Modeling User Satisfaction from the Extraction of User Experience Elements in Online Product Reviews

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CHI'17 Extended Abstracts, *May 06-11, 2017, Denver, CO, USA*
ACM 978-1-4503-4656-6/17/05.
http://dx.doi.org/10.1145/3027063.3053097

Abstract
With the abundance of product reviews available online, online review data represent invaluable resources for understanding the user experience of various products in their real usage environments. Extant online review studies have considered UX elements mostly related to emotions. We collected 64,772 sentences from 4,380 online reviews of three electronic products, and analyzed the content of the online reviews using LIWC in order to extract various UX elements going beyond emotions. The study results show that UX elements extracted from online reviews had significant effects on user satisfaction. In addition to the emotional factors (hedonic, user burden), the results show that expectation confirmation and pragmatic factors play significant roles in determining user satisfaction.

Author Keywords
User experience; User reviews; User satisfaction; LIWC.

ACM Classification Keywords
H.5.2 User Interfaces: Evaluation/methodology

Introduction
It is one of the most important tasks for businesses to understand the thoughts and opinions of consumers on

products as they wish to satisfy their consumers. Product reviews in the online market places play an important role during the purchasing process as well as the usage process. In the process of purchasing a product, consumers decide to make a purchase often based on the reviews of other users. They also provide their comments on their product usage experiences. According to a survey from BrightLocal, 84% of people in US-based consumer panels trusted online reviews as much as a personal recommendation, and 74% of consumers mentioned that positive reviews made them trust the company more [18], collectively indicating that online reviews have a significant impact on both the pre-purchase and post-purchase processes.

There are studies that have targeted actual users in order to design new products based on user behaviors or to evaluate user experience (UX) elements for developed products. These studies have the advantage of gathering rich data on the users' feelings and opinions, through contact with actual users. On the other hand, they also have disadvantages because the experiments are costly and experimental designs may not be free from biases. To overcome these drawbacks, methods of extracting the UX from online text or narratives have been adopted for studying UX [8, 16].

Online reviews commonly contain a variety of feelings that users felt while using a product. For example, there are feelings obtained from the first touch, installation, and use of a product. There have been studies to derive meaningful information from reviews, but most prior studies only considered a part of the UX elements (e.g. positive or negative emotions), and they did not account for the consequences of the UX, such as satisfaction. Therefore, more research is needed to overcome these gaps in the literature.

To sum, the objective of this study is to model user satisfaction by extracting key elements from online reviews. We explore whether the frequent occurrences of UX elements extracted from online reviews affect user satisfaction. By considering the rating of each user as the degree of satisfaction, we can build a regression model for predicting user satisfaction from the frequency of UX elements. Finally, we compare the effect of UX on online reviews for each electrical device.

Related Work

User Experience

Research on user experience commonly seeks to improve users' convenience during their product use. Regarding smartphones, for example, there have been various problems associated with packing multiple features into a small screen. Manufacturers have solved these problems with the help of UX research by incorporating an interface to increase user convenience such as a pen type of interface and speech recognition.

Various definitions of the term UX have been discussed. McCarthy and Wright [12] proposed that technology should be seen as an artifact with which our quality of experience is formed and evaluated. Hassenzahl and Tractinsky [7] posited that UX is the outcome of a user's internal state, the system characteristics, and the usage context. Alben [1] mentioned that UX includes all aspects of interactive use of an end-user product. These studies indicate that UX is a comprehensive term that covers all usage aspects of a product.

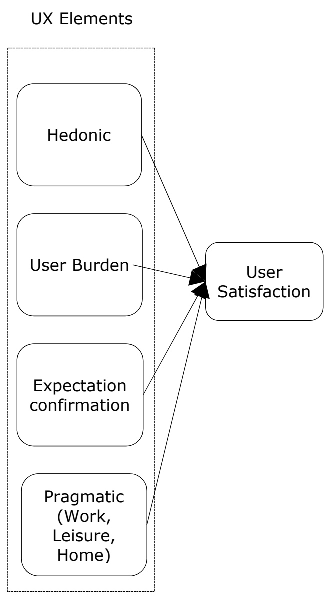

Figure 1: Research Model

UX research has been conducted on various products. According to a survey [2], mobile phones and mobile applications were the most researched products along with artistic fields such as art viewing environments. Currently, there are 2.6 billion smartphone subscribers, and by 2020, the figure will increase to 6.1 billion [11], making smartphones one of the most commonly used IT devices today. Therefore, this study mainly focuses on user reviews of smartphones, and the study also targets tablet PCs and smart TVs, which are similar to smartphones in terms of installed operating systems and usage purposes.

The goal of this study is to extract UX elements from online reviews and to identify important UX elements affecting user satisfaction. In addition, we compare the differences and similarities among the UX elements that affect user satisfaction across different three different IT devices of smart phones, table PCs, and smart TVs.

Analyzing Online Reviews

Recent studies on UX have strived to extract meaningful information from textual data, particularly from online reviews. For example, Yin et al. [17] presented negative emotions in review texts, such as anxiety and anger, which have an effect on the review helpfulness. To analyze users' emotions, they applied both the annotation of users and the use of LIWC software. Hedegaard and Simonsen [8] applied a machine learning technique into the extraction of UX elements from online reviews. They targeted the product categories of software and video games, which have a shorter duration than electronic products. They evaluated their results with the precision and recall of extracted texts. Different from previous studies, in our study, we not only discover UX elements using the LIWC software, but also examine the relationships between the extracted UX elements and user satisfaction.

Research Model

In this paper, our research attempts to analyze the effects of the UX elements extracted from online reviews on user satisfaction. We propose four independent variables from online reviews: expectation confirmation, playfulness, real-life applicability, and user burden. These are the factors mentioned in the literature as crucial elements of UX. Figure 1 illustrates our research model.

Expectation-confirmation theory (ECT) have been widely applied in consumer behavior research. It explains the relationship between consumer expectation fulfillment and the reuse of an object. ECT for information systems (ECT-IS) was developed by Bhattacherjee [3] based on expectation-confirmation theory [13] and the technology acceptance model [4]. Bhattacherjee [3] found that there exist differences between the initial expectation of a specific product prior to purchase or use and post-expectation. The initial expectation, occurring prior to accepting the technology, was typically formed from other people's opinions or information scattered across the media or online; whereas, post-acceptance expectation was composed of the first-stage UX, and had a more realistic, concrete description. Also, Bhattacherjee [3] posited that expectation confirmation is a direct determinant of user satisfaction. In sum, the expectation-confirmation theory suggests that the confirmation of expectation is likely to serve as a key mechanism in determining initial UX of users in their usage of technology and further influence overall

	Smart phone	Smart TV	Tablet PC
1	1083	1598	1699
2	250.50	244.42	241.14
3	16300	23672	24800
4	07/13~ 10/16	03/14 ~ 10/16	03/12 ~ 10/16
5	26	28	18
6	435.68	2178.04	253.69
7	3.86	3.82	3.95

Table 1: Sample Statistics.

Legend
1: # of valid sample reviews
2: # of avg. keywords
3: # of total sentences
4: Date of posting (MM/YY)
5: # of products
6: Avg. price (USD)
7: Avg. rating (/5)

assessment of their level of satisfaction. Thus, we hypothesize that:

H1: The expectation confirmation element extracted from product reviews has a positive effect on user satisfaction.

Hassenzahl [6] categorized the UX characters into two dimensions: pragmatic and hedonic attributes from a cognitive structure perspective. The pragmatic attribute represents the requirements of relevant functionality in the product in order to support the achievement of a user's goals, covering both usefulness [3] and ease of use of products. The hedonic attribute represents the functions and attributes that offer strong potentials for pleasure. Recent studies (e.g., [5,10]) highlighted these two UX elements as important for user satisfaction. Thus, we hypothesize that:

H2: The hedonic element extracted from product reviews has a positive effect on user satisfaction.

H3: The pragmatic element extracted from product reviews has a positive effect on user satisfaction.

We considered three contexts (work, home, and leisure) for the pragmatic element.

Prior research reported that the distribution of most product reviews on Amazon had a bi-modal phenomenon because either highly satisfied or dissatisfied customers were likely motivated to post a review [9]. Therefore, we conjectured that there are various user burden aspects contained in the online reviews. User burden means the negative impact that products may have placed on the users, such as difficulty of use; physical, mental and emotional aspects resulting from the use of a product [15]. In other words, a user burden in online reviews are likely to perform a detrimental role in determining user satisfaction. Thus, we hypothesize that:

H4: The user burden element extracted from product reviews has a negative effect on user satisfaction.

Research Method

Data Crawling

We randomly crawled reviews on Amazon.com for three product categories: smartphones, smart TVs, and tablet PCs. We collected only texts with more than 100 words and less than 1,000 words per a review, and collected about 1,000 reviews per a product item. When the amount of the keyword is small, the review is unlikely to include sufficient UX elements. On the other hand, when the amount of keywords is very large, it is highly likely that the review includes a lot of noises and marginally relevant elements. Table 1 shows the summarized information of the sample.

LIWC

In order to extract the elements of UX from the texts, a Linguistic Inquiry and Word Count (LIWC) 2015 was applied to the analysis of reviews. This software, which has widely been applied for emotion (sentiment) analysis [16,17], was developed by Pennebaker et al. [14] and is used for evaluating linguistic and psychometric properties embedded in texts. Once the text is inputted, the software identifies each word in the text sequentially and looks up the dictionary. If the word in the sentence is found in the dictionary, the weight for the particular category of text data is

	Esti.	t value
Smartphone (R^2=34.1%)		
interpret	3.53	21.16***
Hedonic	0.27	14.33***
Burden	-0.44	-13.78***
Confirm	0.01	0.44
Work	-0.09	-3.39***
Leisure	0.03	0.66
Home	-0.15	-2.12*
Smart TV (R^2=28.5%)		
interpret	3.13	19.36***
Hedonic	0.21	13.02***
Burden	-0.43	-16.03***
Confirm	0.05	3.55***
Work	-0.07	-3.17**
Leisure	0.03	2.11*
Home	0.20	4.58***
Tablet PC (R^2=25.5%)		
interpret	3.26	24.18***
Hedonic	0.22	13.89***
Burden	-0.36	-13.39***
Confirm	0.02	1.64
Work	-0.01	-0.73
Leisure	0.09	4.26***
Home	0.12	2.63**

Table 3: Result of Linear Regression

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

incremented. For each word category, a specific set of words are associated.

UX Element	LIWC Category	Examples	# of words
Hedonic	Positive emotion	love, nice, sweet	681
User Burden	Negative emotion	hurt, ugly, nasty	951
Confirmation	Comparisons	greater, best	439
Pragmatic	Work	job, majors	458
	Leisure	cook, movie	309
	Home	kitchen, landlord	213

Table 2: Dictionary of LIWC and UX Elements

Table 2 shows the dictionary of the LIWC according to the UX elements defined in our research model. We modified some of the dictionary terms and added some new terms so that the UX elements could be searched more accurately. In other words, based on the existing LIWC Dictionary, the corpus of the existing research [8] and the keyword mentioned in the prior user research [10] were utilized.

Results

Using linear regression, we analyzed the impact of the UX elements from online reviews. Table 3 shows the results of the linear regression, with user satisfaction as the dependent variable. In the case of smartphones, the elements of hedonic (t=14.34, p<.001), user burden (t=-13.78, p<.001), work (t=-3.39, p<.001), and home (t=-2.12, p<.05) had significant effects on user satisfaction, collectively explaining 34.1% variance in user satisfaction. Thus, user satisfaction increases when the number of comments about hedonic increases, whereas user satisfaction decreases when the number of comments about user burden, pragmatic in work and home increases.

In the case of smart TVs, hedonic (t=13.02, p<.001), user burden (t=-16.03, p<.001), expected confirmation (t=3.55, p<.001), work (t=-3.17, p<.01), leisure (t=2.11, p<.05), and home (t=4.58, p<.001) had significant effects on user satisfaction with 28.5% of explained variance. Thus, user satisfaction for smart TVs is higher when there are more comments about hedonic attributes, confirmation, pragmatic in leisure and family, and lower when there are more comments about user burden and pragmatic in work.

Finally, in the case of tablet PCs, hedonic (t=13.89, p<.001), user burden (t=-13.39, p<.001), leisure (t=4.26, p<.001), and home (t=2.63, p<.01) had significant effects on user satisfaction with 25.5% of explained variance. Thus, user satisfaction of tablets is higher when there are more comments about hedonic attributes, pragmatic in leisure and home, and lower when there are more comments about user burden.

The Durbin-Watson's statistics for the entire regression model was close to 2 (smartphone: 2.02; smart TV: 1.93; tablet PC:2.03) indicating that there was no serial correlation between residues. In addition, the variance inflation factors (VIFs) of all variables were measured to be less than 1.2, confirming that there was no multi-collinearity problem among the variables in the tested regression models.

Discussion

The results showed that UX elements from online user reviews significantly influence user satisfaction. The common phenomenon observed across the three products was that the hedonic element extracted from online reviews has a positive effect on user satisfaction and a user burden element has a negative effect on user satisfaction *(H2, H4: supported)*. The results are in sync with a user survey and confirmatory modeling research (e.g., [5]), indicating that the approach of analyzing UX elements from online reviews and using them to predict user satisfaction is one of the possible alternatives in consumer research.

In this study, we classified pragmatic elements as work, leisure, and home contexts. The home context has a significant effect on user satisfaction for smart TVs and tablets, but has a negative effect for smartphones. The work context has a negative effect on satisfaction for smartphones and smart TVs, and a leisure context has a positive effect on satisfaction for smart TVs and tablets. The results show that pragmatic elements have different effects depending on the type of technology *(H3: partially supported)*.

The expectation confirmation element has a significant effect on the satisfaction only for smart TVs *(H1: partially supported)*. One possible explanation is the price difference. The average price of a smart TV is higher than the other two products (i.e., Table 1), and the higher cost might have had a bigger effect in comparison with the other products. Future research will need to look into under what conditions expectation confirmation becomes more important.

In summary, this study extracted theoretically defined UX elements from online review texts and examined their effects on user satisfaction. For all three products, the results showed that hedonic element had a positive effect on user satisfaction, and user burden had a negative effect on user satisfaction. In the case of pragmatic element and expectation confirmation, differences were noticed in the effects on user satisfaction of the three products. Our research shows that the major UX elements mentioned in prior user studies can be extracted through the textual analysis of online reviews.

The limitation of this research is that LIWC, one of the keyword extraction methods [14], considers only a single keyword to analyze the dimension, and it does not perform natural language processes such as stemming. A sophisticated natural language processing tool coupled with machine learning techniques or support vector machines [8] might be utilized in a future study. In addition, expansion of data and comparative evaluation with other products might be considered in future studies.

In this study, we introduce a method for predicting consumer satisfaction through UX analysis of online reviews. With the flourishment of e-commerce sites, online reviews are abundant and continuously on the rise. The UX analysis of online reviews has the advantage of obtaining what users have experienced in their natural usage environments, which are unlikely to be available in a controlled experiment environment.

Acknowledgement
This work was supported by the Industrial Strategic Technology Development Program, 10052955, Experiential Knowledge Platform Development Research for the Acquisition and Utilization of Field Expert Knowledge, funded by the Ministry of Trade, Industry & Energy (MI, Korea).

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