The Perception of Usefulness: Iranian Customers' Evaluation of Customer Reviews

Ehsan Shahghasemi *
Mojtaba Hajijafari
Maysam Shirzadifard
Mostafa Ahmadzadeh

(Received 24 June 2017; accepted 02 September 2017)

Abstract
Over the last decade, the retail industry has had a phenomenal growth. All figures show their success and efficiency and many studies have shown the role of customer reviews in encouraging ambivalent purchasers to buy items online. There have been numerous studies on why people read and trust these comments and taking for granted the important role of customer reviews in determining buying decision, this study endeavors to identify and explain the different factors involved in making a comment "useful." We took an Iranian retail website and collected comments on perceived "usefulness" of each review. Our results showed that perceived level of usefulness was related to the word count of the comments, personal experience of the writer with the product, emotional description of the product, and mentioning the strength, weakness points of the product.

Keywords: customer reviews, Digikala, Iran, perception of usefulness, retail Industry.

Ehsan Shahghasemi: (corresponding author). Assistant Professor, Department of Communication, University of Tehran, Tehran, Iran- Email: shahghasemi@ut.ac.ir
Mojtaba Hajijafari: Senior Researcher, Center for Cyberpolicy Studies, University of Tehran, Tehran, Iran- Email: mojtaba.hajijafari@gmail.com
Maysam Shirzadifard: PhD Candidate, Department of Educational Psychology, University of Tehran, Tehran, Iran- Email: m.shirzadi@ut.ac.ir
Mostafa Ahmadzadeh: PhD, University of Tehran, Tehran, Iran- Email: mostefa_ahmedzade@yahoo.com

Introduction

The rise of Web 2.0 technologies of Web 2.0 has had major impacts on all aspects of social and personal life. These new technologies have become the complicated vehicles for mutual creation and satisfaction of interests (Kozinets, 2017). One of the main outcomes of these new technologies has been a shift in the retail industry. In our consumer society, the buying behavior is now more a ritual, a bravado and a show-off, rather than an activity to secure necessary items that satisfy our primary or secondary needs. People carefully evaluate, consult, recommend and buy things as if this is the sole way to determine and enhance their identity. As the figures show, the use of the Internet is on the rise worldwide and accordingly, it is not surprising that the number of online retail businesses is increasing.

The so-called "long tail" feature of the online retail industry makes people certain that rare items can be better found there and not in a conventional brick-and-mortar store. In addition, ease of access, certainty about sellers' behavior (actually most of the work is done by the machine), being notified when an item becomes available, saving time and energy and other features are among some reasons that buyers are shifting towards online retail stores. But, one important aspect of this retail industry is that customers can find reviews from previous buyers of an item and learn about their experience. There are even independent forums dedicated specifically to the customer experience. These platforms are a special category of the discussion communities which facilitate the exchange of information, experiences, and recommendations of particular items. Examples include Amazon and eBay communities and independent consumer reviews platforms such as epinion.com, dooyoo.com, and ciao.co.uk. Virtual or consumer-opinion websites provide consumer reviews on virtually any product and company. Consumer reviews on these portals generally include a textual review of a product, a formal product rating (often numeric in nature), how other readers found the review useful and/or the degree of usefulness, and information about the review writer (Burton & Khammash, 2010).

One intriguing aspect of online retail websites is that customers have shown a great level of interest and trust in other customers' reviews and feedbacks while these opinions (*for example see* Guillory et al., 2016; Xiao & Benbasat, 2014; Liu & Park, 2015; Park & Nicolau, 2015; Qazi et al., 2014; Cheng & Ho, 2015; Krestel & Dokoohaki, 2015). We say "intriguing" because these customers most possibly do not know each other in the real world and nor do they generally show any interest in better knowing each other. The owners of these businesses were fast to understand this and this is why all successful retail websites across the world now allow customer reviews, though the scope of this review depends on website policy. Moreover, some websites allow customer-to-customer interaction and this has changed the locus of gravity from website promotion to customer consensus. As expected, we can see a great setting for fraud here. In 2016, the Competition and Markets Authority took action against an online marketing company that posted fake reviews on behalf of its clients (CMA, 2016). There are many academic studies on fake reviews (*for example*, Chengai, 2016; Kim et al., 2015; Kyungyup et al., 2016; Li et al., 2014; 2015; 2016; Liu et al., 2017; Mukherjee et al., 2011; 2012; Rout et al., 2017; Sivaramakrishnan & Subramaniyaswamy, 2016; Sun et al., 2016; Viviani & Pasi, 2017; Wahyuni & Djunaidy, 2016; Zhang et al., 2016).

Although Iran is a country that has experienced economic difficulties in the past decades and has a high misery index (*see* Dadgar & Nazari, 2012; Farzanegan & Gholipour, 2016; Soltani et al., 2012; Townsend, 2014; World Health Organization, 2010), we still see that this country has a strong consumer culture. Not only has the modernization process ceased to diminish the importance of appearance for Iranians but it has also taken a new boost. In fact, today, cosmetic products are widely used in Iran. In 2010, Iranians were the seventh largest consumers of cosmetics in the world (Shahghasemi & Tafazzoli, 2013) and we think this matter cannot be explained by indices like "lipstick index". Rather, we think there is some strong cultural obligation involved which forces Iranian women and even men to use cosmetic products. Moreover, Iran is now called "the nose job capital of the world" as many as 200,000 Iranians undergo rhinoplasty surgery every year (Hassanpour et al., 2016, p. 134). Having this strong culture of consumption, it is not surprising that Digikala and other retail industries have flourished very fast.

Digikala is an Iranian online retail store. Founded in 2006 by two brothers, Digikala soon became a multi-million-dollar business and today it is valued between 400 to 600 million US dollars. The powerful algorithm of recommendation has helped Digikala find the interests of customers and therefore this business can stimulate buyers to buy more by showing other items that previous buyers of an item have bought, recommending commodities based on user visits, and providing discount bonuses for customers which expire in a short period, if not used. As Digikala now enjoys both advantages of "economy of scale" and "economy of scope", it has become a monopoly in Iran and this might be the reason why some features like user profile information, image, and credits are not available on Digikala's website. As the sole superpower of the online retail industry in Iran, Digikala does not see any reason to give away a part of its power.

Given the importance of Digikala in the consumer life in Iran, it is not surprising that many Iranian and international scholars have studied it with different approaches (*see* Pahlavanyali & Momeni, 2016; Safari et al., 2016; Taleizadeh et al., 2016). As we mentioned above, users have shown great interest and trust in other users' reviews about a commodity and therefore in this study, we want to evaluate what factors contribute to a perceived usefulness of a review.

Review of Literature

As the concept of "perception of the usefulness" pertains to Web 2.0 technologies, studies that have studied it are all new. Given the infancy of this subject, different authors have taken different approaches to conducting their studies.

Filieri (2015) employed the dual-process theory to investigate the informational and normative predictors of information diagnosticity and its links to consumer information adoption. This study extended the application of dual-process theory to online settings. His findings suggested that consumers are primarily influenced by the quality of information and subsequently influenced by customer ratings and overall rankings. He suggested both of the informational and normative cues are critical to consumers in evaluating the quality and performance of products through online customer reviews. He also showed that information quantity and source credibility have a limited effect on information diagnosticity, which ultimately influences consumer perception of the usefulness of information.

Cheng and Ho (2015) focused on how factors of the central and peripheral route in online customer reviews convince readers that these reviews are helpful and could be trusted. In addition, they were interested in how social factors of the reviews might have an impact on consumers. Using content analysis, they analyzed 983 customer reviews from restaurant review websites. Results showed that the larger reviewer's number of followers, the higher level of expertise of the reviewers, the larger image count and word count also make readers feel the review is more practical and useful. In addition, the influence of the peripheral route, the social factors, on readers was higher than that of central route factors.

Park and Nicolau (2015) tried to assess the effect of ratings on usefulness and enjoyment in star ratings in online reviews. Their empirical application was carried out on a sample of 5,090 reviews of 45 restaurants in London and New York. The results showed that people perceived extreme ratings (positive or negative) as more useful and enjoyable than moderate ratings, giving rise to a U-shaped line, with asymmetric effects: the size of the effect of online reviews depends on whether they are positive or negative.

Liu and Park (2015) attempted to identify the factors affecting the perceived usefulness of online consumer reviews by investigating two aspects of online information: (1) the characteristics of review generators, such as disclosure of personal identity, reviewer's reputation and expertise and, (2) reviews themselves, including quantitative (i.e., star ratings and length of reviews) and qualitative measurements (i.e., perceived acceptance and review readability). Their results revealed that a combination of both messenger and message characteristics positively affect the perceived usefulness of a review. Specifically, qualitative aspects of reviews were identified as the most influential factors that make travel reviews useful.

Guillory et al. (2016) In their scenario-based experimental study examined the effect of review source, user or expert, on their usefulness to consumer reviews, and the impact of valence and internet experience on that usefulness in the financial services industry. Their results revealed that there is no significant difference between the usefulness of user reviews and expert reviews. However, they also showed that both internet experience and valance can have an influence.

Methodology

This study attempted to explore the perception of the usefulness of product reviews and in order to do so, two products were chosen on the Digikala website: a cellphone and a laptop, both from the Apple Company. The first 400 comments from both products were transferred to an MS Excel file. Then, the comments were codified based on the author (whether the name is commonly used for male, female or is unidentifiable), the rating of usefulness by other customers, the rating of unusefulness by other customers, the length of the review among others.

This codification strategy helped us in conducting quantitative analyses using SPSS in order to find possible relationships between different characteristics and perception of the usefulness of the review. Comments. We included indices like the perceived level of usefulness, word count of the comment, personal experience of the writer, emotional descriptions in the comment, mentioning the strength/weakness points, gender of the author of the comment, and others to see how these factors might relate.

Findings

Prior to the main analyses, the obtained data for the three quantitative variables of usefulness, unusefulness, and word count were subjected in an exploratory analysis to diagnose the outliers and verify the normality of distribution. Univariate and multivariate outliers, considering leverage, Cook's D, and Mahalanobis distance indices, were removed from the data set. However, the three variables suffered a significantly biased distribution (Table 1). Thus, the raw data were categorized into three classes of low, moderate, and high to represent the rate for each quality.

Table 1. Mean, standard deviation, Min, Max, Skewness, and Kurtosis

Variables	Min	Max	M	SD	Skewness		Kurtosis		Shapiro-Wilk
					Statistic	SD	Statistic	SD	
Usefulness	5	295	19.94	23.872	6.902	0.094	64.611	0.189	0.462*
Unusefulness	0	53	3.86	5.491	3.656	0.094	23.452	0.189	0.674*
Word count	3	1272	84.04	123.188	4.117	0.095	25.868	0.189	0.602*

$^{*}p \leq 0.01$

Table 2 summarizes a set of crosstabs where columns represent levels of usefulness and rows represent gender, name, word count, personal experience, buyer, emotional description, technical description, and strength/weakness. All these variables were categorical (the measurement level for some, were decreased due to biased distribution), therefore Cramer's V was used as the correlation index.

According to these results, gender of the writer (Cramer's v = 0.060, p> 0.05), revealing the full name (Cramer's v = 0.034, p> 0.05), being the buyer of the product (Cramer's v = 0.067, p> 0.05), and technical descriptions of the product in the comments (Cramer's v = 0.080, p> 0.05) were not significantly related to the level of its perceived usefulness. In contrast, perceived level of usefulness was related to the word count of the comment (Cramer's v = 0.103, p< 0.01), personal experience of the writer (Cramer's v = 0.120, p< 0.01), emotional descriptions in the comment (Cramer's v = 0.164, p< 0.01), and mentioning the strength/ weakness points of the products (Cramer's v = 0.254, p< 0.01).

As shown in Table 1, the level of perceived usefulness tends to be higher when the comment contains more words. In the other words, when the word count of a comment is low, people are less likely to perceive it as useful. When the writer of a comment has not personally experienced the product, readers would less likely mark his or her comment as useful. Among those comments whose writers experienced the product personally, the number of usefulness marks tends to be moderate. Including emotional descriptions in a comment raises the probability of the comment being marked as useful while lack of such descriptions was associated with less perception of the usefulness by readers. The best predictor of the perceived usefulness of a comment in this study was the inclusion of strength/weakness of the product in the comment (Digikala provides an option to enumerate strengths and weaknesses of a product). That is, including the statements of strength/ weakness was associated with more useful marks for the comment and vice versa.

Table 2. Crosstabs of usefulness × gender, name, word count, personal experience, buyer, emotional description, technical description, and strength/ weakness

		Usefulness Low	Usefulness Moderate	Usefulness High	Total	Cramer's v	Sig.
Gender	Male	179	168	153	500	0.060	0.302
	Female	15	11	7	33		
	Unidentifiable	41	44	51	136		
Total		235	223	211	669		
Name	Full	176	171	154	501	0.034	0.675
	Partial	59	52	57	168		
Total		235	223	211	669		
Word count	Low	90	64	53	207	0.103	0.007
	Moderate	91	89	83	263		
	High	52	70	75	197		
Total		233	223	211	667		
Personal experience	Yes	79	106	79	264	0.120	0.008
	No	155	117	132	404		
Total		234	223	211	668		
Buyer	Yes	12	19	19	50	0.067	0.226
	No	223	204	192	619		
Total		235	223	211	669		
Emotional description	Yes	168	164	184	516	0.164	0.000
	No	67	59	27	153		
Total		235	223	211	669		
Technical description	Yes	95	111	90	296	0.080	0.116
	No	140	112	120	372		
Total		235	223	210	668		
Strength/ Weakness	Yes	49	101	101	251	0.254	0.000
	No	186	122	110	418		
Total		235	223	211	669		

Crosstabs of association between unusefulness and other variables along with corresponding Cramer's v coefficients are shown in Table 3.

Gender had a predictive relationship with perception of the usefulness (Cramer's v = 0.129, $p< 0.01$). Readers tend to perceive a comment as unuseful when the gender of the writer was unidentifiable. Mentioning the gender (both for male and female) in a comment lowers the probability of being perceived as unuseful. Whenever the writer revealed his/her full name, the level of his/her comment's perceived unusefulness tend to be moderate. The level of perceived unusefulness was fairly high, when the writer did not include a full name (Cramer's v = 0.118, $p< 0.01$). Intriguingly, readers were more likely to mark a comment as unuseful when the writer had personally experienced the product and vice versa

(Cramer's v = 0.137, $p< 0.01$). The same pattern was seen when the writer was the buyer of a product. That is, readers perceived a comment as unuseful, more frequently when the writer was a buyer, and less when she/he was not the buyer of that product (Cramer's v = 0.123, $p< 0.01$). Emotional descriptions (Cramer's v = 0.172, $p< 0.01$) and the inclusion of the strength/ weakness points of a product (Cramer's v = 0.414, $p< 0.01$) also lead to more frequent unuseful marks to a comment.

Table 3. Crosstabs of unusefulness × gender, name, word count, personal experience, buyer, emotional description, technical description, and strength/ weakness

		Unusefulness			Total	Cramer's v	Sig.
		Low	Moderate	High			
Gender	Male	161	197	142	500	0.129	0.000
	Female	17	11	5	33		
	unidentifiable	37	37	62	136		
Total		215	245	209	669		
Name	Full	162	197	142	501	0.118	0.009
	Partial	53	48	67	168		
Total		215	245	209	669		
Word count	Low	68	86	53	207	0.067	0.203
	Moderate	79	95	89	263		
	High	66	64	67	197		
Total		213	245	209	667		
Personal experience	Yes	64	105	95	264	0.137	0.002
	No	150	140	114	404		
Total		214	245	209	668		
Buyer	Yes	6	23	21	50	0.123	0.006
	No	209	222	188	619		
Total		215	245	209	669		
Emotional description	Yes	151	182	183	516	0.172	0.000
	No	64	63	26	153		
Total		215	245	209	669		
Technical description	Yes	94	105	97	296	0.032	0.706
	No	121	140	111	372		
Total		215	245	208	668		
Strength/ Weakness	Yes	20	111	120	251	0.414	0.000
	No	195	134	89	418		
Total		215	245	209	669		

Word count (Cramer's v = 0.067, $p> 0.05$) and technical descriptions of a product (Cramer's v = 0.032, $p> 0.05$) in the comments were not significantly related to the level of perceived unusefulness by readers.

The pattern of correlation between perception of the usefulness and unusefulness to other variables such as word count, personal experience, and so on, leads to the conclusion that usefulness and unusefulness may not be exclusive categories along a range. That is, high number of attached useful marks to a comment does not necessarily mean low number of unusefulness marks on the comment. Furthermore, it is likely that the number of useful and unuseful marks for a comment correlate positively, which might lead to the conclusion that the number of useful and unusefulness marks both act against leaving no comment at all. If so, then perceived usefulness may be better captured by counting the difference between usefulness and unusefulness marks number for a given comment.

Correlation analysis using Pearson's product-moment correlation coefficient verified this idea. The number of useful and unuseful marks correlated significantly ($r = 0.68$, $p < 0.001$). According to this finding, another procedure was used to analyze the relation of perceived usefulness and other variables. This time, useful score of each comment was counted minus its unuseful score. Table 4 represents crosstabs of usefulness (difference) × gender, name, word count, personal experience, buyer, emotional description, technical description, and strength/ weakness.

Table 4. Crosstabs of usefulness (difference) × gender, name, word count, personal experience, buyer, emotional description, technical description, and strength/ weakness

		Usefulness			Total	Cramer's v	Sig.
		Low	**Moderate**	**High**			
Gender	Male	192	159	149	500	0.063	0.276
	Female	13	15	5	33		
	Unidentifiable	46	46	44	136		
Total		251	220	198	669		
Name	Full	191	161	149	501	0.029	0.760
	Partial	60	59	49	168		
Total		251	220	198	669		
Word count	Low	82	72	53	207	0.068	0.187
	Moderate	105	82	76	263		
	High	62	66	69	197		
Total		249	220	198	667		
Personal experience	Yes	102	102	60	264	0.131	0.003
	No	148	118	138	404		
Total		250	220	198	668		
Buyer	Yes	14	19	17	50	0.056	0.352
	No	237	201	181	619		
Total		251	220	198	669		
Emotional description	Yes	189	160	167	516	0.114	0.013
	No	62	60	31	153		
Total		251	220	198	669		
Technical description	Yes	115	104	77	296	0.069	0.203
	No	136	116	120	372		
Total		251	220	197	668		
Strength/ Weakness	Yes	74	85	92	251	0.144	0.001
	No	177	135	106	418		
Total		251	220	198	669		

Results showed that the gender of the writer (Cramer's v = 0.063, $p > 0.05$), revealing the full name (Cramer's v = 0.029, $p > 0.05$), word count of the comment (Cramer's v = 0.068, $p > 0.05$), being the buyer of the product (Cramer's v = 0.056, $p > 0.05$), and technical descriptions of the product in a comment (Cramer's v = 0.069, $p > 0.05$) were not significantly related to the intensity of its perceived usefulness. Perceived level of usefulness was significantly related to, personal experience of the writer (Cramer's v = 0.131, $p < 0.01$), emotional descriptions in the comment (Cramer's v = 0.114, $p < 0.01$), and mentioning the strength/ weakness points of the product (Cramer's v = 0.144, $p < 0.01$).

The level of perceived usefulness (in terms of the difference between useful and unuseful mark's number) is lower when the writer of the comment has experienced the product personally. Including emotional descriptions in a comment does not necessarily raise its perceived usefulness, but using non-emotional description lowers the perceived usefulness of the comment. Again, the best predictor of the perceived usefulness of a comment was strength/weakness point of the product in the comment. This relationship shows that including the statements of strength/weakness leads to more useful marks for the comment.

Conclusion

The online retail industry has been flourishing in recent years. In 2016, the total global retail sales were predicted to reach $22.049 trillion, up 6.0% from 2015. The eMarketer estimated that sales will top $27 trillion in 2020, even as annual growth rates slow down over the next years (eMarketer, 2016). Online shopping has proven to be appealing for people all over the world and one of the reasons is that buyers can read and compare reviews left by other potential buyers or those who have bought products and experienced them.

There have been many studies on why do people read comments on online retail websites and this study has tried to see what factors in these comments are effective in making a comment perceived as "useful" by other customers. Therefore, a study was conducted on two products from the Digikala website that is the Iranian online retail giant. The study showed that the perceived level of usefulness relates to word count of the comment, personal experience of the writer, emotional descriptions in the comment, and mentioning the strength/weakness points of the product.

Based on the finding, customers concentrate more on the length of a comment because a longer comment has a higher possibility of usefulness. The length of comment might have been unintentionally attached to the perceived "commitment" of the commenters. In addition, the length of the comment is directly related to providing more details about a product and this can be another explanation why potential customers found longer comments more useful.

Another important factor is personal use. Customers are more susceptible to trust narratives of people who have experienced something, rather than those narratives who are coming from those who only speculate about possible usage experiences of a product. Therefore, potential customers would see such comments as more reliable.

Emotional description of a product was another factor that affected the perception of the usefulness in the study sample. Therefore, it can be concluded that although the old methods of promoting products are still effective, it seems that what has changed– at least in theory– is the impact that consumers are having in promoting products rather than the providers.

References

Burton, J., & Khammash, M. (2010). Why do people read reviews posted on consumer-opinion portals?. *Journal of Marketing Management, 26,* 230-255.

Cheng, Y.H., & Ho, H.Y. (2015). Social influence's impact on reader perceptions of online reviews. *Journal of Business Research, 68*(4), 883-887.

Chengai, S., Qiaolin, D., & Gang, T. (2016). Exploiting product related review features for fake review ddetection. *Mathematical Problems in Engineering.*

CMA (2016). Online reviews: letting your customers see the true picture. Retrieved May 22, 2017 from https://www.gov.uk/government/publications/online-reviews-and-endorsements-advice-for-businesses/online-reviews-giving-consumers-the-full-picture.

Dadgar, Y., & Nazari, R. (2012). The impact of economic growth and good governance on misery index in Iranian economy. *European Journal of Law and Economics, 4*(1), 1-19.

eMarketer (2016). Worldwide Retail Ecommerce Sales Will Reach $1.915 Trillion This Year; Double-digit growth will continue through 2020, when sales will top $4 trillion. Retrieved June 2, 2017 from https://www.emarketer.com/Article/Worldwide-Retail-Ecommerce-Sales-Will-Reach-1915-Trillion-This-Year/1014369.

Farzanegan, M.R., & Gholipour, H.F. (2016). Divorce and the cost of housing: evidence from Iran. *Review of Economics of the Household, 14*(4), 1029-1054.

Filieri, R. (2015). What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. *Journal of Business Research, 68*(6), 1261-1270.

Guillory, M.D., Lohtia, R., & Donthu, N. (2016). The usefulness of online reviews in financial services. *International Journal of Electronic Marketing and Retailing, 7*(1), 66.

Hassanpour, S.E., Heidari, A., Moosavizadeh, S.M., Tarahomi, M.R., Goljanian, A., & Tavakoli, S. (2016). Comparison of aesthetic and functional outcomes of spreader graft and autospreader flap in rhinoplasty. *World Journal of Plastic Surgery, 5*(2), 133-138.

Kim, J., Watson, J., & Kirmani, A. (2015). Red Flag! The effect of fake reviews on consumer evaluations. *NA-Advances in Consumer Research, 43*.

Kozinets, R.V. (2017). Netnography: radical participative understanding for a networked communications society. In Willig, C. and W. Stainton-Rogers, eds. *Handbook of Qualitative Research on Psychology*, 376-382. London: SAGE.

Krestel, R., & Dokoohaki, N. (2015). Diversifying customer review rankings. *Neural Networks, 66,* 36-45.

Kyungyup, L., Kyungah, H., Sung-Hyon, M. (2016). *Capturing word choice patterns with LDA for fake review detection in sentiment analysis*. Mining and Semantics Proceedings of the 6th International Conference / Web Intelligence (WIMS '16), New York, NY 10121-0701, USA.

Li, Y., Feng, X., & Zhang, S. (2016). Detecting fake reviews utilizing semantic and emotion model. *3rd International Conference on Information Science and Control Engineering (ICISCE)*. 317-320.

Li, H., Chen, Z., Liu, B., Wei, X., & Shao, J., (2015). Spotting fake reviews via collective positive-unlabeled learning. *Proceedings - IEEE International Conference on Data Mining, ICDM,* 899-904.

Li, H., Liu, B., Mukherjee, A., & Shao, J. (2014). Spotting fake reviews using positive-unlabeled learning. *Computación Y Sistemas, 18*(3), 467-475.

Liu, Y., Zhou, W., & Chen, H. (2017). Efficiently promoting product online outcome: An iterative rating attack utilizing product and market property. *IEEE Transactions on Information Forensics and Security, 12*(6), 1444-1457.

Liu, Z., & Park, S. (2015). What makes a useful online review? Implication for travel product websites. *Tourism Management, 47*(2), 140-151.

Mukherjee, A., Liu, B. & Glance, N. (2012). Spotting fake reviewer groups in consumer reviews. *In Proceedings of the 21st International Conference on World Wide Web*, Lyon, France.

Mukherjee, A., Liu, B., Wang, J., Glance, N. & Jindal, N. (2011). Detecting group review spam. *In Proceedings of the 20th International Conference Companion on World Wide Web*, Hyderabad, India.

Pahlavanyali, N., & Momeni, S.M.H. (2016). An empirical study on predicting user acceptance of online apparel shopping in Iran. *International Journal of Online Marketing (ijom), 6*(1), 34-53.

Park, S., & Nicolau, J.L. (2015). Asymmetric effects of online consumer reviews. *Annals of Tourism Research, 50,* 67-83.

Qazi, A., Raj, R.G., Tahir, M., Waheed, M., Khan, S.U.R., & Abraham, A. (2014). A preliminary investigation of user perception and behavioral intention for different review types: customers and designers perspective. *The Scientific World Journal,* 3, 1-8.

Rout, J.K., Singh, S., Jena, S.K., & Bakshi, S. (2017). Deceptive review detection using labeled and unlabeled data. *Multimedia Tools and Applications: an International Journal, 76*(3), 3187-3211.

Safari, M., Forouzandeh, M., & Safahani, N. (2016). An empirical model to explain the effects of electronic customer relationship management on customer e-satisfaction and e-loyalty: Evidence from Iranian service shopping websites. *Journal of Internet Banking and Commerce, 21*(1), 1-11.

Shahghasemi, E., & Tafazzoli, B. (2013). Scrabble the face of your opponent: Iranian blogger's endeavour to discursively undermine Ahmadi Nejad's legitimacy. *Online International Journal of Arts and Humanities*, *2*(8), 198-207.

Sivaramakrishnan, N., & Subramaniyaswamy, V. (2016). Recommendation system with demographic attributes for fake review identification. *Research Journal of Pharmaceutical, Biological and Chemical Sciences, 7*(6), 891-899.

Soltani, A., Angelsen, A., Eid, T., Naieni, M.S.N., & Shamekhi, T. (2012). Poverty, sustainability, and household livelihood strategies in Zagros, Iran. *Ecological Economics, 79,* 60-70.

Sun, C., Du, Q., & Tian, G. (2016). Exploiting product related review features for fake review detection. *Mathematical Problems in Engineering,* 1, 1-7.

Taleizadeh, A.A., Noori-Daryan, M., & Govindan, K. (2016). Pricing and ordering decisions of two competing supply chains with different composite policies: A Stackelberg game-theoretic approach. *International Journal of Production Research, 54*(9), 2807-2836.

Townsend, P. (2014). *The International Analysis of Poverty*. London: Routledge.

Viviani, M., & Pasi, G. (2017). Quantifier guided aggregation for the veracity assessment of online reviews. *International Journal of Intelligent Systems, 32*(5), 481-501.

Wahyuni E.D., & Djunaidy A. (2016). Fake review detection from a product review using modified method of iterative computation framework. *Matec Web of Conferences, 58,* 3003.

World Health Organization (2010). Country cooperation strategy for WHO and Islamic Republic of Iran: 2010–2014. Retrieved March 15, 2017 from http://apps.who.int/iris/bitstream/10665/113238/1/CCS_Islamic_Republic_Iran_2010_EN_14482.pdf.

Xiao, B., & Benbasat, I. (2014). Research on the Use, Characteristics, and Impact of e-Commerce Product Recommendation Agents: A Review and Update for 2007-2012. *International Journal of Electronic Marketing and Retailing*, *7*(1), 66-90.

Zhang, R., Gao, M., He, X., & Zhou, A. (2016). Learning user credibility for product ranking. *Knowledge and Information Systems: an International Journal, 46*(3), 679-705.