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Abstract

Consumer reviews on retailer-hosted platforms present an internal source of information for customers before considering the purchase of a product. While related literature has established a strong link between review ratings and retailer sales, research that integrates external sources is still in its infancy. This is particularly true for the role of social media, in which user actions can induce other users to behave in a similar way. This paper thus examines the role of social media in the assessment of product reviews on retailer-hosted platforms. We find that a higher deviation of a review rating from a product's social media popularity has a positive effect on the perceived helpfulness of the review. Moreover, we see that negative reviews are more likely to receive a helpful vote if the product enjoys substantial popularity on social media, whereas we observe the opposite effect for products with low popularity.

Keywords Decision analytics, information cascades, social media, e-commerce, consumer reviews, online word-of-mouth

1 Introduction

Retailer-hosted online consumer reviews present a key source of information for customers considering purchasing a product (e.g. Dellarocas, 2003; Godes and Mayzlin, 2004; Ngo-Ye and Sinha, 2014). These shared opinions and user experiences not only inform other customers about the quality of a product, but also have a significant and positive impact on retail sales (Chevalier and Mayzlin, 2006). Modern retailer platforms thus enable a social exchange of information that is beneficial for both, the user and the retailer itself (Ghose and Ipeirotis, 2011). However, beyond retailer-hosted (internal) platforms, independent (external) word-of-mouth platforms have emerged as important additional information sources.

While a large body of research studies the effect of internal consumer reviews on purchase decisions, research that integrates the effects of external information sources is still in its infancy (Gu et al., 2012). Early studies in this vein suggest that external reviews or word-of-mouth information sources can substantially influence the decision-making of customers on retailer platforms (Gu et al., 2012). For instance, websites or blogs extend the limited spheres of retailer platforms and often provide highly informative, in-depth product evaluations. Yet another relevant external factor that has been greatly neglected thus far is the role of social media in driving online behavior. From a psychological perspective, such platforms can increase the incentives - or pressures - for adoption decisions (Abrahamson and Rosenkopf, 1993; Algesheimer et al., 2005). For instance, the human preference to conform with others can cause positive feedback loops in which bandwagon processes strengthen *"the desire of people to wear, buy, do, consume, and behave like their fellows"* (Leibenstein, 1950). Hence, an investigation into the influence of social media on the processing of reviews on retailer platforms has been explicitly called for in a recent article in *Information Systems Research* (Yin et al., 2016).

To address this important research gap, it is necessary to better understand the assessment of product reviews on the customers' side. In this context, a relevant feature of retailer platforms is that customers are typically provided with the opportunity to rate the perceived helpfulness of a review, i.e. the extent to which it facilitates their decision-making (Mudambi and Schuff, 2010; Yin et al., 2014). From a theoretical perspective, review helpfulness constitutes a focal point for examining customer decision-making during the purchase process (Korfiatis et al., 2012). However, little is known about why a customer perceives a particular review as either helpful or unhelpful. Among others, this includes the question of whether online customers perceive negative reviews as more helpful than positive reviews. So far, studies examining the effect of review ratings on helpfulness have produced mixed results. As noted by Yin et al. (2016), a possible explanation for these contradictory findings is that prior studies typically fail to account for the initial beliefs of customers before assessing a product review.

For this purpose, this paper examines the effect of social media popularity on the perceived helpfulness of customer-generated product reviews. We collected a unique dataset of retailer-hosted reviews originating from the Amazon app store. In addition, we determined the popularity of each product on social media channels such as Instagram. Our results suggest that a product's popularity on social media significantly influences the assessment of corresponding reviews. In particular, we find that a greater social media popularity of a product decreases the chance that a corresponding review will receive a helpful vote. In addition, we also observe that a significant deviation of a review rating from a product's social media reputation has a positive effect on the perceived helpfulness of the review. In this context, we also see an asymmetry regarding the perception of positive and negative reviews. Specifically, we find that negative reviews are more likely to receive a helpful vote if the product enjoys significant popularity on social media, whereas we observe the opposite effect for products with a low popularity.

This work immediately suggests manifold implications for practitioners, social sciences, and Information Systems research: we present a novel approach to better understanding the role of social media in the assessment of product reviews. In a next step, this allows practitioners in the fields of marketing and public relations to enhance their communication strategies with respect to product descriptions, social media content, and advertising. Moreover, our findings have immediate implications for retailer platforms as they can utilize our results to optimize their customer feedback system and to present more useful product reviews. Ultimately, this study contributes to IS research by addressing the paramount question of how social media affects customers' individual behavior and decision-making.

The remainder of this article is organized as follows. Section 2 establishes the background of our study by detailing the role of social media in the assessment of product reviews. Based on studies from the related literature, this section also derives our research hypotheses. In a next step, Section 3 presents the utilized data sources and introduces the model specification that allows us to test our research hypotheses. Section 4 then lays out our results. Based on our findings, Section 5 presents important implications for research and management, while Section 6 concludes.

2 Theoretical Background and Hypotheses Development

2.1 The Impact of Retailer-Hosted Reviews on Purchase Decisions

Customer-generated product reviews have become a major source of information on modern retailer platforms (Dellarocas, 2003; Godes and Mayzlin, 2004). Existing studies commonly suggest that ratings provided by customers have a significant effect on retailer sales (e.g. Li and Hitt, 2008; Zhu and Zhang, 2010). Studies from the domain of marketing also indicate that customer-created reviews have a greater impact on customer purchase decisions than seller-created information. This rather pronounced effect is primarily explained by the fact that customer-generated information sources are widely considered more credible than seller-generated information or advertisements (Bickart and Schindler, 2001). An interesting fact about customer-generated reviews is that the relative effect of the ratings is different for positive and negative reviews. Specifically, negative ratings reduce sales to a greater extent than reviews with a positive rating increase them (Chevalier and Mayzlin, 2006). A recent study also suggests a negative effect for the variance of customer ratings on retailer sales (Herrmann et al., 2015).

While the aforementioned studies focus on the role of consumer reviews in retail sales, another relevant question is how different types of reviews are actually perceived by other customers. In this regard, a particularly interesting measure is review helpfulness. On many retailer platforms, customers are provided with the opportunity to rate the perceived helpfulness of a review. Helpfulness is defined as the extent to which it facilitates their decision-making (Mudambi and Schuff, 2010; Yin et al., 2014). Helpful reviews are typically highlighted or listed in a separate category, which helps future customers make a more informed purchase decision. Existing research has demonstrated that reviews that are perceived as more helpful also have a greater influence on retailer sales (Dhanasobhon et al., 2007).

Interestingly, studies examining the effect of review ratings on helpfulness have produced mixed results. On the one hand, some studies find that negative reviews are perceived as more helpful by customers (e.g. Sen and Lerman, 2007). On the other hand, the results of, for example, Mudambi and Schuff (2010) indicate the greater helpfulness of positive reviews. As a remedy, a recent study by Yin et al. (2016) claims that an investigation into the way reviews are assessed by customers must take into account the customers' initial beliefs. Specifically, the authors suggest that customers typically see a product's average rating before reading specific reviews.

2.2 The Role of Social Media in Online Behavior

As recently as a few decades ago, the dispersion of word-of-mouth typically occurred among friends and relatives in private interactions or social exchanges. The internet age, together with emerging social media platforms, has (partially) replaced these formerly private interactions with permanently accessible online postings. Among other definitions, social media is typically described as a platform for customer-generated content comprising media impressions that are archived or shared online for easy access by other customers (Xiang and Gretzel, 2010). Nowadays, common examples include billion-dollar brands such as Twitter, Facebook, and Instagram.

Social media platforms play a major role in the spread of information on a very large scale (Guille et al., 2013). This is reflected by a countless number of posts containing opinions, news and product reviews. In addition, social media platforms have increased the speed of information diffusion and the visibility of diverse viewpoints (Chang et al., 2015). The dynamics on such platforms can be seen as a sequence of decisions, with later users being influenced by the actions of earlier users. This effect is known as "social influence", which defines the social phenomenon whereby the actions of a user can induce other users to behave in a similar way (Anagnostopoulos et al., 2008).

The dynamics on social media platforms can evoke further classical psychological behavior patterns. For instance, information cascades can result in a behavior of information adoption in which users tend to ignore their own information signals by making decisions on the basis of the opinions and actions of other users (Anderson and Holt, 1997). This can yield bandwagon effects in which beliefs and trends spread on a large scale with a high probability of any individual to adopt them (Leibenstein, 1950). From a psychological point of view, this tendency to follow the actions or beliefs of others can occur for two reasons. First, humans tend to prefer to conform with others, and second, individuals frequently derive and accept information from others without scrutiny (Anderson and Holt, 1997).

2.3 Research Hypotheses

Nowadays, social networks can be regarded as a highly relevant source of influence that can increase the incentives or pressures for adoption decisions (Freberg et al., 2011). As previously mentioned, we expect products with substantial social media popularity to yield bandwagon effects that reduce the motivation of customers to pay attention to the information provided by retailer-hosted reviews. We thus suppose that a greater degree of social media popularity strengthens the desire of customers to "hop on the bandwagon" regardless of the underlying evidence, thus reducing the perceived helpfulness of a review. Consequently, H1 states:

HYPOTHESIS 1. *An increase in the social media popularity of a product has a negative effect on the perceived review helpfulness of corresponding retailer-hosted reviews.*

Another important question is how social popularity is related to the relationship between product ratings and review helpfulness. Seeking prepurchase information is a natural behavior by customers to maximize the value of what they pay for (Han, 2003). Traditional behavioral theories thus suggest that humans seek out as much information as possible in order to make an informed decision (Wilson, 1999). Therefore, one can expect customers to prefer information that deviates from the prevailing viewpoint. In our context, this is potentially novel information that contradicts a product's popularity on social media. Additionally, humans can also exhibit a tendency to overweigh initial beliefs and positions (Nickerson, 1998). According to cognitive dissonance theory, humans experience psychological discomfort when facing information that is not in line with their prior beliefs (Swann et al., 1987). As a consequence, they can exhibit a tendency to ignore disconfirmatory evidence in order to reduce discomfort and maintain consistency (Darley and Gross, 1983). In keeping with both concepts, we propose the following hypotheses:

HYPOTHESIS 2A. *A higher deviation of a review rating from a product's popularity on social media has a positive effect on the perceived helpfulness of the review.*

HYPOTHESIS 2B. *A higher deviation of a review rating from a product's popularity on social media has a negative effect on the perceived helpfulness of the review.*

As described in the previous sections, related literature produces mixed results regarding the question of whether positive or negative reviews are more helpful to customers. Concordant with the study by Yin et al. (2016), we suppose that the inconsistent findings in previous works are the result of ignoring the initial beliefs of customers before assessing a product review. Based on various studies that suggest a substantial impact of social media on shaping public opinion, we conjecture that a product's social media popularity has an important influence on how review ratings are perceived. Thus, we expect an asymmetry in terms of the effect of review rating on helpfulness between products with a high popularity on social media and those with a relatively low popularity. From a theoretical perspective, possible roles of the rating are two-fold. On the one hand, for highly popular products, one might expect customers to find negative reviews more useful, since they may be more surprising and more informative. As a result, we would observe a negative effect of review rating for products that are relatively popular on social media. On the other hand, based on the human preference to overweigh initial beliefs, one might also expect customers to ignore disconfirmatory evidence, i.e. to ignore negative reviews for highly popular products. We therefore propose the following two hypotheses:

HYPOTHESIS 3A. *The effect of review rating on review helpfulness is (i) negative for products with a high popularity on social media, and (ii) positive for products with a low popularity on social media.*

HYPOTHESIS 3B. *The effect of review rating on review helpfulness is (i) positive for products with a high popularity on social media, and (ii) negative for products with a low popularity on social media.*

3 Data Sources and Empirical Methodology

3.1 Data Sources

We analyze our hypotheses using two disjunct data sources. First, we employ retailer-hosted product reviews gathered from the Amazon app store. Second, we measure the social media popularity of each product on the internet-based photo-sharing platform Instagram.

In selecting our product reviews corpus, we collected consumer reviews from the Amazon app store that appeared in the top-100 overall rankings on July 25, 2017. This includes the top-100 free, as well as the top-100 paid, applications. For each product, we collected the first five pages of the most helpful reviews, in which each page contains ten reviews at most. The complete sample consists of 8717 consumer reviews containing the following information: (1) the numerical rating assigned to the product (i.e. the star rating), (2) the review text, (3) the number of helpful votes for the review, (4) the date on which the review was posted and (5) the page on which the review appears. In addition, we collected the following product-specific information: (i) the price of the product, (ii) the rank on the sales chart, (iii) the release date on Amazon. It is worth noting that the collected dataset exhibits several advantages as compared to alternative sources: first, all reviews are verified by the retailer, i.e. the author of a review must have actually purchased the product. Second, the Amazon platform features a particularly active user base, i.e. a high number of reviews per product (Gu et al., 2012).

Subsequently, we measure the social media popularity of the products in our reviews corpus. For this purpose, we gather the total number of posts related to each product on the photo-sharing platform Instagram, which is a frequent choice in the related literature when it comes to studying the role of social media in human online behavior (e.g. Bakhshi et al., 2014; Ruths and Pfeffer, 2014). To link specific products with their social media popularity, we extract the name of each product in our reviews corpus. The product names of digital applications often consist of a main title and a highly specific subtitle, such as the current version of the application. We thus omit overly specific subtitles and collect the total number of posts related to each product name using Instagram's web search interface.

Finally, to ensure comparability, we remove reviews for the platform Instagram itself (which is also listed in Amazon's top-100 free app charts). We also note that Youtube and Netflix had a duplicate app listed in the top-100 overall rankings. Here, we remove all reviews of the lower-ranked app. In addition, we remove a few reviews that contain no text and all reviews that were not created in our period of study between January 25, 2016 and July 25, 2017. Moreover, we omit reviews for apps that have not been released at the beginning of our study period. These filtering steps result in a final corpus of 3401 customer-generated product reviews.

3.2 Variable Definitions and Descriptive Statistics

Table 1 describes the variables in our analysis. In addition, Table 2 presents summary statistics for the most relevant variables. In the following, *i* indexes a product and *j* indexes a review for a product.

Variable	Description
$RHVotes_{ji}$	Number of helpful votes of review *j* for product *i*
$PDisp_i$	Standard deviation of review ratings for product *i*
$PPaid_i$	Indicator variable, equals 1 if product *i* has a price greater than zero
$PPosts_i$	Number of posts for product *i* on Instagram (in 10,000)
$PRank_i$	Sales rank of product *i* in Amazon top 100 charts
$PSocial_i$	Social media popularity of product *i* on a scale of 1 to 5
$RAge_{ji}$	Age in days of review *j* for product *i* with respect to our crawling date
$RLength_{ji}$	Number of words in review *j* for product *i*
$RPage_{ji}$	Page of review *j* for product *i* with respect to the number of helpful votes
$RSocDev_{ji}$	Absolute deviation between star rating ($RStars_{ji}$) and social media popularity ($PSocial_i$)
$RStars_{ji}$	Star rating assigned by review *j* to product *i*
$RSubj_{ji}$	Degree of subjectivity of the text of review *j* for product *i*

Table 1: Description of Variables.

The dependent variable in this study is review helpfulness $RHVotes_{ji}$. This variable denotes the number of helpful votes for review *j* of product *i* at the end of our study period. A relevant share of 62.1 % of all reviews received at least one helpful vote, while the mean number of votes per review is 71.24.

The key explanatory variables are star rating and social media popularity. The star rating $RStars_{ji}$ ranges from 1 to 5 and has a mean value of 3.81. The variable $PPosts_i$ denotes the number of posts on the social media platform Instagram. For the products in our dataset, Instagram users have published as few as zero posts, but also as many as 24.06 million. The mean number of posts per product is 734,683. Since our analyses in the next sections require a comparability of the measure for social media popularity and star rating, we introduce the variable $PSocial_i$ that scales $PPosts_i$ to a fixed interval between 1 and 5. This corresponds to the range of possible stars that can be given in a rating on the retailer platform. In this context, a $PSocial_i$ value of 5 refers to the product with the highest number of Instagram posts in the sample. Equally, a value of 1 is assigned to reviews that correspond to products with the lowest number of posts. As a main benefit, this approach allows us to calculate the deviation of a review rating from a product's social media reputation. For this purpose, we introduce the variable $RSocDev_{ji}$ which is defined as the absolute deviation between review rating $RStars_{ji}$ and social media popularity $PSocial_i$, i.e. $RSocDev_{ji} = abs(RStars_{ji} - PSocial_i)$. Because both measures are located in a range between 1 and 5, the highest possible deviation is 4.

Consistent with the related literature, we additionally use a fixed set of control variables for each product. The following variables are defined at the product level and can indirectly influence the chance of a helpful vote for a review (Yin et al., 2016). The first control variable is $PRank_i$, which is the Amazon chart rank of a product based on the number of downloads. Second, $PDisp_i$ measures the standard deviation of the star ratings corresponding to product i. Third, we include an indicator variable $PPaid_i$ which equals 1 if the product has a non-zero price. Finally, we also include a set of control variables at the review level. Here, $RAge_{ji}$ denotes the age of a review at the end of our study period, $RLength_{ji}$ reflects the number of words in a review, and $RPage_{ji}$ indicates the page on which a review is listed on Amazon. Moreover, we calculate the degree of subjectivity $RSubj_{ji}$ of a review text using the sentiment classification tool "SentiStrength" (Thelwall et al., 2010).

Variable	Mean	Min	Max	Std. Dev.	1	2	3	4	5	6	7	8	9
1 $RHVotes_{ji}$	71.24	0.00	2935.00	229.36	1								
2 $PDisp_i$	1.15	0.00	1.85	0.51	-0.40	1							
3 $PPosts_i$	73.47	0.00	2406.42	323.74	-0.04	0.09	1						
4 $PSocial_i$	2.50	1.00	5.00	1.05	0.03	-0.19	0.50	1					
5 $RAge_{ji}$	206.09	0.00	546.96	177.74	0.15	-0.25	-0.12	-0.04	1				
6 $RLength_{ji}$	27.37	1.00	617.00	36.73	0.11	-0.07	-0.06	0.07	0.12	1			
7 $RSocDev_{ji}$	1.86	0.00	4.00	1.14	0.08	-0.11	-0.16	-0.36	0.09	-0.12	1		
8 $RStars_{ji}$	3.81	1.00	5.00	1.57	0.12	-0.42	0.03	0.16	0.12	-0.14	0.46	1	
9 $RSubj_{ji}$	1.89	1.00	4.50	0.61	0.11	-0.18	-0.05	0.06	0.14	0.39	0.39	0.03	1

Table 2: Descriptive Statistics and Correlations.

3.3 Empirical Model

We use a log-linear model to analyze the effect of social media on the perceived helpfulness of retailer-hosted reviews. This type of model is not only a common choice for the analysis of word-of-mouth variables, but also exhibits several further advantages (Gu et al., 2012). First, a key benefit of log-linear models is their flexibility, including the ability to handle the many count variables in our dataset. Second, log-linear models are highly interpretable by allowing a percent change in retailer-hosted and social media variables to contribute to a certain percentage change rather than a level change in review helpfulness.

Based on our hypotheses, we specify the following model that allows us to infer the effects of social media popularity on review helpfulness. We start with a baseline model in which we use review helpfulness as the dependent variable, while we include rating dispersion, sales rank, review age, review length, review page, subjectivity and a price indicator as independent variables. Following prior research, we expect strongly significant effects for these retailer-hosted variables. To test our first hypothesis, we additionally include the social medial popularity variable $Ln(PSocial_i)$. For our second hypothesis, we include the deviation between review rating and social media popularity, $Ln(RSocDev_{ji})$. In our third hypothesis, we aim at estimating the marginal effect of the star rating on review helpfulness with respect to different levels of social media popularity. For this purpose, we include $Ln(RStars_{ji})$ and an interaction term $Ln(PSocial_i) \times Ln(RStars_{ji})$. Altogether, the resulting model is

$$\begin{aligned} Ln(RHVotes_{ji}) = {} & \beta_0 + \beta_1 Ln(PDisp_i) + \beta_2 Ln(PRank_i) + \beta_3 Ln(RAge_{ji}) + \beta_4 Ln(RLength_{ji}) \\ & + \beta_5 Ln(RPage_{ji}) + \beta_6 Ln(RSubj_{ji}) + \beta_7 PPaid_i + \beta_8 Ln(PSocial_i) \\ & + \beta_9 Ln(RSocDev_{ji}) + \beta_{10} Ln(RStars_{ji}) + \beta_{11} Ln(PSocial_i) \times Ln(RStars_{ji}) + \epsilon_{ji}, \end{aligned} \tag{1}$$

with intercept β_0 and error term ϵ_{ji}.

Based on the equation above, we expect social media popularity to influence the perceived helpfulness of retailer-hosted reviews. Nonetheless, we acknowledge that social media popularity not only drives review helpfulness, but also can be an outcome of review helpfulness. To address such potential reversed causality issues, we follow an instrumental variable approach. Specifically, we address potential endogeneity in our regression analysis by using 18-month-lagged Bing search interest data as an instrument for social media popularity. This instrument features two advantages. First, it is highly correlated with the current social media popularity (correlation of 0.83). Second, the lagged instrumental variable cannot be influenced by helpfulness votes in our data since current review variables cannot influence search interest data from the past. Before using the instrumental variables in our model, we perform a Wu-Hausman test for endogeneity. The test result for the model of our first hypothesis is 39.72, which indicates that it is necessary to use the instrumental variable approach.

4 Results

We use the model as described in the previous section to examine the effect of social media on review helpfulness. All regression models are reported in Table 3. In the following, we first detail the results and test our hypotheses. We then perform several robustness checks.

	(a)	(b)	(c)	(d)	(e)
Constant	1.988*** (0.231)	5.145*** (0.408)	3.941*** (0.459)	3.682*** (0.299)	3.134*** (0.682)
$Ln(PDisp_i)$	-2.987*** (0.108)	-3.243*** (0.115)	-2.971*** (0.125)	-3.190*** (0.225)	-3.428*** (0.122)
$Ln(PRank_i)$	-0.119*** (0.030)	-0.257*** (0.034)	-0.280*** (0.035)	-0.173*** (0.031)	-0.264*** (0.034)
$Ln(RAge_{ji})$	0.364*** (0.020)	0.359*** (0.020)	0.340*** (0.021)	0.365*** (0.020)	0.353*** (0.021)
$Ln(RLength_{ji})$	0.162*** (0.027)	0.190*** (0.028)	0.266*** (0.030)	0.139*** (0.028)	0.172*** (0.029)
$Ln(RPage_{ji})$	-0.313*** (0.071)	-0.268*** (0.072)	-0.266*** (0.074)	-0.285*** (0.070)	-0.252*** (0.072)
$Ln(RSubj_{ji})$	0.272 (0.141)	0.313* (0.143)	0.089 (0.150)	0.396** (0.143)	0.380** (0.146)
$PPaid_i$	1.188*** (0.064)	0.686*** (0.084)	0.722*** (0.087)	0.991*** (0.068)	0.725*** (0.085)
$Ln(PSocial_i)$		-2.014*** (0.213)	-1.758*** (0.244)	-0.761*** (0.100)	0.155 (0.548)
$Ln(RSocDev_{ji})$			0.918*** (0.128)		
$Ln(RStars_{ji})$				-0.283*** (0.074)	1.522*** (0.410)
$Ln(PSocial_i) \times Ln(RStars_{ji})$					-1.479*** (0.351)
Observations	3,401	3,401	3,401	3,401	3,401
Adjusted R^2	0.404	0.413	0.419	0.418	0.425
Stated: Coefficient and standard deviation			Significance: *p < 0.05, **p < 0.01, ***p < 0.001		

Table 3: Regression linking social media popularity and review helpfulness.

4.1 Model Estimation and Hypotheses Tests

We start our analysis with a baseline model in which we only include retailer-hosted variables. As shown in column (a) of Table 3, all variables except $Ln(RSubj_{ji})$ have a strongly significant effect on the helpfulness of a review. As expected, longer and older reviews are more likely to receive helpful votes. We also note that paid apps are more likely to get a helpful vote, whereas a higher dispersion of star ratings results in a lower chance of this outcome. We also observe that the baseline model fits well with the data, as 40.4 % of the variations in helpfulness are explained by the model.

We now test our first research hypothesis. For this purpose, we incorporate the effect of social media popularity into our regression model. The output for this model is shown in column (b). The coefficient for $Ln(PSocial_i)$ is significant and negative ($\beta = -2.014$, $p < 0.001$). This indicates that a 1.00 % increase in social media popularity decreases helpfulness by 2.014 %. We also note an increase in terms of R^2 from 0.404 for the baseline model to 0.413. All other coefficients remain stable. Thus, H1 is supported.

To test our research hypotheses H2A and H2B, we extend our previous model by additionally including $Ln(RSocDev_{ji})$. The results for this model are shown in column (c). The coefficient for $Ln(RSocDev_{ji})$ is significant and positive ($\beta = 0.918$, $p < 0.001$), indicating that a 1.00 % change in the deviation between star rating and social media popularity increases review helpfulness by 0.918 %. Compared to the previous model, we also observe an increase in terms of R^2 from 0.413 to 0.419, while all other coefficients remain stable. Therefore, we find support for hypothesis H2A.

To test hypothesis H3, we modify the model in column (c) to exclude $Ln(RSocDev_{ji})$ and include $Ln(RStars_{ji})$. As shown in column (d), the coefficient of $Ln(RStars_{ji})$ is significant and negative ($\beta = -0.283$, $p < 0.001$) and the coefficient for $Ln(PSocial_i)$ is still significantly negative. However, we expect the effect of review rating to depend on social media popularity. Thus, we additionally include the interaction term $Ln(PSocial_i) \times Ln(RStars_{ji})$. The results for this model are shown in column (e). The coefficient for the interaction term is significant and negative ($\beta = -1.479$, $p < 0.001$). At the same time, the effect of $Ln(RStars_{ji})$ has become clearly positive ($\beta = 1.522$, $p < 0.001$), while $Ln(PSocial_i)$ is no longer statistically significant. Figure 1 plots the marginal effect of star rating on review helpfulness for several levels of social media popularity along with the 95 % confidence intervals. According to the figure, we observe an asymmetry regarding the effect of review rating on helpfulness. Specifically, the effect is significantly negative for products with a very high popularity on social media, whereas we observe the opposite effect for reviews with a popularity at the lower end of the scale. Thus, hypothesis H3A is supported.

Altogether, the above results provide strong evidence that a product's popularity on social media significantly influences the assessment of corresponding retailer-hosted reviews. In summary, the main findings are as follows. First, a greater social media popularity decreases the chance that a review will receive a helpful vote on the retailer platform. Second, a higher deviation of a review rating from a product's social media reputation has a positive effect on the review's perceived helpfulness. Third, a higher review rating decreases the review helpfulness for products with a very high popularity on social media, whereas a higher review rating increases review helpfulness for products with a very low popularity.

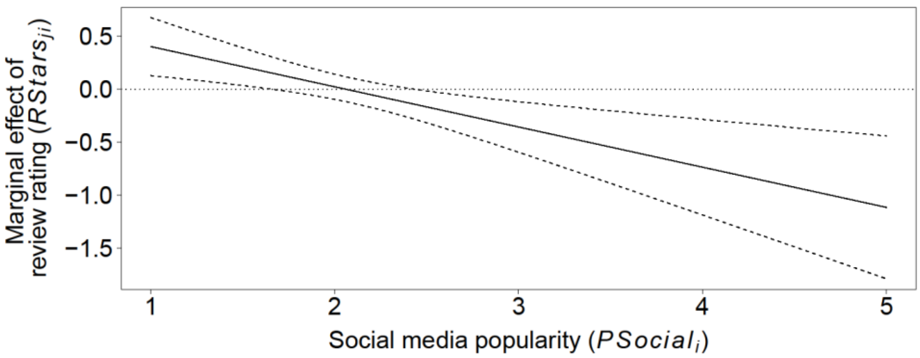

Figure 1: Marginal effects of review rating on helpfulness for different levels of social media popularity.

4.2 Robustness Checks

In the following, we perform multiple checks to confirm the robustness of our approach. First, we repeat our analysis using popularity measures from an alternative social media channel. For this purpose, we collect Twitter popularity ratings on the Twitter hashtag search engine hashtagify.me. The analysis of these ratings allows for an interesting extension of our study since it provides a relative metric for the popularity of a product in a given timeframe. That is, the most popular hashtag based on the relative number of posts in our study period is assigned a popularity value of 100, while a hashtag that is never used is assigned a popularity value of 0. When reestimating our models using this measure, we find very similar effects that confirm our findings. In fact, all relevant regressors are still significant at the 1 % level. As a result, we see that the absolute number of posts as used in our analysis in the previous section serves as a suitable proxy to measure the current popularity of a product on social media.

We also validate our approach by adding quadratic terms of social media popularity to the individual models. According to our results, all models continue to support our hypotheses. Moreover, we extend our model by including further sentiment variables based on the frequently-employed Harvard IV General Inquirer dictionary. This dictionary covers an extensive number of terms and allows us to measure the effect of emotional and cognitive orientations in reviews in more detail. Here, we find statistically relevant effects that are, however, only significant at the 5 % level.

Finally, we also check our models for possible multicollinearity and heteroskedasticity issues. For this purpose, we calculate the variance inflation factors (VIF) for all variables in our models. The VIF of all regressors (except the interaction terms) are below the critical threshold of 4. This finding is also supported by the fact that our independent variables show relatively high significance values with comparatively low standard errors. Overall, this indicates that multicollinearity is not a significant problem in our analysis. To control for possible heteroskedasticity, we reestimate our models with White's heteroskedasticity-robust estimator for standard errors. This analysis confirms all results from the previous section.

5 Discussion

This study contributes to and has implications for the following areas: first, it allows for a deeper understanding of the assessment of consumer reviews on online retailer platforms. Concordant with Yin et al. (2016), our results provide strong evidence that the perceived helpfulness of reviews depends on the initial beliefs of customers. We find that a product's popularity on social media is a main driver in shaping these initial beliefs, with the potential to affect the assessment of corresponding retailer-hosted reviews. Based on this finding, we are also able to resolve the contradictory findings in prior research regarding the effect of product rating on review helpfulness. Specifically, our analysis indicates that for highly popular products, negative information is perceived as more valuable and vice versa. Hence, the empirical results suggest that a confirmation bias may not be readily applicable for consumer reviews on retailer platforms. Instead, our analysis rather suggests that customers seek out as much information as possible in order to make an informed decision.

This study has implications for practitioners in the fields of marketing and public relations. Since the helpfulness of reviews is directly related to the popularity of a product on social media, our findings can help companies to enhance their communication strategies with regard to product descriptions, social media content, and advertisement. In this context, it should not be assumed that negative reviews are generally perceived as more helpful. Instead, the role of review rating in relation to the helpfulness of a review rather depends on the social media popularity of a product. In a next step, our findings can also help retailer platforms to better inform customers who are considering purchasing a product. For instance, retailer platforms might utilize our findings to develop writing guidelines to encourage more useful seller reviews that take into account prior beliefs of potential readers. It is worth noting that a better understanding of why customers perceive a particular review as helpful or unhelpful can help to detect fake reviews (Zhang et al., 2016).

Ultimately, this study also has a number of limitations that can serve as interesting starting points for future research. First, our dataset is limited to digital products from the Amazon app store. To analyze the generalizability of our approach, future studies may want to examine the differential impact of social media in the context high-involvement products, such as electronic devices or durable goods. In this regard, one might suspect that the influence of social media on customer decision-making is stronger for products with low prices and simple functionality. Second, our current analysis is limited to social media posts from Instagram and Twitter. Hence, it might be an interesting project to compare the interactions and effects of different social media channels on retailer platforms. In this context, an intriguing approach would be to collect a panel dataset in order to study the presented effects on a daily basis. Finally, our analysis merely operationalizes social media popularity based on the number of posts on the corresponding platforms. It would be an interesting extension to refine the measure of social media popularity by also integrating the effects of positive and negative sentiment in social media posts.

6 Conclusion

A growing body of literature is attempting to clarify the influence of word-of-mouth on customer purchase decisions. While existing studies show that internal word-of-mouth has a positive impact on retailer sales, research to integrate the role of external sources is still evolving. This is particularly true for the role of social media, which can substantially affect online behavior. The social dynamics resulting from the use of such platforms can increase the incentives for adoption decisions in which bandwagon processes strengthen the desire of the prospective buyer to consume like others. Thus, this study sheds light on the role of social media in regard to the decision-making processes of customers in online market places.

As its main contribution, this paper examines the role of social media in the assessment of customer-generated product reviews on retailer-hosted platforms. In contrast to related studies, which typically focus on internal word-of-mouth sources, we present a study that additionally integrates the effects of social media on the decision-making of customers. Our results show that a product's popularity on social media significantly influences the assessment of corresponding retailer-hosted reviews. In particular, we find that a high deviation of a review rating from a product's social media popularity has a positive effect on the perceived helpfulness of the review. Moreover, we see that negative reviews are more likely to receive a helpful vote if the product is subject to low popularity on social media, whereas we observe the opposite effect for products with high popularity. In a practical sense, our results allow practitioners in the fields of marketing and public relations to enhance their communication strategies regarding product descriptions, social media content, and advertisement. Ultimately, we contribute to IS research by addressing the question of how social media affects customers' individual behavior and decision-making.

7 References

Abrahamson, E., and Rosenkopf, L. 1993. "Institutional and Competitive Bandwagons: Using Mathematical Modeling as a Tool to Explore Innovation Diffusion," *Academy of Management Review* (18:3), pp. 487–517.

Algesheimer, R., Dholakia, U. M., and Herrmann, A. 2005. "The Social Influence of Brand Community: Evidence from European Car Clubs," *Journal of Marketing* (69:3), pp. 19–34.

Anagnostopoulos, A., Kumar, R., and Mahdian, M. 2008. "Influence and Correlation in Social Networks," in *Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, ACM Digital Library, ACM.

Anderson, L. R., and Holt, C. A. 1997. "Information Cascades in the Laboratory," *The American Economic Review* (87:5), pp. 847–862.

Bakhshi, S., Shamma, D. A., and Gilbert, E. 2014. "Faces Engage Us: Photos with Faces Attract More Likes and Comments on Instagram," in *Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems*, New York, New York, USA: ACM Press, pp. 965–974.

Bickart, B., and Schindler, R. M. 2001. "Internet Forums as Influential Sources of Consumer Information," *Journal of Interactive Marketing* (15:3), pp. 31–40.

Chang, Y.-T., Yu, H., and Lu, H.-P. 2015. "Persuasive Messages, Popularity Cohesion, and Message Diffusion in Social Media Marketing," *Journal of Business Research* (68:4), pp. 777–782.

Chevalier, J. A., and Mayzlin, D. 2006. "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research* (43:3), pp. 345–354.

Darley, J. M., and Gross, P. H. 1983. "A Hypothesis-Confirming Bias in Labeling Effects," *Journal of Personality and Social Psychology* (44:1), pp. 20–33.

Dellarocas, C. 2003. "The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms," *Management Science* (49:10), pp. 1407–1424.

Dhanasobhon, S., Chen, P.-Y., and Smith, M. 2007. "An Analysis of the Differential Impact of Reviews and Reviewers at Amazon.com," in *28th International Conference on Information Systems (ICIS)*, Montreal, QC, Canada: Forth Worth, USA.

Freberg, K., Graham, K., McGaughey, K., and Freberg, L. A. 2011. "Who Are the Social Media Influencers? A Study of Public Perceptions of Personality," *Public Relations Review* (37:1), pp. 90–92.

Ghose, A., and Ipeirotis, P. G. 2011. "Estimating the Helpfulness and Economic Impact of Product Reviews: Mining Text and Reviewer Characteristics," *IEEE Transactions on Knowledge and Data Engineering* (23:10), pp. 1498–1512.

Godes, D., and Mayzlin, D. 2004. "Using Online Conversations to Study Word-of-Mouth Communication," *Marketing Science* (23:4), pp. 545–560.

Gu, B., Park, J., and Konana, P. 2012. "Research Note - The Impact of External Word-of-Mouth Sources on Retailer Sales of High-Involvement Products," *Information Systems Research* (23:1), pp. 182–196.

Guille, A., Hacid, H., Favre, C., and Zighed, D. A. 2013. "Information Diffusion in Online Social Networks," *ACM SIGMOD Record* (42:1), pp. 17–28.

Han, T. 2003. "Exploring Price and Product Information Search Behavior in E-Market," in *ITCC 2005*, Los Alamitos, Calif.: IEEE Computer Society, pp. 397–402.

Herrmann, P., Kundisch, D., Zimmermann, S., and Nault, B. 2015. "How do Different Sources of the Variance of Consumer Ratings Matter?" in *36th International Conference on Information Systems*.

Korfiatis, N., García-Bariocanal, E., and Sánchez-Alonso, S. 2012. "Evaluating Content Quality and Helpfulness of Online Product Reviews: The Interplay of Review Helpfulness Vs. Review Content," *Electronic Commerce Research and Applications* (11:3), pp. 205–217.

Leibenstein, H. 1950. "Bandwagon, Snob, and Veblen Effects in the Theory of Consumers' Demand," *The Quarterly Journal of Economics* (64:2), pp. 183–207.

Li, X., and Hitt, L. M. 2008. "Self-Selection and Information Role of Online Product Reviews," *Information Systems Research* (19:4), pp. 456–474.

Mudambi, S. M., and Schuff, D. 2010. "What Makes a Helpful Online Review? A Study of Customer Reviews on Amazon.com," *MIS Quarterly* (34:1), pp. 185–200.

Ngo-Ye, T. L., and Sinha, A. P. 2014. "The Influence of Reviewer Engagement Characteristics on Online Review Helpfulness: A Text Regression Model," *Decision Support Systems* (61:1), pp. 47-58.

Nickerson, R. S. 1998. "Confirmation Bias: A Ubiquitous Phenomenon in Many Guises," *Review of General Psychology* (2:2), pp. 175–220.

Ruths, D., and Pfeffer, J. 2014. "Social Sciences. Social Media for Large Studies of Behavior," *Science* (346:6213), pp. 1063–1064.

Sen, S., and Lerman, D. 2007. "Why Are You Telling Me This? An Examination Into Negative Consumer Reviews on the Web," *Journal of Interactive Marketing* (21:4), pp. 76–94.

Swann, W. B., Griffin, J. J., Predmore, S. C., and Gaines, B. 1987. "The Cognitive-Affective Crossfire: When Self-Consistency Confronts Self-Enhancement," *Journal of Personality and Social Psychology* (52:5), pp. 881–889.

Thelwall, M., Buckley, K., Paltoglou, G., Di Cai, and Kappas, A. 2010. "Sentiment Strength Detection in Short Informal Zext," *Journal of the American Society for Information Science and Technology* (61:12), pp. 2544–2558.

Wilson, T. D. 1999. "Models in Information Behaviour Research," *Journal of Documentation* (55:3), pp. 249–270.

Xiang, Z., and Gretzel, U. 2010. "Role of Social Media in Online Travel Information Search," *Tourism Management* (31:2), pp. 179–188.

Yin, D., Bond, S. D., and Zhang, H. 2014. "Anxious or Angry? Effects of Discrete Emotions on the Perceived Helpfulness of Online Reviews," *MIS Quarterly* (38:2), pp. 539–560.

Yin, D., Mitra, S., and Zhang, H. 2016. "Research Note—When Do Consumers Value Positive vs. Negative Reviews? An Empirical Investigation of Confirmation Bias in Online Word of Mouth," *Information Systems Research* (27:1), pp. 131–144.

Zhang, D., Zhou, L., Kehoe, J. L., and Kilic, I. Y. 2016. "What Online Reviewer Behaviors Really Matter? Effects of Verbal and Nonverbal Behaviors on Detection of Fake Online Reviews," *Journal of Management Information Systems* (33:2), pp. 456–481.

Zhu, F., and Zhang, X. 2010. "Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics," *Journal of Marketing* (74:2), pp. 133–148.