Do You Buy or Not? The Effect of Recommender Slogans on Retail Sites

Hsiaoping Yeh[1], Tsung-Sheng Chang[2*], Fenghung Kuo[1]

[1] Department of Marketing and Distribution Management, National Kaohsiung University of Science and Technology, Kaohsiung City, Taiwan.
[2] Department of Information Management, Da-Yeh University, Changhua, Taiwan.

* Corresponding author. Tel.: +886-4-8511888#3132; email: china@mail.dyu.edu.tw
Manuscript submitted April 3, 2020; accepted October 14, 2020.
doi: 10.17706/ijeeee.2021.11.1.11-20

Abstract: Recommender systems solve the current information overload problem in the online world. By predicting and presenting relevant information, web users do not need to waste time searching and browsing for contents that they are interested in. However, in addition to the accurate contents, slogans associated catching the customers' eyes are worthy of exploration. This study aims to discover the effects of various recommender slogans. Two categories of slogans were designed in the study: slogans associated with customer inputs and slogans associated with price promotion. Actual customers' webpage clickstreams and purchase decisions were collected from a Taiwanese retail shopping Website. The effects of recommender slogans on product categories are different. Customers generally were drawn by the slogans associated with price promotion. This study brought to light the effects of different slogans on online shoppers. With the empirical findings, this study provides online retailers important guidelines regarding online customers' behaviors towards the employment of recommender slogans.

Key words: Slogans, recommender system, online retail, customer behavior.

1. Introduction

Recommender systems, designed to offer products of interest to customers, use people's opinions about items in an information domain to help people choose other items about the item's taxonomy, attributes and descriptions [1]. Prior studies pointed out that customers' choices may be driven by product suggestions and electronic word-of-mouth (eWOM) [2], [3]. East, Lomax, and Narain [4] indicated that over 30% of customers switched their choice due to recommendations. While traditional advertisements challenge the fit customer needs, online recommender systems provide an opportunity to stand out and deliver messages that employ behavioral targeting to enhance the relevance of the message to customers [5]–[7].

Since recommender systems become important decision aids in the e-marketplace and an integral part of the business models of many firms [8], [9], most recommender systems use customer experienced items as inputs for the system's computational techniques (based on methodologies form statistics, data mining or artificial intelligence). For example, social recommender systems (SRSs) is one application that combines recommending messages with information in social media and provides the eWOM of web users to customers [10]. Yet, recommender systems, serving only recommendations, estimate items that have not been purchased by customers who will like the items. Gu, Park, and Konana [11] argued that customers'

referral and WOM have greatly influenced their subsequent purchase behavior online. The online retailers, when they make sales strategies regarding products and marketing, should be able to better manage all the information on social media. Furthermore, Hervas-Drane [12] indicated that products with optimal pricing and assortment and with effective recommendations for the online retailing are essential to sales success. In other words, recommender systems, operating only based on customers' history (such as purchases, cookies, or Webpages views) would not stimulate and increase a customers' purchase decision [10]. Recommender systems offer valuable customized suggestions, as Baum and Spann [5], and the contents of the information are critical for customers to actually click on the suggestions. Matute , Polo-Redondo and Utrillas [13] found that contents of advisements for online reviews sites have great impact on users' repurchase behavior. Li, Huang and Bente [14] stressed that users' eye movements are dependent on the appearance of online banners. Different wordings have distinguishing effects on users' Webpage clicks and even on their purchase behaviors.

The past studies regarding recommender systems were more focused on system design. Researchers have primarily focused on delivering accurate recommendations through the development and improvement of the data calculation algorithms (e.g., Guo, Wang and Li [15]) Although many of the well-tuned algorithms with a wide range of algorithmic approaches to problem accuracy have been solved, delivering these accurate predictions to users in a way that creates the best retailing purposes in terms of strengthening customer satisfaction/loyalty, increasing sales, enhancing purchase intention experience for the online retail practices remains an open problem. Nowadays, customers tend to understand and recognize the functions and consequences of the recommender systems offered by many online retailers. There is very little knowledge about the cues of recommendations in terms of recommender slogans, and how they influence online customer behaviors. In addition, responses to this service were more based on customer perception. Two of the general research questions asked were:

"There are many products on the online retail. Does it have the same sales benefits if used same slogan?"

"Which type's slogan is attracting customer then willing to purchase production?"

The purpose of our study was to identify different advertising slogans the benefit for online retail. The empirical Webpage clickstreams from customers in this study provide more concrete findings, which can contribute to marketing managers in practical operation of online retailing and to marketing and recommender systems literature.

2. Literature Review and Hypotheses

2.1. Recommender Systems and Customer Behavior

Recommender systems assist people to make better choices [16], [17]. They can offer users product alternatives through data processing algorithms in order for them to easily and quickly find their target products. A good or better recommender system is not only able to assist users to look for a single item that closely matches their queries, but also would like to provide all items that are likely to fit the users' interests [18]. An online recommendation solution is used to select a product based on customer behavior records in each phase of the online purchase decision process so that the recommendation ones with richer content can be more effectively provided to the customers and the conversion rate of the online decision is hopefully improved.

In an e-commerce context, the customers' final purchase decision may shift due to the mediated information that is perceived as a need-state for them. One of these mediation information sources online is recommending [19]. Recommender systems are characterized as one style of customer decision support system (DSS) [20], [21]. Since it solves the current information overload problem in the online world, it improves decision quality, and increases confidence in product choice [22]–[24]. Through clicking on

recommendation items, online shoppers often alter their decision rapidly. Generally speaking, if customers surfing a Website see a hyperlink that they view as a relevant message, they may take immediate action, such as clicking and then making a purchase if it is linked to a product with the price and features of all alternatives.

People are often influenced by immediate elements in the environment and their preferences are constructed (e.g., Chapman and Johnson [25], Lichtenstein and Slovic [26]). Since the causes leading to changes in customer preferences and demands are recommenders, purchase advocacy, or referral systems [4], in the various steps of customer decision making processes in e-commerce environments, recommendation techniques have been widely used as criteria for searching products on the Internet and generating advice and recommendations for online customers [27]. Search engines will accord to the advertiser and user past behavior shows different pages [28]. Prior studies have proposed different theories that indicate which factors influence the customers' intent to use recommender systems (summarized in Table 1).

Table 1. Factors of Intention to Use Recommender System

Factors	Description	Source
Production	Production expertise	Xiao and Benbasat [21]; Ahn and Park [29]; Ochi, Rao, Takayama and Nass [30]; Tsao [31]
Experience	System use experience, system recommender quality	Xiao and Benbasat [21]; Choi, Lee, Sajjad and Lee [32]
Trust	Trust in recommender systems which enable to provide alternatives matched customer needs	Chang and Hsiao[10]; Xiao and Benbasat [21]; Choi, Lee, Sajjad and Lee [32]; Wang and Benbasat [33]; Mart ńez-L ópez, Esteban-Millat,Cabal and Gengler [34]
Recommended evaluation	Slogans, social influence, commend content	Chang and Hsiao [10]; Choi, Lee, Sajjad and Lee [32]; Wang, Luse, Townsend and Mennecke [35]
Perceived usefulness	Perceived usefulness of recommended system	Chang and Hsiao [10]; Wang and Benbasat [33]; Mart ńez-L ópez, Esteban-Millat,Cabal and Gengler [34]; Pu and Chen [36]; Kowatsch and Maass [37];

Given the potential advantages of recommenders, it is important for researchers to explore the contexts in which customers are attentive to recommendations. Customers may willing to purchase products based on recommending information. If we understand the ability to deliver the message will gain more sales for online retail.

2.2. Recommender Context

Past research has explored recommender systems based on software generated algorithms that aggregates different types of information provided by a company, an independent party or customers (e.g., Aggarwal and Vaidyanathan [38]; Ochi, Rao, Takayama and Nass [30]; Senecal and Nantel [3]). While the use of recommendations is growing quickly, the specific characteristics of what customers want from these services have yet to be thoroughly researched [39]. This is especially important in the context of recommendations. They must efficiently and effectively aid customer decision making rather than overwhelm them with additional and irrelevant information [40]. By designing relevant and easy to use recommendations that include only targeted features that customers want, marketers will be able to improve customer satisfaction and generate more sales. Further, trustworthy and credible recommendations by researchers (but not fully directed to customers' action in terms of placing orders) suggests that the sources of such systems come from independent sources rather than from retailers [41]–[43]. Therefore, focus should be recommendations based on a variety of information coming from the

host retailer, and the effects of product types on customers' responses to such recommendations on the actual purchases.

The contents, in verbal or graphical forms or the combination of both, provided in recommender systems, perform similarly as those in online advertisements. However, Li, Wei, Tayi and Tao [44] argued that of the various ways of making online presentations for online products, the verbal forms are still the most effective ones in terms of delivering information. The recommender slogans, sometimes called taglines, are the verbal forms of advertisement used to catch online users' attention. McCoy, Eversard, Polak and Galletta [45] studied 536 participants and found that the online slogans have significantly positive effect in re-directing users' browsing Webpages from the current ones. In the reality in online retailing, in order to promote sales, companies often separate different anchors to describe recommender slogans with terms such as "you are probably interested (or "featured recommendation"; "relative items you've viewed")", "the best buy" (or "the hit items"), "others also viewed", and "the most viewed" on a certain product Webpage that the shoppers are viewing.

For the alternatives of recommendation, Aggarwal and Vaidyanathan [38] found that customers expect to be provided with rather recommending alternatives that better match their anchoring ones with product features than the products by promotion. Yet, Ochi, Rao, Takayama and Nass [30] derived the opposite result that customers would value more about the latter over the former. Consequently, customers' expectation and responses are different when they are presented with different contents of recommender slogans.

2.3. Hypotheses

Abstracting from all of the literature, this study focuses on online retail customer reactions related to the acquisition and buying intention of products presented by recommender slogans. When customers surf a retail site, the Web will show slogans messages and they will click on them or not. Therefore, this study posits that different recommender slogans have different impacts on online shoppers' responses while they are viewing the target products as well as different contributions to their shopping intentions to alter their purchase behaviors. Besides, the effectiveness of recommendations, this study is implicitly directed to online retailers.

Two categories of slogans were employed in this study: social-based and marketing-based. The expression of the social-based slogans is market related. That is, "the best buy" and "the most viewed" of the recommendations are based on the data from the market. It such as Wu, Hu and Wang [46] study. They adopted product rank define the index. The expression of the marketing-based slogans is marketing related, particularly for promotion. That is, "price discount" and "flash sale" are for promotional purposes. The social-based product recommending lists are strictly based on the actual sales and product Webpage views. The marketing-based product recommending lists are thus, a consideration of business purposes.

H1. Among recommender slogans with different product types, there are significant different impacts on the tendency of clicking the recommendation products.

H2. Among recommender slogans with different product types, there are significant different impacts on online shoppers' adding to the shopping cart.

H3. Among entitled recommenders with different product types, there are significant different impacts on online shoppers' buying the recommendation products.

3. Methodology

Data were collected from a retail Website in Taiwan. The purpose of this study is to investigate the differentiation among four recommender slogans, termed as "the best buy", "the most viewed", "price discount", and "flash sale", on customers' clicks and their further behaviors of adding to shopping carts and

actual purchase. Four rows of products, each row is entitled with one slogan, were placed below the target product on the same Webpage. All recommendation products and the associating target product are in the same product category. In this Website, products are classified into nine major categories: (1) foods(commodities), (2) sports and leisure, (3) 3C (computer, communication, and consumer electronics), (4) outfits, (5) culture and education, (6) cosmetics and health cares, (7) office supplies, (8) home appliances, and (9) others (e.g., dog food, plants, fertilizer, ore tobacco).

When a user clicked to browse a product page, either by keyword search or direct reach, valid data was recorded if this user further clicked on any products on the area of recommendation product lists. For reliability and consistency, only the first clicks on the area of recommendation for each target product were taken for data analyses. Also, the network IP address was used to screen out multiple record collections for an individual product Webpage. That is, for each product Webpage and for each network IP, a datum was recorded. Note that, the recommended product Webpages are aligned with their associating recommender slogans and products. Additionally, during an individual user browsing in the site, adding to shopping cart and actual purchase of the recommended products were also recorded.

There are around fifteen thousand visits, on average, daily in this Website. In this study, 2700 data samples for each category of products were collected for power tests [47]. The total data samples were 24,300 of anonymous data. That is, all data collected for analyzes includes all Webpage views from guests and members who did not login.

The selection and assigning criteria of recommendation products with the numbers of descriptive features/attributes for each target item is based on McSherry's compromise-driven retrieval algorithm [18], which not only recommends high similarity goods to users but also takes consideration of users' possible compromise attitudes, being seen as good or better in some objective sense and considerably acceptable for recommender systems [18], [48].

4. Results

Chi-square tests were conducted to test the hypotheses. First, for H1, the frequencies (percentages in parentheses) and the test for the correlation between product category and type of recommender slogan are shown in Table 2. As is shown, different recommender slogans do not have the same effect on various product categories. In order to draw customers' attention, these four types of slogans can be all employed but their sequence on the target product page should be differently placed.

For "Foods (Commodities)" and "Home appliances", a marketing-based slogan, i.e., "price discount", tends to draw the customers' attention. For "Outfit", "Office supplies", and "Others", the marketing-based slogan, "flash sale", catches customers' eyes. Furthermore, for "Sports and leisure, "3C", and "Culture and education" types of products, customers are likely to browse more "the most viewed" products. For "Cosmetics and health cares" products, the other social-based slogan, i.e., "the best buy", customers may want to see more other hits in this Website.

Additionally, in Table 2, the total clicks on each slogan are shown almost the same. However, testing on the effects of the slogans on each of the product categories, are significantly different. Therefore, the hypothesis H1 is accepted.

Table 3 shows the data for hypotheses H2 and H3. Different recommender slogans significantly affect the consequences of adding recommended products to shopping carts and actual purchases. Therefore, hypotheses H2 and H3 are both accepted. Nonetheless, the effects of slogans that are in the same basis, i.e., social-based and market-based, appear to be different. For the case of adding recommended products into shopping carts, the slogans of "the best buy" and "flash sale" show the similar effects. Alternatively, for actual purchases, "flash sale" is a key incentive to make the final purchase decision.

Table 2. Frequencies and Correlation Test between Product Category and Slogan

Product category	Slogan				Total
	The best buy	The most viewed	Price discount	Flash sale	
Foods(commodities)	369 (13.70%)	315 (11.70%)	1035 (38.30%)	981 (36.30%)	2700 (100%)
Sports & leisure	747 (27.70%)	936 (34.70%)	585 (21.70%)	432 (16.00%)	2700 (100%)
3C (Computer, Communication, and Consumer Electronic)	729 (27.00%)	747 (27.70%)	711 (26.30%)	513 (19.00%)	2700 (100%)
Outfits	549 (20.30%)	612 (22.70%)	720 (26.70%)	819 (30.30%)	2700 (100%)
Culture & education	801 (29.70%)	855 (31.70%)	639 (23.60%)	405 (15.00%)	2700 (100%)
Cosmetics & health cares	864 (32.00%)	828 (30.70%)	558 (20.60%)	450 (16.70%)	2700 (100%)
Office supplies	666 (24.70%)	486 (18.00%)	567 (21.00%)	981 (36.30%)	2700 (100%)
Home appliances	738 (27.30%)	477 (17.70%)	819 (30.30%)	666 (24.70%)	2700 (100%)
Others	729 (27.00%)	504 (18.70%)	576 (21.30%)	891 (33.00%)	2700 (100%)
Total	6192	5760	6210	6138	24300

From the numbers of records associated with adding products into shopping carts and actual purchases, the conversion rates (CR), i.e., actual purchases/browsed, is 1.5% (369/24300), indicating the recommender system performing in this Website is not effective.

Table 3. Statistical Results of H2 and H3

Slogan	Add to shopping cart [*]	Purchase [**]	Total
The best buy	360 (5.8%)	72 (1.2%)	432 (7.0%)
The most viewed	162 (2.8%)	54 (0.9%)	216 (3.7%)
Price discount	270 (4.3%)	72 (1.2%)	342 (5.5%)
Flash sale	342 (5.6%)	171 (2.8%)	513 (8.4%)
Total	1134 (18.5%)	369 (6.1%)	1503 (24.6%)

[*] *Chi*-square ($df = 3$) = 8.395, $p = .039 < .05$
[**] *Chi*-square ($df = 3$) = 9.947, $p = .019 < .05$

5. Conclusion, Implications, and Future Research

To investigate e-commerce effects on customer behaviors, the full range of scenarios designed for testifying and collecting customer responses in the real online retailing sites, we believe will help the online retailers to comprehend the true customer behaviors of e-commerce and plan marketing strategies.

This study, applying real customers' clickstream data to investigate different effects of recommender settings on customer behaviors contributes to addressing recommender slogans for online retailing. In more detail, the effectiveness of recommender slogans investigated in this study includes acceptance. It is acceptance and usefulness as well as the practical/commercial values, in terms of adding recommendation items in shopping carts and making the order. Marketing managers make enormous efforts to sell their products and services to their customers. Their marketing activities are engaged in order to ensure the customers choose their products from a full range of competing products. The objective of this study is to discover how online shoppers react to recommender systems by providing recommendation items for shoppers' viewing their target products. The online shoppers' attention on their target interests is

distracted by recommender systems. Generally, among different recommender slogans, their actual purchases are mostly affected by the market-based slogans, i.e., "price discount" and "flash sale". This indicates that prices for product sales are still an important factor for the final purchase decision.

With the empirical proof, this study suggests that online retailers increase the practically positive results for recommender systems, not only with pay efforts on adoption of the better computing algorithm but also the messages delivered to customers since customers reflect different responses to different titling messages for recommendation products. Base on Yoo and Kim [49], customers' attention can be significantly drawn by the appearance of advertisements including pictures, texts, and layouts. For the intention of clicks on the Web links, Li, Huang, and Bente [14] used eye movements to survey the effectiveness of the Internet banners and found that the combination of animation and texts draw more attention from the Web users. Hanafizadeh and Behboudi [50] suggest different online products need to have different ad formats. Although the studies pointed out that texts plays an important role in advertisements, there is little knowledge about the influence of their contexts and wordings. Based on the findings in this study, Web retailers are shown that recommender slogans should be on a product type basis, and the wording of the slogans should be well-designed.

It was also found that the percentage of adding into shopping carts and that of the actual purchases for the recommended products after customers' clicks, i.e., conversion rates, are low. There are two issues brought out in this study. First, the major function of recommendation is to offer useful information for Web users. However, for Web retailers, one of purposes of applying recommendations is to increase the chances of final sales. Hence, the CR of the recommendations can be used for the performance evaluation. Second, studies have shown that factors influencing the online sales are Webpage design [51] as well as present prices, pictures, and texts on the Web sites [52], [53]. That is, deals would still not be closed if the recommended products are not expected or fitted to customers' needs. The recommender slogans are the ignitions to make customers' click. The contents of product webpages, however, are also require careful and suitable designs.

This study only focuses on discovering the effects of recommender slogans on retail sites, particularly, by leveraging different product types and different recommender slogans for all similar products. The slogan design features, such as fonts, colors, styles may also have impact on recommender systems. Additionally, the effects of different levels of product similarities as well as the impacts incorporated with customers' experiences, perceptions of trust, and product knowledge are suggested for the further research. Moreover, recommendation products tagged with "other also bought" may not completely classified as similar products of the target items yet they are so for the marketing purpose of cross-selling. This would also be our future study. Lastly, data were collected from Webpage clickstreams in a real shopping Website. Data collected in this study show high interval validity; however, they are anonymous but only IP-controlled. There might be chances that one customer used different IPs and this is a limitation of this study.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Hsiaoping Yeh and Fenghung Kuo conducted the research; Tsung-Sheng Chang analyzed the data. We wrote the paper together. All authors had approved the final version.

References

[1] Srikumar, K. (2004). A framework of agent-based personalized recommender system for e-commerce.

South Asian Journal of Management, *11(2)*, 66-80.

[2] Hsu, W. C., & Chen, L. C. (2017). A novel recommendation system for dental services based on online word-of-mouth. *Information Resources Management Journal*, *30(1)*, 30-47.

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

[4] East, R., Lomax, W., & Narain, R. (2001). Customer tenure, recommendation and switching. *Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior*, *14*, 46-54.

[5] Baum, D., & Spann, M. (2014). The interplay between online consumer reviews and recommender systems: An experimental analysis. *International Journal of Electronic Commerce*, *19(1)*, 129-162.

[6] Nasco, S., & Bruner, G. (2008). Comparing consumer responses to advertising and non-advertising mobile communications. *Psychology and Marketing*, *25(8)*, 821-837.

[7] Pagnani, M. (2004). Determinants of adoption of third generation mobile multimedia services. *Journal of Interactive Marketing*, *18(3)*, 46-59.

[8] 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.

[9] Wakil, K., Akram, B., Kamal, N., & Safi, A. (2014). Web recommender system for private universities' admission in Iraq: UHD case study. *International Journal of e-Education, e-Business, e-Management and e-Learning*, *4(5)*, 329-340.

[10] Chang, T. S., & Hsiao, W. H. (2013). Factors influencing intentions to use social recommender systems: A social exchange perspective. *Cyberpsychology, Behavior, and Social Networking, 16(5)*, 357-363.

[11] Gu, B., Park J., & Konana, P. (2012). The impact of external Word-of-Mouth sources on retailer sales of high-involvement products. *Information Systems Research*, *23(1)*, 182-196.

[12] Hervas-Drane, A. (2015). Recommended for you: The effect of word of mouth on sales concentration. *International Journal of Research in Marketing*, *32(2)*. 207-218.

[13] Matute, J., Polo-Redondo, Y., & Utrillas, A. (2016). The influence of EWOM characteristics on online repurchase intention: Mediating roles of trust and perceived usefulness. *Online Information Review*, *40(7)*, 1090-1110.

[14] Li, K., Huang, G., & Bente, G. (2016). The impacts of banner format and animation speed on banner effectiveness: Evidence from eye movements. *Computers in Human Behavior*, *54*, 522-530.

[15] Guo, Y., Wang, M., & Li, X. (2017). Application of an improved Apriori algorithm in a mobile e-commerce recommendation system. *Industrial Management & Data Systems*, *117(2)*, 287-303.

[16] Ariely, D., Lewenstein, G., & Prelec, D. (2003). Coherent arbitrariness: Stable demand curves without stable preferences. *The Quarterly Journal of Economy*, *118(1)*, 73-106.

[17] Epley, N., & Gilovich, T. (2010). Anchoring unbound. *Journal of Consumer Psychology*, *20(1)*, 20-24.

[18] McSherry, D. (2003). Similarity and compromise. *Proceeding of the 5th International Conference on Case-Based Reasoning Research and Development* (pp. 291-305). Trondheim, Norway.

[19] Lee, G., & Lee, W. J. (2009), Psychological reactance to online recommendation services. *Information & Management*, *46(8)*, 448-452.

[20] Benatia, I., Laouar, M. R., Bendjenna, H., & Eom, S. B., (2015). A cloud-based multi-criteria decision support system for selecting urban housing projects. *Human Systems Management*, *34(2)*, 119-135.

[21] Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly*, *31(1)*, 137-209.

[22] Häubl, G. & Trifts, V. (2000). Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing Science*, *19(1)*, 4-21.

[23] Hostler, R. E., Yoon, V. Y., & Guimaraes, T. (2005). Assessing the impact of Internet agent on end users'

performance. *Decision Support Systems*, *41(1)*, 313-323.

[24] Lee, B. K., & Lee, W. N. (2004). The effect of information overload on consumer choice quality in an on-line environment. *Psychology & Marketing*, *21(3)*, 159-183.

[25] Chapman, G., & Johnson, E. (2002). Incorporating the irrelevant: Anchors in judgments of belief and value, In T. Gilovich, D. Griffin, & D. Kahneman, (Eds.), *Heuristics and Biases: The Psychology of Intuitive Judgment* (pp. 120-138). Cambridge: Cambridge University Press.

[26] Lichtenstein, S., & Slovic, P. (2006). *The Construction of Preference*. Cambridge: Cambridge University Press.

[27] Grenci, R. T., & Todd, P. A. (2002). Solutions-driven marketing. *Communications of the ACM*, *45(3)*, 65-71.

[28] Font-Julian, C. I, Ontalba-Ruipérez, J. A, & Orduña-Malea, E. (2018). Hit count estimate variability for website-specific queries in search engines: The case for rare disease association websites. *Aslib Journal of Information Management*, *70(2)*, 192-213.

[29] Ahn, H. J., & Park, S. (2012). How does customer's product expertise moderate the usefulness of information recommendation agents in online stores? *Information Research*, *17(4)*, 1-17.

[30] Ochi, P., Rao, S., Takayama, L., & Nass, C. (2010). Predictors of user perceptions of web recommender systems: how the basis for generating experience and search product recommendations affect user responses. *International Journal of Human-Computer Studies*, *68(8)*, 472-482.

[31] Tsao, W.-Y. (2013). The fitness of product information: Evidence from online recommendations. *International Journal of Information Management*, *33(1)*, 1-9.

[32] Choi, J., Lee, H. J., Sajjad, F., & Lee, H. (2014). The influence of national culture on the attitude towards mobile recommender systems. *Technological Forecasting and Social Change*, *86*, 65-79.

[33] 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.

[34] Martínez-López, F., Esteban-Millat, I., Cabal, C. C., & Gengler, C. (2015). Psychological factors explaining consumer adoption of an e-vendor's recommender. *Industrial Management & Data Systems*, *115(2)*, 284-310.

[35] Wang, Y. Y., Luse, A., Townsend, A. M., & Mennecke, B. E. (2015). Understanding the moderating roles of types of recommender systems and products on customer behavioral intention to use recommender systems. *Information Systems and e-Business Management*, *13(4)*, 769-799.

[36] Pu, P., & Chen, L. (2007). Trust-inspiring explanation interfaces for recommender systems. *Knowledge-Based Systems*, *20(6)*, 542-556.

[37] Kowatsch, T., & Maass, W. (2010). In-store consumer behavior: How mobile recommendation agents influence usage intentions, product purchases, and store preferences. *Computers in Human Behavior*, *26(4)*, 697-704.

[38] Aggarwal, P., & Vaidyanathan, R. (2005). Perceived effectiveness of recommendation agent routines: search vs. experience goods. *International Journal of Internet Marketing and Advertising*, *2(1-2)*, 38-55.

[39] Aljukhadar, M., & Senecal, S. (2011). Usage and success factors of commercial recommendation agents: A consumer qualitative study of MyProductAdvisor.com. *Journal of Research in Interactive Marketing*, *5(2-3)*, 130-152.

[40] Häubl, G., & Murray, K. B. (2006). Double agents: Assessing the role of electronic product recommendation systems. *Sloan Management Review*, *47(3)*, 8-12.

[41] Lepkowska-White, E. (2013). Are they listening? Designing online recommendations for today's consumers. *Journal of Research in Interactive Marketing*, *7(3)*, 182-200.

[42] Weathers. D., Sharma, S., & Wood, S. L. (2007). Effects of online communication practices on consumer

perceptions of performance uncertainty for search and experience goods. *Journal of Retailing*, *83(4)*, 393-401.

[43] West, P. M., Ariely, D., Bellman, S., Bradlow, E., Huber, J., Johnson, E., Kahn, B., Little, J., & Schkade, D. (1999). Agents to the rescue? *Marketing Letters*, *10(3)*, 285-300.

[44] Li, M., Wei, K.-K., Tayi, G. K., & Tao, C.-H., (2016). The moderating role of information load on online product presentation. *Information & Management*, *53(4)*, 467-480.

[45] McCoy, S., Everard, A., Polak, P., & Galletta, D. (2007). The effects of online advertising. *Communications of the ACM*, *50(3)*, 84-88.

[46] Wu, F. Hu, Y. H., & Wang, P. R. (2017). Developing a novel recommender network-based ranking mechanism for library book acquisition. *The Electronic Library*, *35(1)*, 50-68.

[47] Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112(1)*, 155-159.

[48] Burkhard, H. D. (1998). Extending some concepts of CBR-Foundations of case retrieval nets, In M., Lenz, B., Bartsch-Spörl, H. D., Burkhard, & S. Wess (Eds.), *Case-Based Reasoning Technology* (pp. 17-50). Berlin Heidelberg, New York, Springer-Verlag.

[49] Yoo, J., & Kim, M. (2014). The effects of online product presentation on consumer responses: A mental imagery perspective. *Journal of Business Research*, *67(11)*, 2464-2472.

[50] Hanafizadeh, P., & Behboudi, M. (2013). The right format of Internet advertising (RFIA): A structural equation model. *Information Resources Management Journal*, *26(2)*, 20-42.

[51] Ching, R. K. H., Tong, P., Chen, J.S., & Chen, H. Y. (2013). Narrative online advertising: Identification and its effects on attitude toward a product. *Internet Research*. *23(4)*, 414-438.

[52] Banerjee, P., & Gupta, R. (2016). Design deficiencies in corporate career web-sites in India: A content analysis. *Human Systems Management*, *35(4)*, 291-300.

[53] Santiworarak, L., & Choochaiwattana, W. (2018). A case study of usability design principle in responsive e-Commerce web application. *International Journal of e-Education, e-Business, e-Management and e-Learning*, *8(3)*, 139-144.

Hsiaoping Yeh is an associate professor in the Department of Marketing & Distribution Management at National Kaohsiung University of Science and Technology in Taiwan. She holds a doctorate in industrial engineering from the University of Wisconsin-Madison. Her current research interests are customer relationship management, service innovation, and smart retail.

Tsung-Sheng Chang is an assistant professor in the Department of Information Management at Da-Yeh University in Taiwan, ROC. He holds a PhD from Department of Information Management, National Chung Cheng University, Taiwan. His current research interests are in the areas of e-business, infotainment system and behavior.

Fenghung Kuo is a PhD student in the Department of Marketing & Logistics Management at National Kaohsiung University of Science and Technology in Taiwan. His current research interests focus on customer relationship management, customer behavior, and electronic commerce.