Journal of Data Acquisition and Processing

ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.778106

ENTREPRENEURIAL RECOMMENDATION SYSTEM FOR ANIMES TO INCREASE CUSTOMER SATISFACTION AND REVENUE GENERATION USING ARTIFICIAL INTELLIGENCE AND SOCIAL MEDIA MARKETING

Prof. (Dr.) Broto Rauth Bhardwaj
Bharati Vidyapeeth (Deemed to be University) Institute of Management and Research, New Delhi, Professor and Head, Research, broto.bhardwaj@bharatividyapeeth.edu

Medhavi Bhardwaj
2nd Year, B. Tech. AI & ML, IGDTUW, New Delhi

Sheena Gaur
Faculty, IGDTUW, New Delhi

Shweta Sinha
PhD Scholar, BVDU, Pune, Assistant Professor, Bharati Vidyapeeth (Deemed to be University) Institute of Management and Research, New Delhi

Abstract

Purpose: The purpose of the research paper is to design entrepreneurial recommender system for recommending anime to customers on the basis of customers' purchase data history and customers' rating and customers' preferences.

Methodology: Trying out a particular combination of parameters to build a recommendation system that will recommend new animes to the customers by analysing their purchase data history and customers' preferences. Thus, the revenue of the streaming platforms will increase due to increased customers' engagement, higher customer ratings, and customers' satisfaction.

Findings: To increase customer satisfaction and thus generate more customer engagements and subscriptions and increase the revenue generation of companies.

Introduction

Anime is a popular type of animation that originated in Japan that has become widely populated throughout the world in the last decade. Animes cover a large variety of themes and genres including action, romance, sci-fi, fantasy, comedy, etc. Animes are widely known for their unique art style and have helped in educating the Western demographic about East Asian culture.

Anime, short for "animation," refers to a distinctive style of animated entertainment that originated in Japan. It encompasses a wide range of genres, including action, adventure, romance, science fiction, fantasy, horror, and more. Anime is not limited to a specific age group and caters to viewers of all ages, from children to adults.

There are several recommendation systems being used in the anime industry to help customers discover new anime titles based on their customers' preferences. The most commonly used include collaborative filtering, content-based filtering, hybrid approaches, Natural Language Processing (NLP), and Deep Learning Models. The following paper uses the data sciences analytics and model building for designing the recommender system for better customer engagement through social media marketing tools.

Literature Review

In last few decades we have seen a massive change in the Global business trends. The arrival of Internet combined with the upgradation in both computer hardware and software has opened the whole global market to the consumers. The upgradation in the speed with the introduction of 4G and 5g technology as made the online shopping using social media marketing as one the most convenient ways of shopping using social media marketing for the consumers. Online shopping using social media marketing refers to activity of purchasing goods or services through internet (Kukar-Kinney & Close, 2010). It has provided consumers with ease and comfort to search, compare and select products while sitting at home or workplace without incurring the time and cost associated with physical transactions. The trend has caused many businesses to offer same products at their online stores as well (Adnan, 2014). In the times when products are becoming increasingly similar, experience overtakes price and product as the key differentiator for consumers (1). This not only makes their presence known but also gives them a strong competitive advantage over traditional businesses. But only the presence of an online store is not sufficient to attract and retain consumers; it is essential to study the consumer behavior in online context as well. The identification and study of the critical variables that play significant role in attracting and retaining online shoppers is very important. Adequate studies have been conducted on identification of factors affecting online consumer behavior (Poddar, Donthu, & Wei, 2009)

Karl E. Weick investigates the concept of theorizing, taking reference from Sutton and Staw's discussion of five different article parts. Merton (1967) suggests that approximation can take any one of the four forms: 1)general orientations in which broad frameworks specify types of variables that should be taken into account, without explaining the relationships among them; 2) Analysis of concepts, including their clarifications, definitions but they may not be interrelated; 3) post factum interpretation where ad hoc hypotheses are derived from a single observation, and no efforts are made to explore alternate explanations, or new observations; 4) empirical generalization where an isolated proposition summarizes the relationship between 2 variables, but further interrelations are not attempted. Runkel and Runkel's (1984) state that theory is a continuum rather than a dichotomy.

Theory belongs to the same family of words that includes guess, speculation, proposition, and conjecture. The word theory can be used for a wide range of things from 'a simple guess' to 'a system of assumptions and accepted principles and rules of procedure devised to analyze, predict, or otherwise explain the nature or behavior of a specified set of phenomena', as defined in the American Dictionary. According to Karl E. Weick, the term theory can be used during various stages of the process of theorizing, rather than just using it to label the final conclusion, which is arrived at.

It is often very difficult to sort out the actual theory from amateur attempts while working with people with varying levels of knowledge and expertise. Further the need to properly paraphrase and explain the reason for each citation or reference made either in books, research papers or any other scholarly articles is also emphasized, so that readers can easily understand why the particular reference has been utilized. So, according to Karl, if the references are somehow connected then we approach something closer to actual theory. Data itself isn't actual theory according to Bacharach (Academy of Management Review, 1989). On the other hand, Starbuck (1983) also argues that theorists can make various prescriptions based on data alone without bringing theory in the middle, similar to the way the best doctors treat symptoms directly without relying on the diagnosis for determining the treatment. In both cases, theories and diagnosis provide a summary of relations observed between treatments/prescriptions and symptoms or data. Also, since combinations of data and observable characteristics are more, there will be a larger number of conclusions and relationships between them. Using theories to condense information may lead to loss of data or essential factors which must be taken into account while drawing conclusions. This leads to random errors being injected into the conclusions drawn.

Starbuck (1993) has given a summary of the argument in this way: academic research follows a model similar to that of medical schools, where the scientists try to translate data, which are like symptoms into theories. So, theories are diagnoses and prescriptions are like treatments in this case.

So organizations have been compared to complex human bodies and theories may not necessarily capture all the information or the magnitude or scale to which a derived conclusion can be applied. Neither can theories determine unique prescriptions. So they may not necessarily be able to provide accurate solutions while taking into account various factors of a problem or a situation.

Previously, many studies have conceptualized social media engagement in terms of linguistic content. However, these days, businesses have utilized new ways of connecting and communicating with their target audience- the customers, by using a combination of linguistic ad visual content. This wide variety of content has made researchers start analyzing it through multimodal analysis. s (Shao and Janssens, 2022).

Singh, Gandhi and Kar et al. (2023) [3] studied effects of social media image content in big business firms and companies to increase the social media engagement, which emphasises the importance of strategically designing content in form of images as a marketing strategy. Creating social media posts that engage the audience is the best way to optimize social media use to maximise outreach to more customers. However, according to Benton, about 60% of business to business (B2B) content creators acknowledge it to be one of the biggest challenges (Benton,2017). A computation extensive research model was designed based on the stimulus organism response (SOR) theory. The study used 39129 Facebook posts from 125 companies selected out of the Fortune 500 firms list. Attributes from both images and text were measured using deep learning models. An inferential analysis is used based on the least squares regression. The other machine learning algorithms were used to analyse strength and sound

architecture of the proposed model and determine whether it was a valid and sound source for prediction of engagement metrics. A few prominent examples include: the k-nearest neighbour, support vector regression, random forest, decision trees.
The findings of the undertaken study indicated that the social media image content posted by big business firms had a significant impact on their social media engagement. The visual and linguistic attributes of images were extracted using deep learning methods and models and the distinctive effect of each feature was verified empirically. This study offers many practical insights which have been formed by observing various online marketing methods such as embedded marketing, advertising with the help of image processing and statistical information of social media.
Social media (websites, platforms, applications, etc.) allow companies to increase the spread of information by sharing their knowledge and information with users and customers (Wukich,2022).
It helps the firms by offering an insight to understand the rapidly evolving needs of the customer market so that they can provide rapid responses accordingly. The main aim of organizations is to reach the full potential of social media engagement to increase their sales, achieve full customer satisfaction, and increase the quality of decision making within the company (Rutter, Barnes, Roper, Nadeau, and Lettice, 2021; Simon and Tossan, 2018). Gandhi and Kar's study aims to answer 2 main questions:
1) Why is social media engagement influenced by attributes of images in social media posts?
2)How do an image's linguistic and visual attributes in particular affect its engagement (the number of likes, comments and shares a post with an image receives) on social media?
They have provided a conceptual model which evaluates firm generated content using the SRM lens to verify the effects on social media engagement, using multimodal analysis.

AffectNet

Existing annotated databases of facial expressions in the wild are small and mostly cover discrete emotions (aka the categorical model). There are very limited annotated facial databases for affective computing in the continuous dimensional model (e.g., valence and arousal).

To meet this need, we have created **AffectNet**, a new database of facial expressions in the wild, by collecting and annotating facial images. **AffectNet** contains more than 1M facial images collected from the Internet by querying three major search engines using 1250 emotion related keywords in six different languages. About half of the retrieved images (~440K) were manually annotated for the presence of seven discrete facial expressions (categorial model) and the intensity of valence and arousal (dimensional model). AffectNet is by far the largest database of facial expressions, valence, and arousal in the wild enabling research in automated facial expression recognition in two different emotion models. Two baseline deep neural networks are used to classify images in the categorical model and predict the intensity of valence and arousal. Various evaluation metrics show that our deep neural network baselines can perform better than conventional machine learning methods and off-the-shelf facial expression recognition systems.

Emotion Recognition is a common classification task. For instance, given a tweet, you create a model to classify the tweet as being either positive or negative. However, human emotions consist of myriad emotions and cannot be constrained to just these three categories. On the contrary, most of the datasets available for this purpose consist of only two polarities — positive, negative, and at times neutral. For example, Bhardwaj et. al (2023) suggests that applications of neural networks, decision sciences and artificial intelligence, ICT based mobile systems in enhancing e-governance can enhance the customers' experience in sustainable online education. Moreover, enhancing sustainable dynamic digital capability using strategic intelligence through artificial intelligence in techno-preneurship can enhance how the customers may perceive and experience their products and services online through social media and digital marketing Bhardwaj et. al (2023). It has also been used to reduce the carbon footprint by using more sustainable technology driven methods and tools such as
artificial intelligence: application of big data analytics in designing new product and services development Bhardwaj et. al (2023).

Recommendation Systems

Recommendation systems analyse customers' preferences, behaviour, and historical data to provide personalized recommendations. By understanding individual tastes and customers' preferences, these systems can suggest relevant content, products, or services, enhancing the customers' experience.

With the vast amount of content available today, it can be challenging for customers to navigate and find what they're looking for. Recommendation systems can suggest relevant content based on customers' preferences and browsing patterns, enabling customers to discover new and interesting items they may have otherwise missed. This helps customers explore a wider range of options and diversify their interests.

In e-commerce, recommendation systems can significantly impact sales by suggesting products that are likely to be of interest to customers. By presenting personalized recommendations, these systems can drive customers' engagement, encourage repeat visits, and increase the likelihood of making a purchase. This leads to higher customer satisfaction and improved conversion rates. For example, delivering inclusive sustainable education using technology can leverage and meet financial challenges faced by the customers and thereby increase the customer satisfaction (Bhardwaj et al., 2025). Similarly, determinants of behavioral decision making of entrepreneurial investors based on customers' experiences can be enhanced using technology driven recommender systems (Bhardwaj, Gupta, Neihsiel, (2022). Interestingly, it was studied in the research by researchers based on determinants of start-up survivability: a behavioral framework for entrepreneurial sustainability enhances customer relationship and experience (Bhardwaj et al., 2023). Moreover, Bhardwaj, Jain, Gupta, Dixit (2022) studied the influence of marketing strategies of trade promotion organizations on entrepreneurial country competitiveness and economic growth using application of structural equation modeling and found that customers'' experiential management systems can greatly influence the branding and positioning of the entrepreneurial firms and companies for expansion and growth. Similarly, Bhardwaj (2020) studied the influence of knowledge management on product innovation by intrapreneurial firms and found that the there is significant role of the technology enablement for enhancing customer's experience for repeat purchase. The study also further was extended by Bhardwaj (2020) by studying the role of knowledge management in enhancing the customers' experience through entrepreneurial ecosystems through corporate entrepreneurship and strategic intent in high-tech firms. Similarly, Bhardwaj (2019) extended the research to study the factors of adoption and diffusion of technology entrepreneurship and finding the implications of knowledge management in sustainable product innovation in technologyentrepreneurship in south Asian firms.

Recommendation systems streamline the search and discovery process by providing tailored suggestions. Customers can save time and effort that would otherwise be spent manually searching through a large volume of options. By offering relevant recommendations, these systems simplify decision-making and make the overall customers' experience more efficient.

RESEARCH METHODOLOGY

The methodology includes the empirical study focusing on the factors influencing adoption of digital marketing strategies in cosmetics industry. The study included primary data and respondents were randomly collected. A random sample of 200 online shoppers was taken and a questionnaire was mailed to them, out of which 140 responded. The data collected was analyzed using SPSS tool.

An online questionnaire, containing the input variable items from the conceptual frame work will be used in google form format. A pilot questionnaire having 22 questions and covering various items has been made see the viability of the study. The items of the questionnaire will be used to measure the dependent and independent variables discussed in the study. The study would involve the simple random sampling technique with sample size about 140 respondents. Table-1 shows number of items for measuring each variable and sources of these items and which recent studies have validated these scales. The variables were accounted for by using 5 point Likert scale indicating: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree and 5 = Strongly Agree.

DATA ANALYSIS

The research methodology used the SPSS method. Data analysis of Cosmetics for digital marketing is given below:

Table 1: Descriptive Statistics

	Mean	Std. Deviation	Analysis N	Missing N
website_des	3.7426	.97370	136	0
Sense using AI based voice	3.5515	.98748	136	0
interaction	3.4412	1.04538	136	0
pleasure	3.5882	.94650	136	0
pers_inf	3.4926	1.04702	136	0

stop_pur_inconsistent_exp	3.3382	1.16886	136	0
tech_not_help	3.2426	1.15146	136	0
not_auto	3.2206	1.10682	136	0
slow_tech	3.2794	1.00142	136	0
prod_not_avail	3.5515	1.07373	136	0

Table 1 above shows that the website design, sense of AI based voice has significant influence on the purchase behavior of the customers. Also, interaction online, pleasure achieved, degree of privacy policy may lead to inconsistent behavior in purchase decisions. The average values are recorded for each factor are give out of the scale of 0 to 5.

Moreover, the study also shows that experience online, technology being helpful, by not being completely automated, slow technology, and product not available can highly influence the online shopping behavior of the customers. The stopping purchases due to inconsistencies shows the most deviation.

Table 2: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.867
Bartlett's Test of Sphericity	Approx. Chi-Square	512.169
	df	45
	Sig.	.000

Table 2 shows that the degree of reliability in the data collected is 0.86 which is very highly acceptable and reliable for the Kaiser- Meyer- Measure of sampling adequacy.

Table 3: Communalities

	Initial	Extraction
website_des	1.000	.502
Sense	1.000	.645
interaction	1.000	.475
Pleasure	1.000	.603
pers_inf	1.000	.632
stop_pur_inconsistent_exp	1.000	.532
tech_not_help	1.000	.636
not_auto	1.000	.797
slow_tech	1.000	.569
prod_not_avail	1.000	.397

Extraction Method: Principal Component Analysis

Here the table shows which features were extracted from a set of 42 questions and a large number of responses. Extraction of less than 50%(value<0.5) indicates that the attribute doesn't have a significant impact on the positive rating of the website (its ease of use).

Most responders rated it with a low score, so it will contribute towards the low rating of a website by the customers. A value greater than 0.5 on the other hand indicates that the attribute was easily extracted from the responses given by the participants in the survey, and most of them gave a high rating in this field. So these attributes contribute more to the good performance of the website and the positive reviews by the customer.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.630	46.298	46.298	4.630	46.298	46.298	3.391	33.911	33.911
2	1.160	11.599	57.897	1.160	11.599	57.897	2.399	23.986	57.897
3	.854	8.537	66.434						
4	.711	7.113	73.547						
5	.566	5.662	79.209						
6	.559	5.593	84.802						
7	.462	4.624	89.426						
8	.443	4.431	93.857						
9	.315	3.149	97.006						
10	.299	2.994	100.000						

Extraction Method: Principal Component Analysis.

Here the principal components of the data have been analyzed and the results have been characterized in form of percentages of total variance in data and cumulative percentages for eigen values, extraction sums of square loadings, rotation sum of square loadings

Component Matrix[a]

	Component	
	1	2
website_des	.618	-.346
sense	.746	-.298
interaction	.627	-.287
pleasure	.744	-.225
pers_inf	.768	-.205
stop_pur_inconsistent_exp	.729	-.037

tech_not_help	.606	.519
not_auto	.614	.648
slow_tech	.702	.278
prod_not_avail	.623	.097

Extraction Method: Principal Component Analysis.
a. 2 components extracted, where personal information has the highest extraction rate(0.768) for component 1 and not automated has the highest extraction rate for component 2.

Rotated Component Matrix[a]

	Component	
	1	2
website_des	.702	.092
Sense	.776	.207
interaction	.674	.145
pleasure	.731	.264
pers_inf	.738	.294
stop_pur_inconsistent_exp	.607	.405
tech_not_help	.176	.778
not_auto	.106	.886
slow_tech	.397	.642
prod_not_avail	.441	.450

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

Component Transformation Matrix

Component	1	2
1	.802	.597
2	-.597	.802

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization. The main diagonal elements have higher values.

Correlations

		purchase_online_six	sense	interaction	pleasure	entertainment	website_des
purchase_online_six	Pearson Correlation	1	-.056	-.130	-.152	-.096	-.064
	Sig. (2-tailed)		.515	.133	.079	.266	.464
	N	135	135	135	135	135	135

sense	Pearson Correlation	-.056	1	.494**	.578**	.440**	.488**
	Sig. (2-tailed)	.515		.000	.000	.000	.000
	N	135	136	136	136	136	136
interaction	Pearson Correlation	-.130	.494**	1	.410**	.332**	.316**
	Sig. (2-tailed)	.133	.000		.000	.000	.000
	N	135	136	136	136	136	136
pleasure	Pearson Correlation	-.152	.578**	.410**	1	.481**	.415**
	Sig. (2-tailed)	.079	.000	.000		.000	.000
	N	135	136	136	136	136	136
entertainment	Pearson Correlation	-.096	.440**	.332**	.481**	1	.450**
	Sig. (2-tailed)	.266	.000	.000	.000		.000
	N	135	136	136	136	136	136
website_des	Pearson Correlation	-.064	.488**	.316**	.415**	.450**	1
	Sig. (2-tailed)	.464	.000	.000	.000	.000	
	N	135	136	136	136	136	136

**. Correlation is significant at the 0.01 level (2-tailed).

These findings indicate the extent to which the attributes are related to each other in form of correlation coefficients. A higher correlation means a larger level of interdependency between the 2 attributes and a smaller coefficient means less relation and dependency between them.

FINDINGS AND DISCUSSION

The factors that effect that contribute heavily towards the digital experience of consumers are Website design, sensory experience, and pleasure during online shopping using social media marketing , personalized information about the product with values more than 0.7 in principal component analysis.

The findings suggest that the customers are willing to pay more for having better online experience and thereby it helps them to increase their willingness to buy online products from the websites that are providing better experiential marketing to the customers online.

The implications include the application of online experience design for the customer for sustainability and retention of the customers and also the growth through the higher sales online.

The results of present study confirms the statistical and significant association of all determinants of proposed conceptual framework with sustained customer relationship. This research work is among rare contributions in online consumer behavior from a particular industry context (luxury cosmetics) focusing on experienced online consumers rather than concentrating on intentions of inexperienced online buyers.

CONCLUSION

The main objective for this study is to investigate relationship of online store atmosphere, customized information, AI effectiveness, customer experience and online repurchase intention with sustainable customer relationship. The results shows the association between the independent and dependent variables. The study is of significant importance since it explores unique dimensions of online store atmosphere (informativeness, website navigation, entertainment and website design) and focuses on variables effecting the sustained customer relationship. Another unique attribute about this study is that the data is collected from experienced online consumers only with at least one purchase in last 6 months. This research not only contributes to the existing body of knowledge, but it will also suggest some practical implications for marketers to retain their clients. It was observed from the data analysis that the use of AI driven Speech Emotions, Prosody, Dialects and Accents can create more brand loyalty, emotional association and affinity towards the various brands when used during the various advertisement design. Voice modulation and frequency of pitch was found to have profound impact on the outcomes of the repurchase of brands when this technology is used.

REFERENCES

Weick, K. E. (1995). What Theory is Not, Theorizing Is. *Administrative Science Quarterly*, *40*(3), 385–390. https://doi.org/10.2307/2393789

Savakis, Andreas & Etz, Stephen & Loui, Alexander. (2000). Evaluation of image appeal in consumer photography. Human Vision and Electronic Imaging V. 3959. 10.1117/12.387147.

Singh, S., Gandhi, M., Kar, A.K. and Tikkiwal, V.A. (2023), "How should B2B firms create image content for high social media engagement? A multimodal analysis", *Industrial Management & Data Systems*, Vol. 123 No. 7, pp. 1961-1981. https://doi.org/10.1108/IMDS-08-2022-0470

Wukich, C. (2022), “Social media engagement forms in government: a structure-content framework”, Government Information Quarterly, Vol. 39 No. 2, 101684.

Simon, F. and Tossan, V. (2018), “Does brand-consumer social sharing matter? A relational framework of customer engagement to brand-hosted social media”, Journal of Business Research, Vol. 85, pp. 175-184.

Rutter, R.N., Barnes, S.J., Roper, S., Nadeau, J. and Lettice, F. (2021), "Social media influencers, product placement and network engagement: using AI image analysis to empirically test relationships", Industrial Management and Data Systems, Vol. 121 No. 12, pp. 2387-2410.

Benton, L. (2017), "Five reasons why B2B companies fail at content and social media marketing", B2B News Networks, available at: https://www.b2bnn.com/2017/09/five-reasons-b2b-companies-failcontent-social-media-marketing/ (accessed 15 May 2022).

Shao, K. and Janssens, M. (2022), "Who is the Responsible Corporation? A multimodal analysis of power in CSR videos of multinational companies", Organization Studies, Vol. 43 No. 8, pp. 1197-1221.

Abdul-Muhmin, A. G. (2010). Repeat purchase intentions in online shopping using social media marketing : The role of satisfaction, attitude, and online retailers' performance. Journal of International Consumer Marketing, 23(1), 5-20.

Anderson, R. E., & Srinivasan, S. S. (2003). E-satisfaction and e-loyalty: A contingency framework. Psychology & marketing, 20(2), 123-138.

Ballantine, P. W. (2005). Effects of interactivity and product information on consumer satisfaction in an online retail setting. International Journal of Retail & Distribution Management, 33(6), 461-471.

Brunner-Sperdin, A., Scholl-Grissemann, U. S., & Stokburger-Sauer, N. E. (2014). The relevance of holistic website perception. How sense-making and exploration cues guide consumers' emotions and behaviors. Journal of Business Research, 67(12), 2515-2522.

Chang, H. H., & Chen, S. W. (2008). The impact of customer interface quality, satisfaction and switching costs on eloyalty: Internet experience as a moderator. Computers in Human Behavior, 24(6), 2927-2944.

Chiu, C. M., Chang, C. C., Cheng, H. L., & Fang, Y. H. (2009). Determinants of customer repurchase intention in online shopping using social media marketing . Online Information Review, 33(4), 761-784.

Chiu, C. M., Hsu, M. H., Lai, H.& Chang, C. M. (2012). Re-examining the influence of trust on online repeat purchase intention: The moderating role of habit and its antecedents. Decision Support Systems, 53(4), 835-845.

Dailey, L. (2004). Navigational web atmospherics: explaining the influence of restrictive navigation cues. Journal of Business Research, 57(7), 795-803.

de Farias, S. A., Aguiar, E. C., & Melo, F. V. S. (2014). Store atmospherics and experiential marketing: A conceptual framework and research propositions for an extraordinary customer experience. International Business Research, 7(2), 87-99.

Floh, A., & Madlberger, M. (2013). The role of atmospheric cues in online impulse-buying behavior. Electronic Commerce Research and Applications,12(6), 425-439.

Gao, L., & Bai, X. (2014). Online consumer behaviour and its relationship to website atmospheric induced flow: Insights into online travel agencies in China. Journal of Retailing and Consumer Services, 21(4), 653-665.

Gupta, S., & Hee-Woong, K. (2007). Developing the commitment to virtual community: The balanced effects of cognition and affect. Information Resources Management Journal, 20(1), 28. Ha, H. Y., & Janda, S. (2014). The effect of customized information on online purchase intentions. Internet Research, 24(4), 496-519

Ha, Y., & Im, H. (2012). Role of web site design quality in satisfaction and word of mouth generation. Journal of Service Management, 23(1), 79-96.

Han, H., & Ryu, K. (2012). The theory of repurchase decision-making (TRD): Analyzeing the critical factors in the post purchase decision-making process. International Journal of Hospitality Management, 31(3), 786-797.

Hausman, A. V., & Siekpe, J. S. (2009). The effect of web interface features on consumer online purchase intentions. Journal of Business Research, 62(1), 5-13.

Hellier, P. K., Geursen, G. M., Carr, R. A., & Rickard, J. A. (2003). Customer repurchase intention: A general structural equation model. European Journal of Marketing, 37(11/12), 1762-1800.

Huang, Z., & Benyoucef, M. (2013). From e-commerce to social commerce: A close look at design features. Electronic Commerce Research and Applications, 12(4), 246-259. Hussain, R., & Ali, M. (2015).

Effect of Store Atmosphere on Consumer Purchase Intention. International Journal of Marketing Studies, 7(2), 35-43.

Khalifa, M., & Liu, V. (2007). Online consumer retention: Contingent effects of online shopping using social media marketing habit and online shopping using social media marketing experience. European Journal of Information Systems, 16(6), 780-792.

Khan, I. (2012). Impact of customer satisfaction and retention on customer loyalty. International Journal of Technology Enhancements and Emerging Engineering Research, 1(2), 106-110.

Orel, F. D., & Kara, A. (2014). Supermarket self-checkout service quality, customer satisfaction, and loyalty: Empirical evidence from an emerging market. Journal of Retailing and Consumer Services, 21(2), 118-129.

Poddar, A., Donthu, N., & Wei, Y. (2009). Web site customer orientations, Web site quality, and purchase intentions: The role of Web site personality. Journal of Business Research, 62(4), 441- 45

Ranganathan, C. (2012). The role of extrinsic cues in consumer decision process in online shopping using social media marketing environments. Journal of Electronic Commerce in Organizations (JECO), 10(1), 52-71.

Rose, S., Clark, M., Samouel, P., & Hair, N. (2012). Online customer experience in e-retailing: An empirical model of antecedents and outcomes. Journal of Retailing, 88(2), 308-322.

San-Martín, S., & Camarero, C. (2012). A cross-national study on online consumer perceptions, trust, and loyalty. Journal of Organizational Computing and Electronic Commerce, 22(1), 64-86.

Sethuraman, R., Kerin, R. A., & Cron, W. L. (2005). A field study comparing online and offline data collection methods for analyzeing product attribute preferences using conjoint analysis. Journal of Business Research, 58(5), 602- 610.

Shin, J. I., Chung, K. H., Oh, J. S., & Lee, C. W. (2013). The effect of site quality on repurchase intention in Internet shopping using social media marketing through mediating variables: The case of university students in South Korea. International Journal of Information Management, 33(3), 453-463.

Srinivasan, S. S., Anderson, R., & Ponnavolu, K. (2002). Customer loyalty in e-commerce:An exploration of its antecedents and consequences. Journal of retailing, 78(1), 41-50

Stieger, S., & Reips, U. D. (2010). What are participants doing while filling in an online questionnaire: A paradata collection tool and an empirical study. Computers in Human Behavior, 26(6), 1488-1495.

Tong, C., Wong, S. K. S., & Lui, K. P. H. (2012). The influences of service personalization, customer satisfaction and switching costs on e-Loyalty. International Journal of Economics and Finance, 4(3), 105

. Tsai, H. T., & Huang, H. C. (2007). Determinants of e-repurchase intentions: An integrative model of quadruple retention drivers. Information & Management, 44(3), 231-239.

Wang, X. (2011). The effect of unrelated supporting service quality on consumer delight, satisfaction, and repurchase intentions. Journal of Service Research, 14(2), 149-163.

Wen, C., Prybutok, V. R., & Xu, C. (2011). An integrated model for customer online repurchase intention. Journal of Computer Information Systems, 52(1), 14-23.

Zhang, Y., Fang, Y., Wei, K. K., Ramsey, E., McCole, P., & Chen, H. (2011). Repurchase intention in B2C ecommerce—A relationship quality perspective. Information & Management, 48(6), 192-2