Too Much Information - Interaction Effects between WoM Valence and Other Sources of Social Information on Product Choice

Leonard Rackowitz
University of Hamburg
Michel Clement
University of Hamburg, Germany

Cite as:
Rackowitz Leonard, Clement Michel (2020), Too Much Information - Interaction Effects between WoM Valence and Other Sources of Social Information on Product Choice. *Proceedings of the European Marketing Academy*, 49th, (64112)

Paper from the 49th Annual EMAC Conference, Budapest, May 26-29, 2020.

Too Much Information - Interaction Effects between WoM Valence and Other Sources of Social Information on Product Choice

Abstract:

Sources of social information, such as online customer reviews, rankings, trend information, and personalized recommendations are ubiquitous on the internet. Prior marketing research has focused on understanding how these information sources separately impact consumer decision making. However, often they are presented simultaneously. In this research, the authors measure interaction effects between WoM valence and other sources of social information by conducting a conjoint choice experiment. Applying a hierarchical Bayes estimation on a sample of 2,123 participants, the authors find that the importance of WoM valence for choice is significantly enhanced by greater WoM volume, an increasing sales trend, and a personalized recommendation, but is not affected by changes in the sales rank. When a product is rated three stars, consumers prefer one additional star over more reviews. The authors explain the underlying process responsible for the findings, and discuss management implications.

Keywords: Social influences, online customer reviews, choice-based conjoint experiment

Track: Digital Marketing & Social Media

1. Introduction

To guide consumers in their decision making process, websites of different kinds (e.g., online retailers, social media platforms, news websites) integrate information about what products or services others chose, how they evaluated them, or which option is recommended to them. Consumers are presented different sources of social information, which are either based on others' opinions like online customer reviews (OCRs) or based (at least partly) on others' choices like rankings, trend information, and personalized recommendations.

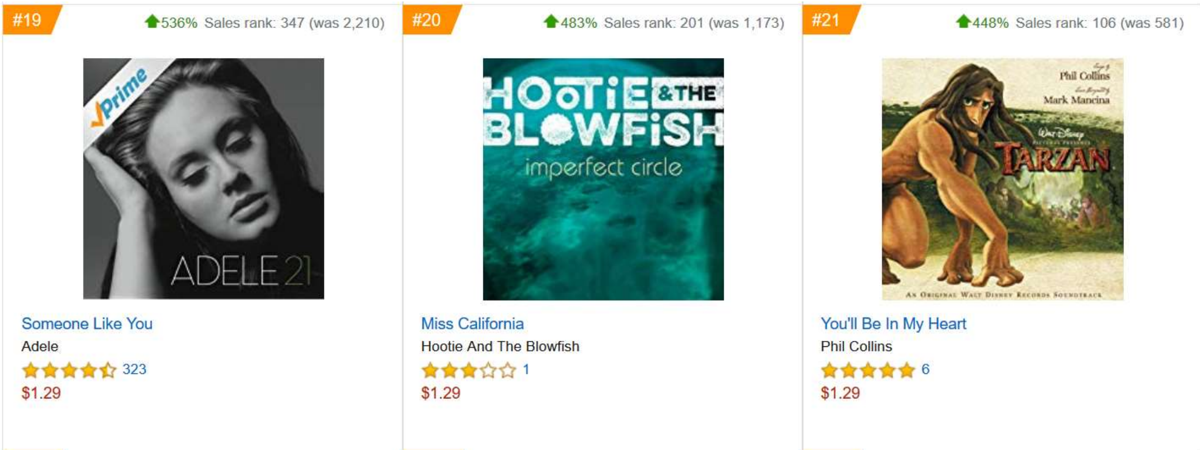
Prior research in marketing has mainly focused on understanding how these sources of social information separately impact consumer decision making. A multitude of studies shows a significant effect of OCRs (e.g., Babić Rosario, Sotgiu, Valck, & Bijmolt, 2016), the rank position (e.g., Ghose, Ipeirotis, & Li, 2014; Ursu, 2018), and personalized recommendations (e.g., Dellaert & Häubl, 2012) on consumer behavior. Some research exists on the effect of trend information, representing the display of the change of a target figure over time, on choice (Ho, Kowatsch, & Ilic, 2014).

However, often these sources of social information are not presented to consumers in isolation from each other, but simultaneously. For example, when consumers search for new music in Amazon's search category "Movers & Shakers" they are confronted with a list of songs and each song's WoM valence, WoM volume, sales rank, previous sales rank, and sales trend information (see Figure 1). This raises the question of how consumers take this variety of information collectively into consideration when making product choices.

The goal of this work is to explore how the effect of WoM valence on product choice is moderated by other sources of social information.

Theoretically, sources of social information convey different cues to consumers. WoM valence mainly conveys a quality cue (Babić Rosario et al., 2016; Kim & Gupta, 2012; Liu, 2006), WoM volume a popularity cue (Babić Rosario et al., 2016), and trend information a popularity cue (Ho et al., 2014). Some literature says that the sales rank conveys a popularity cue (Cai, Chen, & Fang, 2009), but Ursu (2018) shows that it only affects search. A personalized system recommendation conveys a cue about the personal fit (Chen, Wu, & Yoon, 2004; Pathak, Garfinkel, Gopal, Venkatesan, & Yin, 2010).

Figure 1: Amazon's "Movers & Shakers in Songs"



Source: https://www.amazon.com/gp/movers-and-shakers/dmusic/digital-music-track

There are two reasons why we focus on interaction effects between WoM valence and the other mentioned sources of social information. First, WoM valence is ubiquitous and an integral part of online retailing (Moe & Trusov, 2011). 65.2% of US internet users always or often read OCRs before purchasing (eMarketer, 2018). Second, WoM valence conveys a quality cue. A good enough quality is a basic requirement for further purchase considerations which is shown, for example, in an experiment where poorly rated products (1.1-2.3 stars) are chosen in only less than 5% of all cases (Kostyra, Reiner, Natter, & Klapper, 2016).

No previous study has investigated interaction effects between trend information and other social information sources. Some previous research has in parts already touched on the investigation of interaction effects between the other mentioned social information sources. Overall, results are mixed which may be among other reasons due to the fact that all studies but two are based on secondary market data. The data basis is important to mention since OCRs, rankings, sales trends, and recommendations are endogenous which is challenging to control for using non-experimental data. OCRs depend on a product's quality, price (Li & Hitt, 2010), and past sales (Godes & Mayzlin, 2004). In rankings, more relevant products or products with better quality are at the top. After controlling for endogeneity, rankings only drive what consumers search, but conditional on search, do not influence purchase (Ursu, 2018). Trend information represent sales developments over time and affect purchase decisions (Ho et al., 2014). Recommendations drive sales and sales drive recommendations (Pathak et al., 2010). Additional challenges with market data in regards to measuring OCR effects are unobserved marketing activities (Chintagunta, Gopinath, & Venkataraman, 2010) and unobserved reviews found on other websites that can affect sales (Ho-Dac, Carson, & Moore, 2013).

To fill the research gap, we, first, develop a conceptual framework. We, then, investigate consumer choice between several product options that differ on social information and are the same on other relevant attributes by using a conjoint choice experiment. The advantages of this approach are that interactions may be analyzed on consumer level opposed to aggregate market level and results are free from the aforementioned biases.

From a management point of view, this research is important since consumers regularly make trade-off decisions in choice sets of products presented with several sources of social information simultaneously.

2. Conceptual Framework

We build our conceptual framework on the assumption that consumers' choice probability is a function of different sources of social information. We consider both direct effects of all sources of social information on choice probability and interaction effects between WoM valence and the remaining sources of social information.

Our conceptual framework is primarily based on the Theory of Cognitive Dissonance. It states that when confronted with two or more contradictory ideas, believes, or values simultaneously, a person experiences psychological stress. In this situation one tries to find a way to relief the feeling of discomfort (Festinger, 1957). Applying this theory to this research context, we believe that consumers experience mental discomfort if quality cues and popularity cues or cues about personal fit point into opposite directions simultaneously. There may be different strategies to relief the feeling of discomfort, but focusing on decision making one would expect an individual in that case to rather adopt a different product.

3. Methodology and Data

We chose a choice-based conjoint experiment as method because it allows us, first, to keep the number of all possible combinations balanced and, second, to keep our results free from the aforementioned biases. We recruited 2,123 participants (M_{age} = 40.7 years, 55.4% female, regionally representative for Germany) using a commercial German panel provider. We applied a fractional full factorial design. Participants were asked fifteen times to choose which song they would buy from a selection of four songs. The songs were shown next to each other and only differed by the attribute levels of the five sources of social information (see Table 1). We implemented the dual-response none option, because it mostly produces the best results (Wlömert & Eggers, 2016). Creating fifteen versions, 225 unique choice sets were ultimately shown. We applied the design principle of level balance and orthogonality (Huber & Zwerina, 1996). The order of attributes shown was randomly assigned to each participant and stayed constant for all choice tasks. Thirteen choice sets were then used for estimation and two of them were fixed holdout tasks used for internal validation.

Table 1: Attributes and attribute levels

WoM valence	WoM volume	Sales trend	Sales rank	Recommendation
3 stars	6 reviews	Negative	Rank #29	No recommendation
4 stars	10 reviews	Positive	Rank #16	Recommendation
5 stars	30 reviews		Rank #9	
	100 reviews		Rank #4	

We apply a multinomial logit model to estimate the preferences β (Louviere, Hensher, & Swait, 2000) and the hierarchical Bayes procedure that accounts for heterogeneity in participants' tastes (Rossi & Allenby, 1993). After a burn-in phase of 200,000 iterations, 1,800 iterations per participant are saved using every 50th posterior utility draw and calculated into Bayesian point estimates (Allenby, Arora, & Ginter, 1995).

4. Empirical Analysis

The model performance is validated in-sample and out-of-sample. We find that the median estimates for all levels within each attribute follow the expected order. Out-of-sample validation is done by predicting the choices that respondents did in the two fixed holdout tasks. Applying the first choice method, hit rates for the two holdout tasks are relatively high.

Table 2 shows the Bayesian estimates for Model 1. All sources of social information have a significant positive effect on choice probability. WoM valence has the highest relative importance and its effect sizes diminish. For WoM volume, effect sizes decrease as well.

Model 2 extends Model 1 by the interactions. We find robust significant effects for the five sources of social information on choice probability.

Table 2: Bayesian estimates for Model 1 and Model 2

		Model 1		Model 2	
Attribute	Attribute level	Coefficient	Sig.	Coefficient	Sig.
WoM Valence	High	1.472	***	1.685	***
	Med	.214	***	.213	***
	Low[RC]	-1.685		-1.897	
WoM Volume	100	.886	***	1.007	***
	30	.248	***	.245	***
	10	-.343	***	-.406	***
	6[RC]	-.791		-.845	
Trend	Pos	.788	***	.921	***
	Neg[RC]	-.788		-.921	
Rank	4	.541	***	.677	***
	9	.230	***	.301	***
	16	-.137	***	-.183	***
	29[RC]	-.634		-.796	
Recommendation	Yes	.887	***	1.046	***
	No[RC]	-.887		-1.046	
Valence x Volume	Val_High x Vol_100			.118	***
	Val_High x Vol_30			.091	***
	Val_High x Vol_10			-.033	**
	Val_High x Vol_6[RC]			-.176	
	Val_Med x Vol_100			.107	***
	Val_Med x Vol_30			.035	***
	Val_Med x Vol_10			.039	***
	Val_Med x Vol_6[RC]			-.182	
	Val_Low x Vol_100			-.225	***
	Val_Low x Vol_30			-.127	***
	Val_Low x Vol_10			-.006	***
	Val_Low x Vol_6[RC]			.358	
Valence x Trend	Val_High x Trend_Pos			.091	***
	Val_Med x Trend_Pos			-.003	
	Val_Low x Trend_Pos			-.088	***
	Val_High x Trend_Neg[RC]			-.091	
	Val_Med x Trend_Neg[RC]			.003	
	Val_Low x Trend_Neg[RC]			.088	
Valence x Rank	Val_High x Rank_4			-.015	
	Val_Med x Rank_4			.059	
	Val_Low x Rank_4			-.044	
	Val_High x Rank_9			.014	
	Val_Med x Rank_9			-.064	
	Val_Low x Rank_9			.050	
	Val_High x Rank_16			-.002	
	Val_Med x Rank_16			-.034	
	Val_Low x Rank_16			.036	
	Val_High x Rank_29[RC]			.003	
	Val_Med x Rank_29[RC]			.039	
	Val_Low x Rank_29[RC]			-.042	
Valence x Recommendation	Val_High x Rec_Yes			.072	**
	Val_Med x Rec_Yes			.009	
	Val_Low x Rec_Yes			-.081	**
	Val_High x Rec_No[RC]			-.072	
	Val_Med x Rec_No[RC]			-.009	
	Val_Low x Rec_No[RC]			.081	
	None	.744		1.067	
	Number of cases	137,995		137,995	
	Root likelihood (RLH)	.551		.600	

‘RC’ marks the reference categories.
‘Sig.’ means significance level.
A parameter is indicated as significant if the difference of 0 between the population mean (alpha) of that parameter and the one of its reference parameter lies outside of the 99%, 95%, or 90% highest density interval (HDI) of posterior iterations:
*** = 0 lies outside of the 99% HDI; ** = 0 lies outside of the 95% HDI; * = 0 lies outside of the 90% HDI.

However, we also find some of the interaction terms to be significant, which means that there are additional effects when certain level combinations appear simultaneously.

Utility for high valence songs increases with the number of reviews. Contrarily, for three-star rated songs, utility significantly decreases when WoM volume increases. Adding together all of the utility components of WoM valence and volume, we find that the utility curve for three-star rated songs is flatter and more linear than the one of four and five-star rated songs. This means that more reviews on a three-star level help less than more reviews on a four or five-star level. Interestingly, utility increases more when WoM valence increases from three to four stars than when WoM volume increases on a three-star level.

As proposed, utility increases for five-star rated songs when the trend changes from negative to positive. Contrarily, for three star rated songs, utility significantly decreases when the trend becomes positive. Thus, two positive cues (i.e., high quality and increasing popularity) mutually support each other, but two contradictory cues weaken each other. There are no significant interactions between WoM valence and the sales rank.
Utility for high valence songs is significantly higher when they are recommended versus not recommended. Contrarily, for three-star rated songs, utility is significantly lower when they are recommended. So, two positive cues mutually support each other, but two contradictory ones weaken each other. Thus, our findings are in line with the Cognitive Dissonance Theory.

5. General Discussion

This work makes several contributions. The first main contribution is the experimental analysis of interaction effects between WoM valence and other sources of social information. We find that all tested information sources directly affect choice. The importance of WoM valence for choice is significantly enhanced by greater WoM volume, an increasing sales trend, and a personalized recommendation, but is not affected by changes in the sales rank. This means that a poorly rated product gains less compared to a highly rated one when receiving more reviews, when its sales trend increases, or when it is recommended. Or in other words, volume, the sales trend, and personalized recommendations enhance the positive effect of high valence on choice. When a product is rated three stars, consumers prefer one additional star over more reviews.

The second main contribution is the finding that the Theory of Cognitive Dissonance applies, when a quality cue (i.e., WoM valence) and a popularity cue (i.e., the sales trend) or a cue about personal fit (i.e., personal recommendation) appear simultaneously.

Our findings should be taken into account by future research and marketing practice when analyzing data or making predictions containing several sources of social information simultaneously. Otherwise, results or predictions may be biased.

Our results highlight the importance of the different sources of social information for consumer choice and how they mutually influence consumers. From a website perspective (e.g., online retailers, social media platforms, news websites), the interaction effect between WoM valence and personalized recommendations suggests that recommender engines should recommend highly rated products instead of poorly rated ones. Social information can be also used as a low cost alternative to price promotions. For example, ads may show trending high valence products with their respective social information as a justification of the promotion.

Manufacturers, can also incorporate social information into promotions. For example, recommended content via search engine advertising or social media may contain the average consumer rating of the promoted item to increase the effect of the paid recommendation due to the interaction effect. It is also advisable to early on buy ad space on the retailer's website for new products to generate purchases that drive the sales trend, personalized recommendations through recommender engines, the sales rank, and OCRs. Investing at an early stage can improve social information (i.e., a positive sales trend, a high rank, recommendations, and many reviews) that can in turn enhances the sales effect of the advertisement. Further, our findings should also be considered in companies' review acquisition strategies. Customers can be motivated to write reviews by sending reminder emails after purchase asking to support the brand. Those emails can be complemented by offering incentives such as discounts, vouchers, or gifts. Additionally, already on the product page, manufacturers can mention that reviews will be rewarded. While these strategies are intended to increase the review volume, it is unclear if and how they may affect the WoM valence. As previous research shows, manufacturers should quickly respond to negative reviews with a situationally customized response approach to reduce their contagiousness to other customers (Herhausen, Ludwig, Grewal, Wulf, & Schoegel, 2019).

References

Allenby, G. M., Arora, N., & Ginter, J. L. (1995). Incorporating prior knowledge into the analysis of conjoint studies. *Journal of Marketing Research*, *32*(2), 152–162.

Babić Rosario, A., Sotgiu, F., Valck, K. de, & Bijmolt, T. H. A. (2016). The effect of electronic word of mouth on sales: A meta-analytic review of platform, product, and metric factors. *Journal of Marketing Research*, *53*(3), 297–318.

Cai, H., Chen, Y., & Fang, H. (2009). Observational learning: Evidence from a randomized natural field experiment. *American Economic Review*, *99*(3), 864–882.

Chen, P.-Y., Wu, S.-y., & Yoon, J. (2004). The impact of online recommendations and consumer feedback on sales. *ICIS 2004 Proceedings*, 58.

Chintagunta, P. K., Gopinath, S., & Venkataraman, S. (2010). The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science*, *29*(5), 944–957.

Dellaert, B. G. C., & Häubl, G. (2012). Searching in choice mode: consumer decision processes in product search with recommendations. *Journal of Marketing Research*, *49*(2), 277–288.

EMarketer (2018). *Surprise! Most Consumers Look at Reviews Before a Purchase*. Retrieved from https://www.emarketer.com/content/surprise-most-consumers-look-at-reviews-before-a-purchase. (Last accessed: December 4, 2019).

Festinger, L. (1957). *A theory of cognitive dissonance*. Stanford: Stanford University Press.

Ghose, A., Ipeirotis, P. G., & Li, B. (2014). Examining the impact of ranking on consumer behavior and search engine revenue. *Management Science*, *60*(7), 1632–1654.

Godes, D., & Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, *23*(4), 545–560.

Herhausen, D., Ludwig, S., Grewal, D., Wulf, J., & Schoegel, M. (2019). Detecting, preventing, and mitigating online firestorms in brand communities. *Journal of Marketing*, *83*(3), 1–21.

Ho, E., Kowatsch, T., & Ilic, A. (2014). The sales velocity effect on retailing. *Journal of Interactive Marketing*, *28*(4), 237–256.

Ho-Dac, N. N., Carson, S. J., & Moore, W. L. (2013). The effects of positive and negative online customer reviews: do brand strength and category maturity matter? *Journal of Marketing*, *77*(6), 37–53.

Huber, J., & Zwerina, K. (1996). The importance of utility balance in efficient choice designs. *Journal of Marketing Research*, *33*(3), 307–317.

Kim, J., & Gupta, P. (2012). Emotional expressions in online user reviews: How they influence consumers' product evaluations. *Journal of Business Research*, *65*(7), 985–992.

Kostyra, D. S., Reiner, J., Natter, M., & Klapper, D. (2016). Decomposing the effects of online customer reviews on brand, price, and product attributes. *International Journal of Research in Marketing*, *33*(1), 11–26.

Li, X., & Hitt, L. M. (2010). Price effects in online product reviews: An analytical model and empirical analysis. *MIS quarterly*, 809–831.

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, *70*(3), 74–89.

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: analysis and applications*: Cambridge University Press.

Moe, W. W., & Trusov, M. (2011). The value of social dynamics in online product ratings forums. *Journal of Marketing Research*, *48*(3), 444–456.

Pathak, B., Garfinkel, R., Gopal, R. D., Venkatesan, R., & Yin, F. (2010). Empirical analysis of the impact of recommender systems on sales. *Journal of Management Information Systems*, *27*(2), 159–188.

Rossi, P. E., & Allenby, G. M. (1993). A Bayesian approach to estimating household parameters. *Journal of Marketing Research*, *30*(2), 171–182.

Ursu, R. M. (2018). The Power of Rankings: Quantifying the Effect of Rankings on Online Consumer Search and Purchase Decisions. *Marketing Science*, *37*(4), 530–552.

Wlömert, N., & Eggers, F. (2016). Predicting new service adoption with conjoint analysis: external validity of BDM-based incentive-aligned and dual-response choice designs. *Marketing Letters*, *27*(1), 195–210.