	-0.29%	11
		Total	-1.78%	23
	Late	Expert	-1.50%	11
		Consumer	0.00%	11
		Total	-0.75	22
	Total	Expert	-3.13%	35
		Consumer	-0.14%	32
		Total	-1.70%	67

Table 5.1: Descriptive statistics for pupil dilation (cont.)

Pupil dilation _laptop	Early	Expert	-2.85%	12
		Consumer	0.51%	10
		Total	-1.32%	22
	Mid	Expert	-1.05%	12
		Consumer	1.00%	11
		Total	-0.07%	23
	Late	Expert	-1.84%	11
		Consumer	0.21%	11
		Total	-0.81%	22
	Total	Expert	-1.91%	35
		Consumer	0.58%	32
		Total	-0.72%	67

The results indicate that there is no significant within-subjects effect (product type) on pupil dilation. However, recommendation source has a significant effect on pupil dilation. Expert recommendations resulted in an average pupil dilation of -2.5% while consumer recommendations resulted in an average pupil dilation of 0.2%. The difference between them is significant at p value of 0.003 which is less than 0.05. Based on the statistical results, we conclude that H1 is supported, indicating that there was higher interest in consumer recommendations than expert recommendations.

The negative value of pupil dilation on expert recommendations indicates that participants have lower interest when browsing expert recommendations. Although the positivity (or less negativity) of pupil dilation on consumer recommendation was not very high relative to the baseline, we can deduce that consumer recommendations attracted more user interest than expert recommendation on the recommended product in the context of online shopping.

5.2. DATA ANALYSIS ON FIXATION DURATION PER SECOND

The fixation duration for each task was calculated by adding all fixation time based on the timestamp of product recommendation page. We then calculate the fixation duration per second (FDPS) by dividing the total fixation duration by total browsing time of the recommendation page using following equation.

$$FDPS = Fixation\ Duration \div Total\ browsing\ time$$

We use FDPS to control for different browsing time of the recommendation pages among subjects. For example, a FDPS value of 0.6 indicates that for every 1 second a subject spent on the recommendation page, he/she fixated 0.6 second on the content. This measure revealed the attention levels of the subjects. A higher FDPS indicates a higher level of attention on the recommendation page.

8 sets of data were excluded from the analysis because they were outliers. The average sample size for each experimental condition is 10.5.

Table 5.2 shows the descriptive statistics for FDPS.

Table 5.2: Descriptive statistics for FDPS

	Timing	Source	Mean	# of Subjects
FDPS_cell phone	Early	Expert	0.773	12
		Consumer	0.720	11
		Total	0.748	23
	Mid	Expert	0.780	12
		Consumer	0.668	9
		Total	0.732	21
	Late	Expert	0.653	10
		Consumer	0.765	9
		Total	0.706	19
	Total	Expert	0.740	34
		Consumer	0.718	29
		Total	0.730	63
FDPS_laptop	Early	Expert	0.800	12
		Consumer	0.783	11
		Total	0.792	23
	Mid	Expert	0.700	12
		Consumer	0.647	9
		Total	0.677	21
	Late	Expert	0.706	10
		Consumer	0.764	9
		Total	0.733	19
	Total	Expert	0.737	34
		Consumer	0.735	29
		Total	0.736	63

Based on the results, there is neither main within-subjects effects nor between-subjects effects on FDPS. However, there is an interaction effect of product type*recommendation timing on FDPS ($p=0.05$).

The mean FDPS of the two types of products and three recommendation timing are listed in table 5.3.

Table 5.3: Mean values of FDPS for recommendation timing and product type

	Cell phone	Laptop
Early recommendation	0.747	0.792
Mid recommendation	0.724	0.673
Late recommendation	0.709	0.735

The result does not seem to support our hypothesis which states that earlier recommendations result in higher attention than late recommendations. The interaction effect indicates that certain differences between the two product types may have a moderating effect in user attention across different recommendation timings. The two product types, cell phones and laptops, have a lot in common. They are both popular electronic products used by most students. They also have similar product life span of about 3 to 5 years. The most notable difference between these two types of products is the average price. In our product database, the prices of the cell phones range from $5 to $850. However, the prices of the laptops range from $280 to $3000. In our experiment, the price difference between the two types of products were not strictly controlled.

Figure 5.1 illustrates the mean FDPS value of each of the two types of products at each of the recommendation timing.

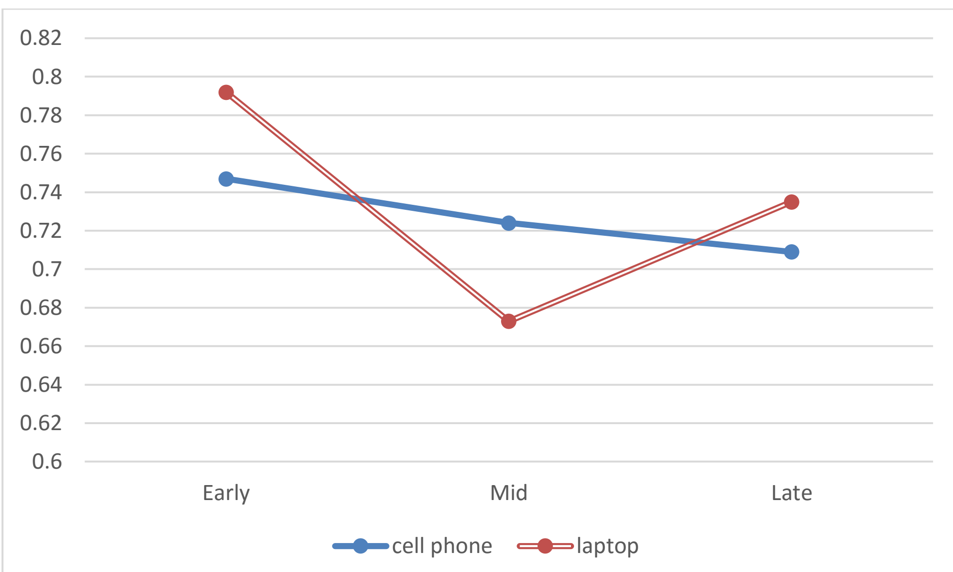

Figure 5.1: Interaction effect of recommendation timing and product type

Figure 5.1 suggests that early recommendations could have greater influence than mid recommendations followed by late recommendations for cell phones but not necessarily the case for laptops. For laptops, early recommendations captured the most user attention. The effect of recommendation timing might be moderated by some characteristics of the products, i.e. product price. Cell phones buyers are potentially less influenced by recommendation timings due to its lower average cost. H2 is not supported.

6. DISCUSSION AND CONCLUSION

This study used eye-tracking data to explain the effect of different recommendation timing and source on user attention and interest. We explored participants' visual attention and interest during online shopping tasks.

The results suggest that pupil dilation varies across sources of recommendations while fixation intensity is significantly influenced by the interaction effect of product type and recommendation timing. Trustworthiness of consumer recommendations, which was found to be higher for consumer recommendations by Bettman et al. (1998) and Senecal & Nantel, (2004), may have contributed to higher user interest through larger pupil dilations when viewing consumer recommendations, which is in line with the similarity-attraction paradigm (Byrne, 1971). Former and potential consumers are more similar in terms of experiences, goals, interest, etc. These similarities result in a higher level of attraction between them. The attraction is the foundation of the interest that consumers have on online consumer recommendations. Based on our results, it is concluded that using consumer reviews as the source for recommender systems has its advantages in gaining consumers' interest than using expert reviews as the source for recommender systems. More interest on the recommendation page indicates that the recommended products have higher impact on the consumers' decision making process.

As for recommendation timings, our hypothesis that earlier recommendation will result in higher levels of consumers' attention was also supported by the fixation data, when we compared early recommendations versus mid and late recommendations. Also, the significant interaction effect of recommendation timings and product types can be further investigated in future research. The product price might have a significant moderating effect on consumers' attention levels at different recommendation timings that can be studied in future research.

Overall, eye-trackers are used as a source for objective, non-invasive, continuous, and quantitative data which has the potential to help researchers studying human attention, mental load, cognitive processes, etc.

7. CONTRIBUTIONS AND IMPLICATIONS

This research contributes to understanding the characteristics of online recommender systems. Although the algorithms used in online recommender systems are very important in predicting consumers' needs, characteristics of online recommender systems can determine how much time and effort the customers are willing to spend to look into the information and recommendations provided.

Despite the importance of online recommender systems to online retailers, no guideline exists for online recommender systems on which features of online recommender systems that can help to boost sales. The findings from this research can help some online retail business owners to increase the effectiveness of their recommender systems. The source and timing of online recommender systems can be well utilized to fit various businesses.

Business owners can test the sources and timing of their recommender systems to achieve the optimized setting for their individual business settings. The optimal result might vary for different products or services.

8. LIMITATIONS AND FUTURE RESEARCH

This research has some design limitations which resulted in difficulties in extracting more detailed eye-tracking data for certain elements on the product recommendation page. Also, the recommender system algorithm can also be improved to control the quality of recommended products. Another limitation is that the length of the recommendation pages was not controlled. With improvement of the recommendation content, the fixation data can be used to carry out more controlled comparisons. Also, all of our subjects are undergraduate students from Missouri University of Science and Technology, which may limit the generalizability of the study. It is possible that their judgement on recommendation types vary from those with different demographic background or from different cultures.

In the future, this research can be extended to study consumers' cognitive process and behavioral intention in decision making. Consumers' perceived difficulty of the shopping task and perceived usefulness of the recommender system can potentially affect attention and interest, which can be examined in future research.

Also, a well-controlled recommender system can be designed to assess how consumers with different price sensitivities react to product recommendations in terms of the price and features of the recommended product. Eye-tracking data has the potential to provide explanations at the cognitive level or even sub-conscious level on consumers' actions in decision making.

Consumers' decision making processes can be decomposed by reviewing and analyzing the fixation and pupil dilation data. In such cases, the advantages of the non-invasive, objective, and continuous nature of eye-tracking data can be very valuable.

REFERENCES

Aciar, S., Zhang, D., Simoff, S., & Debenham, J. (2007). Informed recommender: Basing recommendations on consumer product reviews. *IEEE Intelligent Systems, 22*(3), 39-47.

Adomavicius, G., Bockstedt, J. C., Curley, S. P., & Zhang, J. (2013). Do recommender systems manipulate consumer preferences? A study of anchoring effects. *Information Systems Research, 24*(4), 956-975.

Ansari, A., Essegaier, S., & Kohli, R. (2000). Internet recommendation systems. *Journal of Marketing Research, 37*(3), 363-375.

Balabanovic, M. (1997). *Adaptive Web page recommendation service.* Paper presented at the Proceedings of the International Conference on Autonomous Agents.

Balabanović, M., & Shoham, Y. (1997). Content-Based, Collaborative Recommendation. *Communications of the ACM, 40*(3), 66-72.

Bettman, J. R., Luce, M. F., & Payne, J. W. (1998). Constructive Consumer Choice Processes. *Journal of Consumer Research, 25*(3), 187-217.

Brisson, J., Mainville, M., Mailloux, D., Beaulieu, C., Serres, J., & Sirois, S. (2013). Pupil diameter measurement errors as a function of gaze direction in corneal reflection eyetrackers. *Behavior Research Methods, 45*(4), 1322-1331.

Byrne, D., & Griffitt, W. (1973). INTERPERSONAL ATTRACTION. *Annual Review of Psychology, 24*(1), 317.

Cavanagh, J. F., Wiecki, T. V., Kochar, A., & Frank, M. J. (2014). Eye tracking and pupillometry are indicators of dissociable latent decision processes. *Journal of Experimental Psychology: General, 143*(4), 1476-1488.

Cosley, D., Lam, S. K., Albert, I., Konstan, J. A., & Riedl, J. (2003). *Is seeing believing? How recommender interfaces affect users' opinions.* Paper presented at the Conference on Human Factors in Computing Systems - Proceedings.

DeNale, R., & Weidenhamer, D. (2016). Quarterly Retail E-Commerce Sales 1st Quarter 2016. Retrieved from https://www.census.gov/retail/mrts/www/data/pdf/ec_current.pdf on May15th, 2016.

Duan, W., Gu, B., & Whinston, A. B. (2008). The dynamics of online word-of-mouth and product sales-An empirical investigation of the movie industry. *Journal of Retailing, 84*(2), 233-242.

Einhäuser, W., Koch, C., & Carter, O. L. (2010). Pupil dilation betrays the timing of decisions. *Frontiers in Human Neuroscience, 4*.

Galinsky, A. D., & Mussweiler, T. (2001). First offers as anchors: The role of perspective-taking and negotiator focus. *Journal of Personality and Social Psychology*, *81*(4), 657-668.

Gilzenrat, M. S., Nieuwenhuis, S., Jepma, M., & Cohen, J. D. (2010). Pupil diameter tracks changes in control state predicted by the adaptive gain theory of locus coeruleus function. *Cognitive, Affective and Behavioral Neuroscience, 10*(2), 252-269.

Guan, Y., Cai, S., & Shang, M. (2014). Recommendation algorithm based on item quality and user rating preferences. *Frontiers of Computer Science*, *8*(2), 289-297.

Hess, E. H., & Polt, J. M. (1960). Pupil Size as Related to Interest Value of Visual Stimuli. *Science, 132*(3423), 349-350.

Hess, E. H., & Polt, J. M. (1964). Pupil size in relation to mental activity during simple problem-solving. *Science, 143*(3611), 1190-1192.

Hoeks, B., & Levelt, W. J. M. (1993). Pupillary dilation as a measure of attention: a quantitative system analysis. *Behavior Research Methods, Instruments, & Computers, 25*(1), 16-26.

Iacobucci, D., Arabie, P., & Bodapati, A. (2000). Recommendation agents on the Internet. *Journal of Interactive Marketing, 14*(3), 2-11.

Jacob, R., & Karn, K. S. (2003). Eye tracking in human-computer interaction and usability research: Ready to deliver the promises. *Mind*, *2*(3), 4.

Jacobs, R. S., Heuvelman, A., Ben Allouch, S., & Peters, O. (2015). Everyone's a critic: The power of expert and consumer reviews to shape readers’ post-viewing motion picture evaluations. *Poetics*, *52*, 91-103.

Johnson, C. I., & Mayer, R. E. (2012). An eye movement analysis of the spatial contiguity effect in multimedia learning. *Journal of Experimental Psychology: Applied*, *18*(2), 178-191.

Just, M. A., & Carpenter, P. A. (1980). A theory of reading: From eye fixations to comprehension. *Psychological Review, 87*(4), 329-354.

Kang, O., & Wheatley, T. (2015). Pupil dilation patterns reflect the contents of consciousness. *Consciousness and Cognition, 35*, 128-135.

Kim, Y. S., Yum, B. J., Song, J., & Kim, S. M. (2005). Development of a recommender system based on navigational and behavioral patterns of customers in e-commerce sites. *Expert Systems with Applications*, *28*(2), 381-393.

Kliegl, R., Nuthmann, A., & Engbert, R. (2006). Tracking the mind during reading: The influence of past, present, and future words on fixation durations. *Journal of Experimental Psychology: General, 135*(1), 12-35.

Klin, A., Jones, W., Schultz, R., Volkmar, F., & Cohen, D. (2002). Visual fixation patterns during viewing of naturalistic social situations as predictors of social competence in individuals with autism. *Archives of General Psychiatry, 59*(9), 809-816.

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience, 13*(10), 1292-1298.

Krugman, H. E. (1964). Some applications of pupil measurement. *Journal of Marketing Research, 1*(000004), 5.

Laeng, B., Sirois, S., & Gredebäck, G. (2012). Pupillometry a window to the preconscious? *Perspectives on psychological science, 7*(1), 18-27.

Lee, K. C., & Kwon, S. (2008). Online shopping recommendation mechanism and its influence on consumer decisions and behaviors: A causal map approach. *Expert Systems with Applications*, *35*(4), 1567-1574.

MacLachlan, C., & Howland, H. C. (2002). Normal values and standard deviations for pupil diameter and interpupillary distance in subjects aged 1 month to 19 years. *Ophthalmic and Physiological Optics, 22*(3), 175-182.

Mason, L., Pluchino, P., Tornatora, M. C., & Ariasi, N. (2013). An eye-tracking study of learning from science text with concrete and abstract illustrations. *Journal of Experimental Education, 81*(3), 356-384.

Naber, M., Alvarez, G. A., & Nakayama, K. (2013). Tracking the allocation of attention using human pupillary oscillations. *Frontiers in Psychology, 4*(DEC).

O'Regan, J. K. (1980). The control of saccade size and fixation duration in reading: The limits of linguistic control. *Perception & Psychophysics*, *28*(2), 112-117.

Orquin, J. L., & Mueller Loose, S. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica, 144*(1), 190-206.

Purnawirawan, N., Dens, N., & De Pelsmacker, P. (2014). EXPERT REVIEWERS BEWARE! THE EFFECTS OF REVIEW SET BALANCE, REVIEW SOURCE AND REVIEW CONTENT ON CONSUMER RESPONSES TO ONLINE REVIEWS. *Journal of Electronic Commerce Research, 15*(3), 16.

Rayner, K. (1978). Eye movements in reading and information processing. *Psychological Bulletin*, *85*(3), 618-660.

Schonfeld, E. (2007). Web sales pitches are getting better, thanks to new programs designed to sell you stuff you didn't even know you wanted, reports Business 2.0 Magazine. Retrieved from http://money.cnn.com/magazines/business2/business2_archive/2007/07/01/100117056/index.htm on May 15th, 2016.

Senecal, S., & Nantel, J. (2004). The influence of online product recommendations on consumers' online choices. *Journal of Retailing, 80*(2), 159-169.

Shi, A., Tan, C.-H., & Sia, C. L. (2013). Timing and basis of online product recommendation: the preference inconsistency paradox *Human Interface and the Management of Information. Information and Interaction for Learning, Culture, Collaboration and Business* (pp. 531-539): Springer.

Shimojo, S., Simion, C., Shimojo, E., & Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature Neuroscience, 6*(12), 1317-1322.

Stass, J. W., & Willis, F. N. (1967). Eye contact, pupil dilation, and personal preference. *Psychonomic Science, 7*(10), 375-376.

Triesch, J., Ballard, D. H., Hayhoe, M. M., & Sullivan, B. T. (2003). What you see is what you need. *Journal of Vision, 3*(1), 86-94.

Tsai, M. J., Hou, H. T., Lai, M. L., Liu, W. Y., & Yang, F. Y. (2012). Visual attention for solving multiple-choice science problem: An eye-tracking analysis. *Computers and Education, 58*(1), 375-385.

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science, 185*(4157), 1124-1131.

Utz, S., Kerkhof, P., & van den Bos, J. (2012). Consumers rule: How consumer reviews influence perceived trustworthiness of online stores. *Electronic Commerce Research and Applications, 11*(1), 49-58.

Wang, W., & Benbasat, I. (2007). Recommendation agents for electronic commerce: Effects of explanation facilities on trusting beliefs. *Journal of Management Information Systems, 23*(4), 217-246.

Wierda, S. M., Van Rijn, H., Taatgen, N. A., & Martens, S. (2012). Pupil dilation deconvolution reveals the dynamics of attention at high temporal resolution. *Proceedings of the National Academy of Sciences of the United States of America, 109*(22), 8456-8460.

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