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Towards an understanding of the role of Interface Design in Customer Review Search Quality – An investigation of Postchoice Regret

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ABSTRACT

Online customer reviews represent an important source of aggregate product information. Today, these reviews compete for customer attention with the vast amount of other information presented on ecommerce websites, including product characteristics, alternative products, and context-based advertisements, among others. When customers' ability to process this information is overloaded, valuable information contained in online product reviews may go unnoticed. This research examines the role of peer endorsement system interface design in customer perceptions of information search quality and its impact on the phenomenon of post-choice regret. An experimental methodology is employed to determine the relationship between interface design and customer anxiety over potential missed information. Over two hundred ecommerce customers took part in this experimental research, which compared the peer endorsement system offering of Amazon.com with Google Products. The results of this research shed some light on the way that customers use and value content provided by these systems.

Keywords

Regret, peer endorsement system, ecommerce, regulatory orientation, information overload

INTRODUCTION

Developments in Internet and computing technology have made information overload a major problem for many end users, and by extension ecommerce organizations as well[1]. The huge amount of information available on ecommerce sites today has made shoppers into multitaskers. A typical page for a single product contains much more than simple product information. Often these pages also display information about competing or similar products, special offers or promotions of the day, and increasingly, large numbers of online customer reviews (Mudambi and Schuff, 2010). Online customer reviews represent an important source of aggregate product information (Wang and Benbasat, 2007), and for many products play an integral part in telling the product's overall marketing story (Ghose and Han, 2009; Mudambi and Schuff, 2010). When effective, reviews have the ability to aid the purchaser in reaching a more informed decision, thus helping the online retailer increase their conversion rate (Barton, 2006).

Despite its value, disseminating and retaining information from online customer reviews places certain demands on the cognitive load of ecommerce customers. When customers' information processing abilities are overloaded, the natural response is to view all the information coming in as equally important (Keller and Staelin, 1987; Maes, 1994). In such a scenario, marketers often lose control of the advertising message, and crucial product information integral to the sales process may become largely ineffective, leading to fewer purchases (Kuksov and Villas-Boas, 2010).

The concept of information overload has been researched a great deal in the ecommerce literature, as well as outside IS in the areas of marketing, management and psychology, among others (Kuksov and Villas-Boas, 2010). However, as new

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[1] http://wywww.mckinseyquarterly.com/Organization/Talent/Recovering_from_information_overload_2735

technologies are introduced, our understanding of the antecedents to, and impact of, information overload must constantly adapt to take these changes into account. Online customer reviews represent a technology with profound implications for any online sales environment (Mudambi and Schuff, 2010; Hu and Liu, 2004). In this study, we address the implications of interface design and customer review presentation, to explore the way in which peer endorsement systems (PES), systems designed to collect and display online customer reviews, help as well as hinder the ecommerce sales process. Specifically, we put forth a theory of online post-choice regret. Regret in the traditional sense is a negative emotion borne of valence between a choice made and the lost opportunity for other options that could have been chosen (Loomes and Sugden, 1982). As we will show, post-choice regret is intimately tied to information quality and the ability of an individual to made the best use of all available information (Das and Kerr, 2010; Sugden, 1985). For this reason, a good understanding of the role of post-choice regret in ecommerce decision making is both appropriate and necessary in order to fully appreciate the impact of information overload in a sales context.

To test the research model, we employ an experimental methodology that looks at the contrast between two major PES interfaces that approach the presentation of customer review data in fundamentally different ways. The results of the experiment make several unique and important contributions to the IS literature, and will be of interest to practitioners involved in PES design and implementation. First, the study is unique in that it compares and contrasts two best of breed PES systems that are currently implemented and important information search tools for millions of ecommerce customers. Additionally, the study makes strong theoretical contributions by drawing from well established work in psychology, marketing, and extant IS literature. As we will show, post-choice regret is an important but oft-overlooked construct with implications that go to the heart of electronic customer relationship management. The rigorous treatment it receives here, combined with a timely and relevant emphasis on real world human-system interaction sets this study apart from the extant body of PES literature.

In the remainder of the paper we provide a thorough overview of the extant regret literature. A theoretical model of the relationship between information search quality, post-choice regret, and retailer satisfaction is then presented, followed by details of the experimental methodology employed. The paper concludes with some discussion and ideas for future study.

BACKGROUND AND MODEL DEVELOPMENT

Research on the economic impact of regret dates back to Loomes and Sugden (1982)'s regret theory. Under regret theory, regret is a negative feeling borne of an action one takes that one subsequently wishes one had not (Tsiros and Mittal, 2000). For example, after buying a luxury automobile, a person might obtain new information leading them to conclude that a less expensive alternative would have been the better choice. Thus, regret is the realization, post-choice, that a different action might have led to a better outcome (Das and Kerr, 2010).

Psychological research classifies regret as a cognitive emotion comprised of elements such as; thoughts of opportunities lost, mistakes made, and the actions one might take to correct them if given a chance (Zeelenberg, 1999). However, despite its retrospective nature, regret can still occur, prior to any action, as a result of perceived possible negative outcomes associated with an action (Miller and Taylor, 1995). This is the view adopted by Zeelenberg (1999), who posits that "choices are influenced by anticipated regret, and that such anticipation is affected by whether or not one expects to learn the outcomes of un-chosen options".

Regret based on the quality of a purchased product results from a post-choice comparison of that product and some previously unknown information that creates valence between the product chosen and its (previously available, now lost) alternative (Tsiros and Mittal, 2000). A person can also regret a decision independent from any product selection. For example, a person who chooses not, or is for some other reason unable, to practice adequate diligence while choosing an automobile may later regret the decision, even if the outcome is entirely favorable from a product perspective. They like the car, but the dealership down the road sells it for a thousand dollars cheaper.

The accepted definition of regret suggests a natural relationship between feelings of regret and the quality of information used in decision-making. Individuals with access to more and better information are aware of more options, and better equipped to evaluate unchosen alternatives (Bell, 1982; Simonson, 1992). However, despite the information-based nature of regret, the construct has received only limited attention in the IS literature. Hung et al. (2007), in a rare study that examined the impact of decision support systems (DSS) on decision regret, attribute this lack of attention in part to the fact that regret is a post-use feeling, and IS as an academic field has, until recently, placed tremendous importance on technology adoption and implementation. One notable exception to this is the area of online auctions. While still not an area of intense research, regret has been examined in studies that looked at ebay auction formats (Tan et al., 2005) and adverse selection of luxury goods (Qin et al., 2009). We make a substantial contribution to this literature by offering one the first experimental analyses of regret in information systems research, and the first in the context of peer endorsement systems.

Disconfirmation Anxiety

Disconfirmation refers to the perceived difference between a customer's expectations and what they actually receive (Spreng et al., 1996). When a customer's expectations do not match up with reality, it creates problems for online web retailers (McKinney et al., 2002). Past IS literature has referred to this phenomenon as expectation disconfirmation. Failing to meet expectations has been shown to lead to a decline in online trust, perceptions of the system, and intention to transact additional business with the retailer (McKinney et al., 2002). Disconfirmation studies often involve taking a measure of a person's expectations with some product, service, etc. and then collecting a measure of the degree to which the person's expectations match up with reality (i.e. the degree of disconfirmation). We adopt a novel approach by foregoing the introduction of the actual disconfirmation. Instead, we define disconfirmation anxiety as a measure of the fear or concern that the person holds for some potential future disconfirmation that may or may not ever actually occur. For this study, we identify of types of disconfirmation anxiety.

Product disconfirmation anxiety refers to perceptions of worry around the existence of information that, if found, would make a customer question the quality of the product they have selected post-choice. Consider a scenario. A customer, just having purchased a camera online, later comes across a critical review of the product. The critical review identifies several key flaws in the product with specific implications for the customer. The review therefore provides new information that disconfirms the customer's decision. This creates a discrepancy between the customer's perception of product quality at the time of purchase, and the new perception fostered by the introduction of this new information (Lee et al., 2010). We propose that the PES system itself, through the delivery of complete and high quality information, impacts the customer's attitude towards the likelihood of future product disconfirmation, which we term product disconfirmation anxiety.

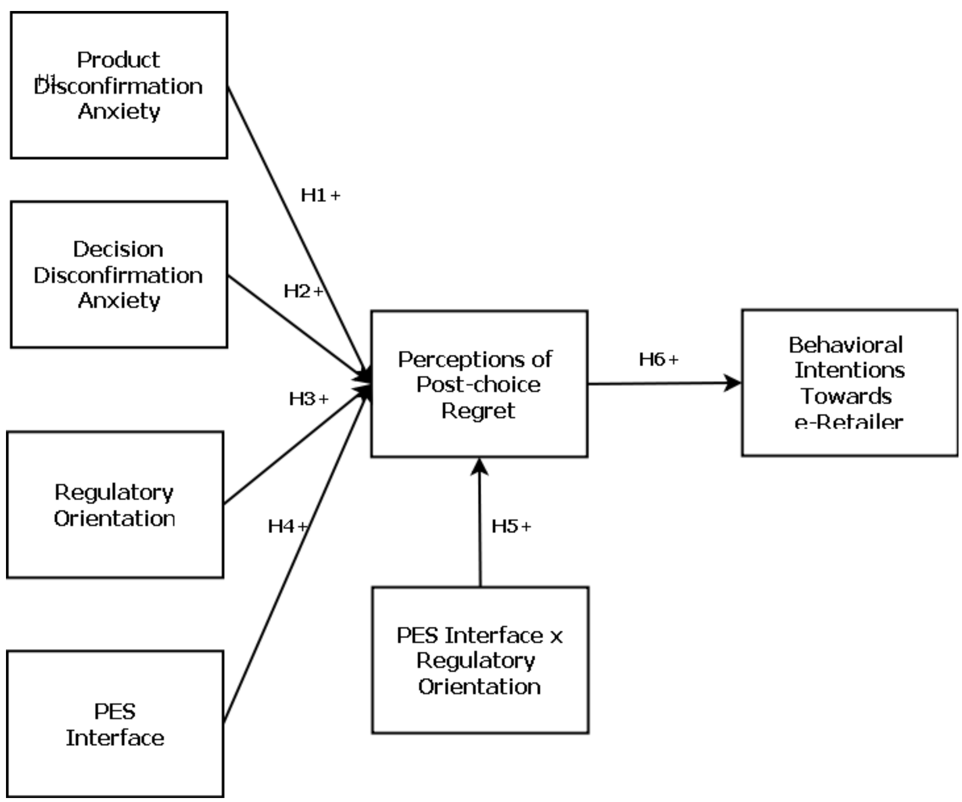

Figure 1. Theoretical model of the role of regret in online decision making.

Decision disconfirmation anxiety is experienced when the customer perceives that information exists that, if found, will cause the customer to doubt the logic or wisdom used in making a decision, independent of the final outcome (Zeelenberg, Van Dijk, Van der Pligt, Manstead, Van Empelen, and Reinderman 1998). Like product disconfirmation, decision disconfirmation is fundamentally related to the quality of the information search, or the methods used when arriving at the decision. To use our camera example, consider situation in which a customer purchases a camera at one retailer, only to find the same camera

$100 cheaper on another website. The customer has, through inadequate information search, overlooked an important alternative buying option. Eventually, the later discovery of this lower priced product creates valence between the choice made and what could have been, causing the customer to doubt the quality and wisdom of their decision. Perceptions of worry over the existance of information that would cause this type of disconfirmation is what we term here decision disconfirmation anxiety.

In the IS literature, disconfirmation has been shown to impact perceptions of web-site quality and customer opinions of an e-retailer (McKinney et al., 2002). Since disconfirmation is directly tied to customer expectations derived from available information, improving information quality is one method for reducing the potential for future disconfirmation, thereby decreasing perceptions of disconfirmation anxiety. We therefore propose that a peer endorsement system interface that reduces information noise, allowing only the most relevant product story to come through, provides the greatest chance of ensuring that the customer is aware of the most relevant data for making intelligent informed decisions. This is hypothesized to decrease anxiety over fears of future product or decision disconfirmation.

Numerous studies have identified the relationship between disconfirmation and regret (Das and Kerr 2010). Independent of concrete disconfirmation information, disconfirmation anxiety arises from the mere potential for disconfirmation, and often this is enough to make a person experience post-choice regret (Tsiros and Mittal, 2000). To reduce this anxiety, an individual may select a different product that is less suitable, but better understood, merely because the product holds less potential for subsequent disconfirmation (Loomes and Sugden, 1982; Bell, 1982) ("the bird in the hand is worth two in the bush" for example). To make well-informed decisions about products that are both high quality and satisfy their needs, customers must be able to sort through noisy data and isolate as much of the information relevant to their decision as possible.

This gives us the following hypotheses.

H1: Product Disconfirmation Anxiety (PDA) is positively correlated with perceptions of post-choice regret

H2: Decision Disconfirmation Anxiety (DDA) is positively correlated with perceptions of post-choice regret

Regulatory Orientation and Interaction Effects

According to the theory of regulatory fit, individuals experience regulatory fit when "their strategies for goal pursuit match their regulatory orientation" (Lee et al., 2010). The theory identifies two types of problem solving strategies; eagerness and vigilance. The adoption of one or the other of these strategies makes up a person's regulatory orientation. (Higgins, 2000). Prevention oriented individuals favor vigilance strategies, and gain regulatory fit when solving problems that let them stay within the established boundaries and rules of a problem domain. They typically value structure and precise instruction, with clearly defined goals and concrete criteria for success (Higgins, 2005). Prevention oriented individuals are generally more risk adverse, and work to minimize losses whenever possible. Promotion oriented individuals would rather use eagerness strategies, and see general effort as the way to achieve results (Lee et al., 2010). When possible, those with a promotional regulatory orientation look to maximize gains, and so are generally more tolerant of risk and willing to take a chance. Higgins (2005) uses the example of a student wanting to make an A in a course. Prevention-oriented students follow the syllabus carefully, believing that sticking to the rules and established "best practices" will yield results. Promotion focused individuals are less precise. They may read more material across a variety of topics, believing that overall effort, regardless of application, will lead to success (Higgins 2005, 2000).

Past research has shown that regulatory fit has several interesting results for e-commerce organizations. For example, Avnet and Higgins (2006) showed that regulatory fit increases the amount a customer is willing to pay for a product, by influencing the perceived attitudes toward both the brand and the product itself. . Lee et al. (2010) identified regulatory fit as a key antecedent to engagement with an advertising message. This engagement increases positive perceptions of a brand and product. Engaged customers also view gains as greater, and losses as less significant, adopting an overall more positive outlook towards a particular transaction (Lee et al., 2010). In an ecommerce context, the interface provides the problem solving environment in which users employ strategies to complete effective information search and ultimately make good decisions. When a person makes a decision to purchase that incorporates strategies matching their regulatory orientation, their appraisal of the decision increases, which lowers their baseline regret for that decision. In light of this, we propose that PES interface and regulatory orientation will not only impact perceptions of post-choice regret directly, but that the interaction between the interface used and the innate regulatory orientation of the individual will also decide whether or not a person experiences a level of post-choice regret. From this we derive the following hypotheses:

H3: Observed differences in post-choice regret will be statistically attributable to the PES interface used.

H4: Observed differences in post-choice regret will be statistically attributable to the regulatory orientation of the participant.

H5: The interaction between a person's regulatory orientation and the PES interface will be positively correlated with perceptions of post-choice regret

Behavioral Intentions towards an online Retailer

Behavioral Intentions toward Retailers refers a purchaser's willingness to transact business with a retailer in the future. Research in the regret literature identifies a negative relationship between regret and repurchase intention towards the retailer that sold the product (Tsiros and Mittal, 2000). We posit that in an online setting, the sheer number of customer reviews available for many products, and the large number of vendor-provided product comparisons, give the impression that the retailer has conducted an exhaustive information search, and the information interface becomes the sales agent that actually convinces the customer which product to choose. Since online retailers are now providing the information mechanisms upon which purchasers inform their decisions, any subsequent disconfirmation, and the regret that arises from it, are naturally attributed to the retailer. Thus, apportionment of culpability for post-choice regret is hypothesized to directly influence future Behavioral Intentions towards the retailer..

H6: Perceptions of post-choice regret will negatively impact behavioral intentions toward the retailer

INTERFACE COMPARISON

The peer endorsement system interface used by Amazon.com (PES1) has up until this point garnered the most attention from the academic community (Mudambi and Schuff, 2010). Like many PES systems, PES1 allows customers to view peer-authored reviews for any of its millions of products. Within this system, each product may have any number of reviews, with some products garnering literally thousands of reviews from the community. Each review includes as much open-ended response as the reviewer cares to provide, together with a "star" rating of 1 to 5. All the star ratings for a product are pooled together and the cumulative rating is displayed prominently on the product's main page (Mudambi and Schuff, 2010). We compare this interface with Google's PES offering, Google Products (PES2). PES2, which is still in beta and became available to the public in 2009, uses Google search technology to provide a summary of peer endorsement system content that is compiled from numerous e-retailers.

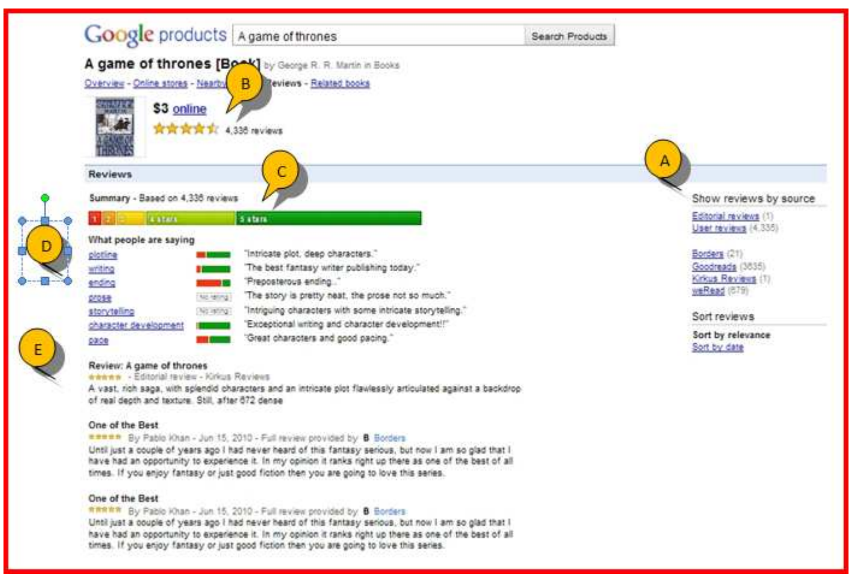

Figure 2. Typical example of PES2 review results.

A unique feature of PES2 is its ability to aggregate peer and editorial reviews from multiple sources. Review sets are grouped by their source of origin (Figure 1-A). PES2 also incorporate a star rating system that represents reviewers' overall assessment of the product's quality on a 1 to 5 scale, with 1 being the lowest. The product's summary score, in stars, is prominently displayed at the top of the page (Figure 1-B). Additionally, a stacked bar chart is employed to graphically represent star scoring within each rank, 1 to 5 (Figure 1-C). Unique to PES2, the bar chart is color-coded, with red representing the lowest reviews and green representing the highest reviews. To generate additional summary content, PES2 mines interior comments from individual reviews, and aggregates them into product appropriate topical categories (Figure 1-D). The positive or negative tone of these topical comments is graphically represented by stacked bar charts employing the same red and green color scheme, with a representative comment displayed alongside each bar of the chart. Full product reviews from the selected review set are displayed at the bottom of the page (Figure 1-E).

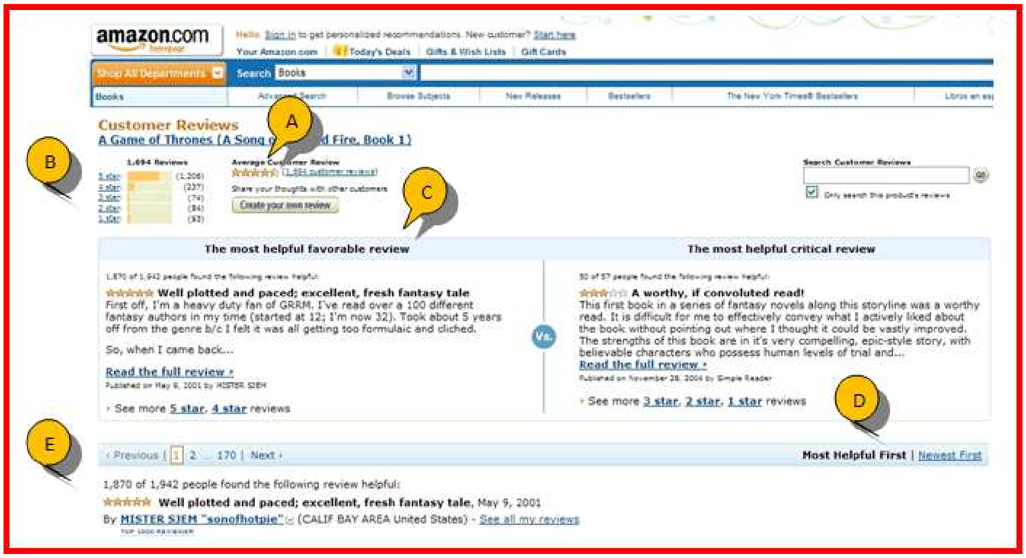

Figure 3. Typical example of PES1 review results.

As with PES2, PES1 incorporates a star rating system representing the reviewers' overall assessment of product quality(1 to 5 scale, 1 the lowest (Figure 2-A)). PES1 also provides a horizontal bar chart of the products' star rating, grouped by number of stars (Figure 2-B). PES1 does not collect reviews from external sources, relying instead on reviews provided by its own customers. A unique feature of PES1 is the "helpfulness" score applied to individual reviews. This one feature has been discussed at length by other IS researchers (Mudambi and Schuff, 2010). The system asks customers to rank the usefulness of any reviews they read, so that the most helpful reviews, as voted by the community, bubble to the top. To aid with this, review helpfulness is then used as the default sorting method for PES1 content (Figure 1-D). The positive and negative reviews voted to have the greatest utility are subsequently displayed side-by-side, offering contrasting opinions of the product being reviewed (Figure 2-C).

Like PES2, full reviews are displayed at the bottom of the page (Figure 2-E). For products with a large number of reviews, selection of the most useful review is biased by this sort order. A customer shopping for a product is unlikely to read every review when the number of reviews is large. Thus, reviews near the top of the list are likely to be most frequently read, and are most likely to garner the most votes regarding their utility.

DESIGN AND DATA COLLECTION

A total of 242 people participated in the experiment. Of these participants, all were college students with some familiarity with buying products online, and peer endorsement systems in general. 77% were female, with 54% making less than $40,000 a year. 56% reported working with or using computers more than four hours a day.

We used an experimental design with repeated measures, and randomly assigned subjects to one of two treatment groups. Repeated measures designs like the one employed here have three useful advantages. First, because the participants essentially serve as their own control group, the risk of confounding effects is minimized. Second, because each subject is treated and observed twice, fewer subjects are needed to achieve similar results with single measure tests. Finally, the positive correlation between treatments gives the test a high statistical power.

The downside to this type of experimental design is the possibility of a learning effect. In order to analyze the data as one complete set, it was necessary to test for this. A learning effect is a measured effect of a treatment taken at a previous time on the treatment administered at the current time. Grizzle (1965) presents a suitable test for checking for the presence of a learning effect. In this fashion, we conducted an ordinary least squares (OSL) analysis of variance to determine whether treatments were impacted by any direct carry-over. We failed to detect any carry-over effect for the variables of interest (product disconfirmation anxiety (p-value=0.206); decision disconfirmation anxiety (p-value=0.160); perceived post-choice regret 0.166). Thus, the order of treatments, in this case PES1 to PES2 or PES2 to PES1, does not have a significant impact on the results. We therefore proceeded treating the dataset as a whole.

	Treatment 1		Treatment 2	
Group 1	Products shown using Amazon.com PES (PES1)	Observation	Products shown using Google Products PES (PES2)	Observation
Group 2	Products Shown using Google Products PES (PES2)		Products shown using Amazon.com PES (PES 1)	

Table 1. Experimental Research Design

The specific nature of the experiment was as follows: Participants were selected from a pool of students and then randomly assigned into one of two treatment groups. After answering a set of demographic questions, participants were shown a set of three product pages containing results from either PES1 or PES2. Subjects were allowed to peruse the reviews, and were given no instruction into the way in which they should use the system. The merits or limitations of the individual PES' were not emphasized in any way. After a time, participants completed a short survey instrument containing measures for decision and product disconfirmation anxiety, perceptions of post-choice regret, and behavioral intentions. The treatments were then flipped, and participants viewed the same three products using results from the other interface. After a similar period of time had elapsed, participants then retook the survey instrument, answering questions for each of the four constructs once more, this time based on the second interface.

In order to avoid confusion, reverse coded questions were avoided wherever possible. For this reason higher scores on all variables represent positive feelings. Thus higher post-choice regret scores are actually associated with lower perceptions of post-choice regret. The same rule applies for decision and product disconfirmation anxiety. Space was also provided for subjects to provide qualitative feedback on what they saw as the helpful features of the interface. Amazon.com (PES 1) results are presented first, followed by Google Products (PES 2).

	Min	Max	Mean	Std Dev.	Skewness	Kurtosis
Decision Disconfirmation Anxiety	1	5	3.560	0.817	-0.634	0.345
Product Disconfirmation Anxiety	1	5	3.198	0.689	0.030	0.433
Perceived Post-choice Regret	1	5	3.446	0.69	-0.292	0.333
Behavioral Intentions	98	85				

Table 2. Descriptive Statistics for PES1.

	Min	Max	Mean	Std Dev.	Skewness	Kurtosis
Decision Disconfirmation Anxiety	1	5	3.150	0.955	-0.268	-0.876
Product Disconfirmation Anxiety	1	5	2.952	0.722	0.230	0.757
Perceived Post-choice Regret	1	5	3.174	0.803	0.004	-0.105
Behavioral Intentions	1	5				

Table 3. Descriptive Statistics for PES2.

PLS MODEL ANALYSIS

Data for this study was analyzed using a partial least squares (PLS) modeling technique through SmartPLS (Ringle et al., 2005). PLS is a statistical technique that allows for the measurement of multi-item latent constructs (Chin, 1998).

Consistent with Higgins (2001), the regulatory focus questionnaire items were divided into two main factors. A confirmatory factor analysis of these items reflected the expected two factors (Table 4). Scores for each of these factors were then summed, and users were assigned a Boolean value for regulatory orientation based on which sum score was higher (0 for promotional regulatory orientation, or 1 for prevention regulatory orientation) (Higgins, 2001). Interface was operationalized in a similar way. Users of PES1 were coded as zero in this analysis, and PES2 users were coded 1.

Variable	Factor1	Factor2
Promotion 1	-0.52239	0.55133
Promotion 2	-0.31857	0.72768
Promotion 3	-0.38137	0.53678
Promotion 4	-0.62536	0.54546
Promotion 5	-0.33015	0.53491
Prevention 1	0.69363	0.53613
Prevention 2	0.68251	0.50972
Prevention 3	0.61271	0.37616
Prevention 4	0.69133	0.53788
Prevention 5	0.71448	0.19886

Table 4. Results of Regulatory Focus Questionnaire Factor Analysis

Structural model estimation allows for hypothesis testing and estimation of path coefficients. Overall, this model accounts for 46% of the observed variance in behavioral intentions towards the retailer. Additionally, the antecedents of post-choice regret proposed here together produce an R-squared value of 0.711. Decision anxiety is strongly associated with perceptions of post-choice regret (t-value 11.96), as is product anxiety (t-value 2.108). This indicates that, as expected, feelings of worry over the accuracy and completeness of information is enough to cause a person to experience post-choice regret, even before an actual disconfirmation occurs. The relationship between PES interface and perceptions of post-choice regret is also significant (t-value 2.02). This provides some evidence that PES interfaces are not created equal in terms of influencing post-choice regret. Regulatory orientation was found significant antecedent of perceptions of post-choice regret (t-value 2.07). Consistent with expectations, users who naturally adopted a preventive regulatory orientation were more susceptible to feelings of post-choice regret than those with a promotional orientation. This is in keeping with the work of (Higgins, 2005; Lee and Aaker, 2004) who find that prevention oriented individuals seek to minimize loss and protect what they have. Interestingly, the interaction between orientation and interface was found to be strongly associated with perceptions of post-choice regret (t-value 2.26). We can conclude from this that regulatory fit is indeed occuring in an ecommerce environment, and that certain regulatory orientations are most suited to a particular interface design. Finally, perceptions of post-choice regret were shown to be significantly related to behavioral intentions towards the ecommerce retailer (t-value 18.97).

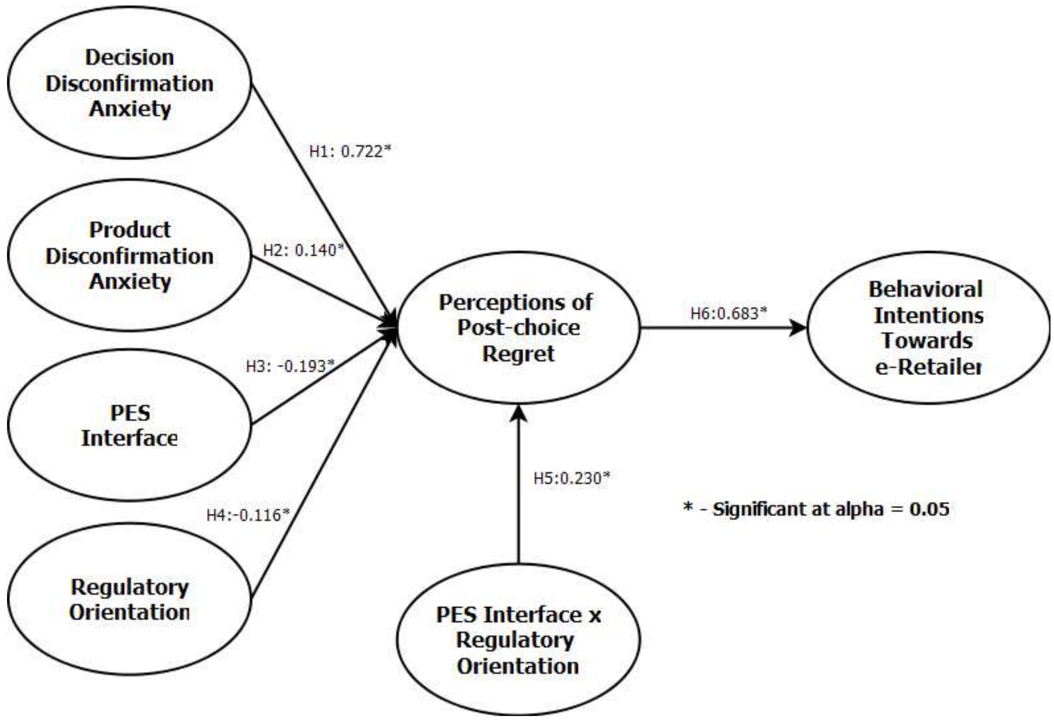

Figure 4. Results of PLS structural Analysis..

Discussion

The strong relationship identified here between post-choice regret and behavioral intentions towards ecommerce retailers has significant implications for practitioners and academics. Too often, regret has been ignored in the IS literature due to its post-adoption nature. In this study we showed that it is possible to capture feelings of post-choice regret at the time of the decision, and our finding of the strong link between decision and product anxiety and post-choice regret shows that it may be possible to identify and minimize the potential for future negative feelings at the time of purchase. The contrast of Amazon.com's PES with that of Google Products provides some evidence that different interfaces may impact user confidence in the information provided by these systems. To follow up on this, we asked participants a series of open ended questions at the end of the experiment regarding which interface they liked better. Many users felt that, in general, the summation features of PES2 were useful, but that this benefit was lessened by the fact that PES2 did not preserve the narrative context of the reviews as in PES1. This finding should prove useful for researchers looking for new and creative ways to provide summarized review content and improve the performance of PES systems. Finally, the finding that a person's regulatory orientation and the PES interface combine to lessen perceptions of post-choice regret is fascinating. Interestingly, the path coefficients for both interface and orientation were originally negative. This implies that as users went from PES1 to PES2 they scored lower on questions measuring post-choice regret. Transition from 0 (promotional regulatory orientation) to 1 (preventative regulatory orientation) was also associated with lower post-choice regret scores. When these values are taken together, however, their interaction resulted in a positive benefit for PES users. This implies that regulatory fit may indeed provide some real benefits for an ecommerce environment, thus warranting further study.

This study suffers from some key limitations that deserve mention. First, the use of Boolean values for regulatory orientation, although consistent with Higgins, (2001) loses some statistical power by not preserving the continuous nature of the variables that comprised the instrument. A future study could examine other methods of analyzing regulatory orientation, such as the use of priming tasks as outlined by (Lee and Aaker, 2004). Another limitation concerns the use of Amazon.com's PES system. Because of the widespread market penetration of Amazon, many experiment participants had some prior familiarity with the presentation format and output provided by the system. This is in contrast to the beta offering presented by Google Products, which many participants were not familiar with. However, we believe it is reasonable to assume that this is not a major problem of the study given that Google and Amazon have comparative name recognition in the ecommerce marketplace.

REFERENCES

1. Avnet, T., E.T. Higgins. (2006). How regulatory fit affects value in consumer choices and opinions. *Journal of Marketing research* 43(1) 1–10.
2. Bell, D.E. (1982). Regret in decision making under uncertainty. *Operations research* 30(5) 961–981.
3. Das, N., A.H. Kerr. (2010). " Woulda, Coulda, Shoulda": A Conceptual Examination of the Sources of Post-choice Regret. *The Journal of Marketing Theory and Practice* 18(2) 171–180.
4. Ghose, A., S.P. Han. (2009). An Empirical Analysis of User Content Generation and Usage Behavior in Mobile Digital Media. *ICIS 2009 Proceedings* 190.
5. Grizzle, J.E. (1965). The Two-Period Change-Over Design and Its Use in Clinical Trials. *Biometrics* 21(2) 467-480.
6. Higgins, E.T. (2000). Making a good decision: Value from fit. *American Psychologist* 55(11) 1217–1230.
7. Higgins, E.T. (2005). Value from regulatory fit. *Current Directions in Psychological Science* 14(4) 209.
8. Hu, M., B. Liu. (2004). Mining and summarizing customer reviews. *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining. ACM*, 168–177.
9. Hung, S.Y., Y.C. Ku, T.P. Liang, C.J. Lee. (2007). Regret avoidance as a measure of DSS success: An exploratory study. *Decision Support Systems* 42(4) 2093–2106.
10. Keller, K.L., R. Staelin. (1987). Effects of quality and quantity of information on decision effectiveness. *Journal of Consumer Research* 14(2) 200–213.
11. Kuksov, D., J.M. Villas-Boas. (2010). When more alternatives lead to less choice. *Marketing Science* 29(3) 507–524.
12. Lee, A.Y., J.L. Aaker. (2004). Bringing the Frame Into Focus: The Influence of Regulatory Fit on Processing Fluency and Persuasion. *Journal of Personality and Social Psychology* 86(2) 205–218.
13. Lee, A.Y., P.A. Keller, B. Sternthal. (2010). Value from Regulatory Construal Fit: The Persuasive Impact of Fit between Consumer Goals and Message Concreteness. *Journal of Consumer Research* 36(5) 735–747.
14. Loomes, G., R. Sugden. (1982). Regret theory: An alternative theory of rational choice under uncertainty. *The Economic Journal* 92(368) 805–824.
15. Maes, P. (1994). Agents that reduce work and information overload. *Communications of the ACM* 37(7) 30–40.
16. McKinney, V., K. Yoon, et al. (2002). The measurement of web-customer satisfaction: An expectation and disconfirmation approach. *Information Systems Research* 13(3) 296.
17. Miller, D.T., B.R. Taylor. (1995). Counterfactual thought, regret, and superstition: How to avoid kicking yourself. *Society for Experimental Social Psychology.*
18. Mudambi, S.M., Schuff, D. (2010). What makes a helpful Online Review? A study of customer reviews on Amazon.com. *MIS Quarterly* 34(1) 185–200.
19. Qin, L., A. Gulati, L. He, W. Fang. (2009). Adverse Selection for Luxury Goods in Online Auctions. *Journal of Internet Commerce* 8(3) 268–287.
20. Simonson, I. (1992). The influence of anticipating regret and responsibility on purchase decisions. *Journal of Consumer Research* 19(1) 105–118.
21. Spreng, R.A., S.B. MacKenzie, R.W. Olshavsky. (1996). A reexamination of the determinants of consumer satisfaction. *The Journal of Marketing* 15–32.
22. Sugden, R. (1985). Regret, recrimination and rationality. *Theory and Decision* 19(1) 77–99.
23. Tan, C.H., X. Yang, H.H. Teo, G. Lin. (2005). An Empirical Investigation of the Auction Buyer's Choice to Buy Out or Bid: Cry of Regret or Laugh of Satisfaction? *ICIS 2005 Proceedings* 62.

24. Tsiros, M., V. Mittal. (2000). Regret: A model of its antecedents and consequences in consumer decision making. *Journal of Consumer Research* 26(4) 401–417.

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

26. Zeelenberg, M. (1999). Anticipated regret, expected feedback and behavioral decision making. *Journal of Behavioral Decision Making* 12(2) 93–106.

27. Zeelenberg, M., W.W. Van Dijk, J. Van der Pligt, A.S.R. Manstead, P. Van Empelen, D. Reinderman. (1998). Emotional reactions to the outcomes of decisions: The role of counterfactual thought in the experience of regret and disappointment. *Organizational behavior and human decision processes* 75 117–141.