Summer 7-5-2020

The Impact of Positive Online Review Tags on Snacks Sales: A Case of Bestore in Tmall

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Abstract: Customers' reviews in e-commerce sites play a significant role in influencing potential customers' purchasing decisions which ultimately affects products sales. Chinese e-commerce sites like Tmall, Taobao and JD.com contain a collection of aspect tags that group reviews with similar comments tags to help customers browse reviews and evaluate products more conveniently. To validate whether these tags are useful and actually playing a role in promoting future sales, we collected data including product information and review tags on a regular basis for consecutive 8 weeks from Bestore, a snack seller on Tmall. We classified the collected review tags into 9 types based on their semantic meanings. Finally, we analyzed and performed generalized estimating equations (GEE) modeling on the data set consisting of 234 products with a total of 734 tags. The results show that most of the aspect tags are related to immediate period sales volume and certain tags are more capable of nowcasting next immediate sales.

Keywords: E-commerce, online review, tag, sales

1. INTRODUCTION

It is increasingly common for people to share their views of various content over the Internet, and equally easy to find others' views (Bertola & Patti, 2016). When it comes to online shopping, this trend has exerted influence on how people actually decide whether to make a purchase. Most consumers tend to read reviews of a target product to help them make an informed decision (Zhang et al., 2016). A study by Mudambi and Schuff (2010) showed that consumers who search for information online about products and compare them with alternatives would normally have to weigh it against numerous reviews posted by other consumers. W. J. Duan, B. Gu, and A. B. Whinston (2008) summarized this trend as consumers helping each other in searching the space of possible solutions to their need.

Online reviews affect sales of products to a certain degree, which has been suggested in many studies (W. Duan, B. Gu, & A. B. Whinston, 2008; W. J. Duan et al., 2008; Forman, Ghose, & Wiesenfeld, 2008). Based on the mechanism found in which online reviews have an impact on sales, it is possible for companies to design and implement ways to influence sorting and effective visualization in e-commerce sites. Effective designs can motivate potential customers to a large degree as they can manipulate online reviews to match their requirements. For example, websites like Amazon, YouTube and Yelp sort their reviews according to various review factors to help enhance objects' exposure to users (Ren & Nickerson, 2014). Previous research has identified relevant factors such as sentiment, helpfulness, newness, the number of likes and source credibility to be useful design considerations.

Floyd, Freling, Alhoqail, Cho, and Freling (2014) demonstrated in their study the relationship between sales volume and different properties of reviews. They found that the effects of negative reviews on products are more salient than positive ones and usually cause unfavorable impacts on product attitudes. Therefore, it is necessary for retailers to detect and address service and product failure promptly, otherwise dissatisfied

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customers may post negative online reviews that may deter many potential customers.

Zhu and Zhang (2010) studied review data from the video game industry and found that online reviews were more influential for less popular games. In other words, for a commodity that has few customer reviews (i.e. not popular), the reviews play a more important role. Negative reviews may become extremely salient in this situation. Hence sellers should also take corresponding measures to solve this kind of problem.

According to Zha, Yu, Tang, Wang, and Chua (2014), there is a common problem with the display of most reviews. Current reviews are mostly not well organized, causing difficulties in information navigation and knowledge acquisition. Therefore, there is a need to design a mechanism that can help to present reviews and display them in a friendly way for customers to browse. The tag mechanism in Tmall is a representative design to allow more user friendly information acquisition in practice. As is shown in Figure 1, tag names are displayed in the form of buttons above the list of reviews. These tags organize a collection of phrases from all the reviews that contain identical or similar meaning by grouping them with a tag name and the number of appearances, which can help potential customers browse relevant reviews more conveniently and efficiently. The number that follows the name of the tag is the quantity of reviews that are aggregated by the tag, i.e. the number of reviews that share similar content. Tags with positive reviews of products distinguish themselves in red font, while those with negative reviews appear in green font. This mechanism provides more convenience for potential consumers to view both relevant positive reviews and negative reviews respectively.

Figure 1. Tmall's display of tags

When a tag is clicked, reviews that belong to this tag ("tag review") would be listed below, with the main content relevant to the name of the tag marked in red. As is shown in Figure 2, customers can easily choose which reviews to browse

Figure 2. Listing of reviews that belong to a certain tag

.The tag mechanism described in this study is a common feature in most Chinese e-commerce platforms such as Taobao and JD.com, but is not a prominent feature in other international e-commerce websites such as Amazon and eBay (Amazon uses keyword tags). Coincidentally, knowledge about the usefulness of the review tag is currently lacking. Furthermore, there has been much research on products such as electronic products, hotels, and movies with little attention to food (Floyd et al., 2014). Snacks are a type of food commodity that has some unique product properties such as taste, smell, volume and variety. The impact of these tags on an industry with an estimated output value of 3 trillion yuan in 2020 is worthy of serious attention (Zhuoqiong, 2019). We chose Bestore (良品铺子), which is a prominent corporation mainly engaged in producing and selling snacks, as our research case as all relevant data sources can be collected from its official web page on Tmall.

In this study, we wanted to know whether review tags would have an effect on sales, and if so, to what degree, and since Tmall also offers the valence of each tag (positive or not), we decided to explore the effects of those positive tags. In addition, we wanted to explore the aspect tags' effects. Tags that are classified into different aspect types according to their names' semantic meanings would reveal the properties of products that customers most care about. Further, if tags are to be related with product sales, it is natural that tags could be considered as potential predictors for future sales, which would contribute to more precise prediction results of existing sales nowcasting models. Taken together, we posit the following research questions:

(1) To what extent are positive review tags inter-related?
(2) How are the positive review tags associated with product sales, price and discount rate?
(3) To what extent are different positive tags associated with product sales in the current period?
(4) To what extent are positive review tags capable of nowcasting product sales in the immediate period?

This study contributes to knowledge on several aspects of the tag mechanism in e-commerce. First, the original research adds to the limited knowledge on the tag mechanism and its impact on product sales. Second, the research enhances our knowledge on food products, and specifically snacks, which are a popular product in China but under-researched. Third, the research unveils the importance of e-commerce and product properties that customers care about most when purchasing snacks. Lastly, the research provides a model for nowcasting of product sales.

The remainder of the paper is structured as follows. Section 2 presents relevant work on the following three aspects: (1) the relationship between reviews volume and sales, (2) the research on exploring what product properties people care about when making purchasing decisions, and (3) the introduction of a generalized estimating equation model that we use on our data set. Section 3 describes our data set and some preprocessing work in detail. Section 4 explains specific variables for the experiments and shows our experiment results. Section 5 discusses the experiment results. Section 6 concludes our work and discusses limitations of the study, along with directions for further research on this topic.

2. LITERATURE REVIEW

2.1 Research on online reviews

In recent years, online reviews have played an increasing role in influencing consumer decision making. Online reviews help customers understand the pros and cons of different products to find the most suitable one for their needs and consumer advocacy has been shown to significantly affect product sales (Moe & Trusov, 2011; Salehan & Dan, 2016). In the industry research report by Deloitte (2012) a big proportion of consumers claims that their purchasing decisions are largely influenced by online reviews.

According to Bickart and Schindler (2001) customers are more willing to accept product information from online reviews rather than the information provided by vendors. As messages coming from similar others are more persuasive (Berger, 2014), the information from others who have experience with products is always thought to be more useful and closer to what they want to know. Similarly, information coming from consumers who share their reviews with their families, friends or colleagues are more influential as the reviews not only make sense of the shopping experiences but also enhance the social relationships (Peters & Kashima, 2007).

Studies have identified various ways that reviews influence consumer decision making. For instance, users are more likely to attach importance to negative messages than positive ones, and pay more attention to negative messages. Negative online reviews play a more significant role than positive online reviews (Park & Lee, 2009). Chen, Wang, and Xie (2011) also mentioned that both positive and negative online review information play a crucial role in increasing sales, and specifically, negative online reviews have a greater impact than positive online review information.

Online reviews have been measured in multiple ways to capture their effects from various aspects. Studies typically focus on the following metrics of online reviews: volume, valence, composite valence–volume, and variance (Rosario, Sotgiu, Valck, & Bijmolt, 2016). Volume refers to "the total amount of electronic word-of-mouth interaction", that to say, the total number of online reviews for a product (Y. Liu, 2006). Yang, Kim, Amblee, and Jeong (2011) research confirmed there is a direct relationship between the volume of a product's online reviews and the product sales. Online review volume indicates information about the number of people who have purchased the product. In addition, it can increase customers' awareness of and reduce their uncertainty about the product, thus leading to the increasing of sales (Chen et al., 2011). Amblee and Bui (2011) investigated the impact of online reviews by analyzing the sales of digital micro-products. They showed that online reviews can be a form of social signal representing various types of reputation that affect sales which eventually contributes to the success of e-commerce businesses.

Valence indicates the nature of the review which can be negative, positive, mixed or neutral. It is also referred to as "sentiment" or "favorability" of online reviews which contains two layers of meaning: the objective information and the affect expressed therein (Babić Rosario, Sotgiu, De Valck, & Bijmolt, 2016). Sometimes the sentiment in online reviews is not straightforward and thus requires intelligent language processing techniques to unveil its meaning. For instance, to help customers gain more information from online reviews and make a decision Ullah, Amblee, Kim, and Lee (2016) applied Natural Language Processing technology to study and analyze the emotional content contained in online reviews of a large number of products.

Variance is a less popular metric in the investigation of online reviews. A low variance of online reviews means customers agree that the product is either good or bad, which explains why the influence of online reviews on sales can be either positive or negative (Babić Rosario et al., 2016). A high variance of online reviews indicates a high mismatch cost and affects sales, even though information on customers' preferences towards the product is still available (Sun, 2012).

In sum, online reviews have been studied in various aspects. Regardless of the attributes that are of interest such as volume, valence or variance, understanding the mechanisms that govern product sales and online reviews is very important. Table 1 presents a summary of recent research related to online reviews.

Table 1. Summary of research on online reviews

Article	Data source	Data collection method	Data size	Data analysis method	Key findings
X. Liu, Lee, and Srinivasan (2019)	Major online retailer in the United Kingdom	Site data provider	500,000 reviews of 600 product Home and Garden	Supervised deep learning	Review content has a higher impact on sales when the average rating is higher, ratings variance is lower, the market is more competitive or immature, or brand information is not accessible.
Chen et al. (2011)	Amazon.com	Online search	120 digital cameras	First-difference econometric models	Customers' shopping statistics can help consumers to buy products that are really useful to themselves, and reveal the influence of word of mouth on product sales.
Moe and Trusov (2011)	A national retailer of bath, fragrance and beauty products	Record weekly	500 products	Developed models	The existing rating on the product has an impact on the customer's rating behavior.
Amblee and Bui (2011)	Amazon.com	Online search	133 Amazon Shorts e-books	Regression analysis	The reputation of a product can be presented through electronic word-of-mouth.
Park and Lee (2009)	Undergraduate students	Online survey	440 responses	Regression analysis	The relationship among e-WOM effect, the e-WOM website reputation and information direction can be different beyond different product type.
Yang, Kim, Amblee, & Jeong, (2011)	Korean film council (KOFIC) (2006)	A search engine provided by KOFIC web site	117 movies	OLS and panel data analysis	Consumers prefer products with larger sales or large e-WOM volume.
Sun (2012)	Amazon.com and BN.com	Online search	892 books	DID estimation approach	Previous ratings of product have a significant impact on customers to make purchase-decision.
Salehan & Dan (2016)	Amazon.com website	Crawler software	20 products	Regression analysis	Words containing positive emotions are more likely to be read.
Rosario et al. (2016)	Platforms of products	Wayback machine	1,532 effect sizes	Meta-analysis	There is a significant positive relationship between product sales and e-WOM, but products, platforms or metric factors may lead to another result.
Ullah et al. (2016)	Amazon.com website	A custom software tool	15,849 online reviews	NLP techniques	The emotional content of reviews are different in experience and search goods, but a large number of reviews help customers understand product well.
Y. Liu (2006)	Yahoo Movies Web site	Online search	40 movies 12,136 WOM message	Regression analysis"	WOM information during both a movie's prerelease and opening week, especially the volume, can have a significant impact on box office revenue.
Ha, Bae, and Son (2015)	Online booksellers in Korea	Online search	4,892 online reviews	Regression analysis	Online reviews from personal bloggers have the most significant effect on product sales than other ones by researching the source of online reviews including personal-blogger reviews, seller-blogger and seller-site.
Chong, Li, Ngai, Ch'ng, and Lee (2016)	Amazon.com	Web crawling and scraping	40,000 products	Sentimental and neural network analysis	The interplay effects of online volume, online valence, sentiments and discounts play a more important role on the prediction of sales volume than single variables.
Liang, Li, Yang, and Wang (2015)	IOS app store	Online research	149 apps	Multifacet sentiment analysis	Although consumers' opinions on product quality occupy a larger portion of consumer reviews, their comments on service quality have a stronger unit effect on sales rankings.

2.2 Tags in online reviews

With the increasing volume of reviews, the issue of information overload is inevitable. For example, best-selling products in Amazon commonly contain thousands of reviews (Amazon, 2019). A huge volume of reviews makes it difficult for consumers to obtain relevant and useful decision making information. Therefore, it is rational to extract and organize only core information. The implementation of review tags thus performs a vital function in reducing, summarizing and guiding potential buyers to retrieve and process useful information.

Because the number of reviews generated on the e-commerce sites far exceed the capacity of personal information processing, consumers have to resort to some heuristic rules to simplify the task of reading reviews. For example, potential buyers can judge the reviewer's reputation directly through the volume of online reviews posted and the average rating, without further reading the review text. Buyers can focus on low ratings, high ratings, or recently published reviews, because these reviews are relatively small and have high diagnostic accuracy (Q. Liu, Karahanna, & Watson, 2011).

Generally, information labels have three content requirements: user generated (opinion credibility), majority views (avoid overly biased views), and sufficient semantics to be retained (easy to understand) (Ames & Naaman, 2007). Tag based review summarization is a new feature on e-commerce websites to alleviate the problem of information overload faced by consumers. This features divides the reviews into categories based on product attributes (such as screen, battery, call quality), or user experience (such as novel style, good quality, beautiful appearance), and gives each class a label. In addition to tag names, labels usually mark instances (review bars) and tag polarity (corresponding merits or demerits), and display relevant reviews when the user clicks on the tag (Liu Jingfang, 2016).

There are previous studies that name these classified tags as 'aspect tags', namely tags that illustrate what the reviews are commenting on (Kayaalp, 2014; Levi, Mokryn, Diot, & Taft, 2012). Moreover, many researchers have been trying to explore effective methods that can identify aspects that certain reviews focus on. B. Liu (2012) summarizes four approaches to extract aspect tags, namely: (1) extraction based on frequent nouns and noun phrases, (2) extraction by exploiting opinion and target relations, (3) extraction using supervised learning, and (4) extraction using topic modeling.

Yu, Zha, Wang, and Chua (2011) tried to identity important product aspects from online consumer reviews. Important aspects feature two phenomena: (a) a large number of reviews would contain relevant information about the aspects, and (b) other consumers' reviews on important aspects would greatly affect potential customers' purchasing desire. These phenomena support the current study to classify review tags and to find the most influential review tags that can affect customer purchasing behavior, because product aspects that many customers care about most would also be reviewed most. Hence, by finding significant relevance between sales and reviews focusing on different aspects, i.e. assembled by different types of tags, we can also identify which aspects of products are important.

Tags on Tmall's product webpage are the more general form of aspect tags because they are not restricted to specific properties of products. For example, a tag like "the peanut tastes good" focuses on the property of food taste in essence, and the corresponding aspect tag should be "taste". Meanwhile a tag like "Seller is patient" shows the quality of service offered by the seller, so the corresponding aspect tag would be "service". Therefore, we chose to aggregate tags from Tmall into aspect tags according to the product properties that tags are focusing on. Our work is simplified by Tmall's existing tag mechanism, since we do not need to extract aspect tags directly from review text.

2.3 Analyzing review effects

Research has adopted various methods and models to explore the relationship between review volumes and sales. W. Duan et al. (2008) used a simultaneous equation system to explore the relationship between movies' box office revenue and online reviews. The findings showed that while higher average ratings do not lead to higher movie sales, the greater number and generating speed of review posts do. Moreover Clemons, Gao, and Hitt (2006) used multivariate linear regression and reached a similar conclusion when focusing on online reviews' effects on beer sales.

Dewan and Ramprasad (2009) performed both Granger causality estimates and two-stage least squares on album sales and reviews data to solve the potential problem of endogeneity. The regression results also indicate the important role of review volume's contribution to higher sales. All researchers above have adopted difference of review quantity to show significant influence on sales. Therefore, we also adopt difference of review quantity for our explanatory variables, while the distinction is that we assemble these reviews using classified tags.

When data consists of weekly repetitive observations, i.e. longitudinal data which are collected on a regular basis from the same group of research objects, where observations are correlated with each other for the same object but independent between different objects, the generalized estimating equation (GEE) would be a good method. The GEE approach is an extension of generalized linear models designed to handle categorical repeated measurements arising from within-subject designs. GEE also relaxes the restriction on distribution of dependent variables and offers robust parameter estimates compared with other similar models (Ziegler, 2003). Furthermore, the interpretation of GEE results is identical to that for commonly used models for uncorrelated data (e.g., logit and probit) (Zorn, 2001).

The adoption of the GEE method to analyze online review data has been limited. This is probably due to the fact that most studies used only cross-sectional data. Nevertheless, a few successful examples provide guidelines for using GEE in e-commerce. For example, Senecal and Nantel (2004) adopted the GEE method to investigate consumers' usage of online recommendation sources and their influence on online product choices. Their results successfully indicate that subjects who consulted product recommendations selected recommended products twice as often as subjects who did not consult recommendations. Sodero, Rabinovich, Aydinliyim, and Pangburn (2017) used the GEE method which addresses the inherent endogeneity among the variables to establish links between inventory, prices, and sales empirically, using a large data set comprising a wide array of products sold on Amazon.com.

3. METHODOLOGY

3.1 Data collection

Tmall is a well-known B2C e-commerce platform in China established by Alibaba Corporation in 2012. It has become one of the most popular online shopping websites in China. On 11 November 2019, Tmall made a sales record of 268.4 billion RMB in a single day (Tmall, 2019). In Tmall, commodities with enough reviews would have tags displayed on the corresponding web page which would appear automatically as a key feature offered by Tmall.

A Java crawler program was developed to collect all the needed information on snacks available for sale on Bestore's official website on Tmall. Our data includes all available properties of snacks and tags. In addition, Tmall displays only monthly moving sales data of products, i.e. cumulative sales from 30 days ago to now, and we collected sales data weekly in order to compute sales differences between weeks. Our collection started on 18 June 2018, and we collected the same data on Sundays. In total we collected 8 weeks' (T_1-T_8) data containing 234 different products' sales data and 734 unique tags. The 234 food products collected for the analysis were classified into 9 snack types according to Bestore's official classification of their products. Table 2 depicts the product classification statistics.

Table 2. Product classifications

Ordinal	Type	Explanation	Examples	Quantity
1	坚果炒货	Roasted seeds and nuts	熟花生米，夏威夷果，巴旦木	44
2	肉类熟食	Meat and cooked food	牛肉丝，小香肠，鸭脖子	48
3	果脯蜜饯	Preserved fruit	山楂球，红枣片，黄桃干	53
4	甜心糕点	Cake and pastry	沙琪玛，麻花，肉松饼	16
5	饼干膨化	Cookies and puffed food	薯条，薯片，锅巴	13
6	糖果布丁	Candy and pudding	棒棒糖，巧克力，果冻	12
7	山珍素食	Vegetarian diet	金针菇，水果茶，乌龙茶	3
8	海味河鲜	Seafood and fish, shrimps etc. from rivers.	海带丝，鱿鱼丝，小黄鱼干	35
9	良品礼盒	Gift box (several types of products packaged together)	果冻礼包，干果坚果炒货组合，饼干组合	10

3.2 Data Preprocessing

3.2.1 Tag formulation

In Tmall, tags with different names are classified according to their semantic meanings and different products contain certain variations of tags. In total, 734 tags were collected and were re-classified into 9 categories as listed in Table 3. We defined the following parameters to facilitate tag analysis:

Tag_{p,i,t_n} is the total number of tag category i at time n of product p.

$\Delta Tag_{p,i,t_{n+1}} = Tag_{p,i,t_{n+1}} - Tag_{p,i,t_n}$ is the first difference of the total number of tag category i of product p at time n+1 minus the total number of tag category i of product p at time n.

$\Delta Log(Tag)_{p,i,t_{n+1}} = \log(1+\Delta(Tag)_{p,i,t_{n+1}})$ if $\Delta(Tag)_{p,i,t_{n+1}} > 1$ or $\Delta Log(Tag)_{p,i,t_{n+1}} = \log(1-\Delta(Tag)_{p,i,t_{n+1}})$ if $\Delta(Tag)_{p,i,t_{n+1}} < 1$ is the natural logarithm of the first difference of the total number of tag category i at time n + 1 minus the total number of tag category i at time n.

The difference parameter $\Delta Log(Tag)_{p,i,,t_{n+1}}$ allowed us to associate the incremental increase (decrease) of the total number of tags with the incremental increase (decrease) in sales from time n to time n + 1.

Table 3. Tag Classifications

Ordinal	Tag Names	Explanation	Examples	Quantity
1	Food Taste	Taste of food (flavor, texture of food)	蛋糕很好吃；虾干好吃；味道好	503
2	Food Quality	Freshness, sanitation, look (size, shape, color)	分量够；干净；质量不错	130
3	Packaging	Packaging of food	包装很好；包装不错；	8
4	Delivery Service	The quality of delivery service (e.g. Slow or fast)	发货快；邮费便宜；快递不错	7
5	Food Smell	Smell of food (e.g. Fragrant or unpleasant)	气味不错	13
6	Food Price	Price of food (e.g. Cheap or expensive)	便宜；划算；实惠	11
7	Customer Service	Quality of service offered after purchasing	服务好；态度不错	6
8	Purchase Influence	Influence on buyer's surrounding people (e.g. buyer's friends praise the product)	人群	1
9	Emotion	Personal likes and dislikes for products (e.g. a buyer writes 'I love it very much'.)	超爱鸭舌；喜欢草莓干；鱼嘴大赞	55

3.2.2 Sales formulation

To analyze tags' effect on sales, we defined product sales parameters to be used in the GEE model.

$G_{p,t_{n+1}} = \frac{Sales_{p,t_{n+1}} - Sales_{p,t_n}}{Sales_{p,t_n}} \times 100\%$ is the normalized sale growth rate of product p at time n + 1.

$D_{p,t_{n+1}} = \frac{Current\ Product\ Price_{p,t_{n+1}}}{Original\ Product\ Price_{p,t_n}} \times 100\%$ is the normalized Chinese discount rate (打折) of product p at time n + 1.

$P_{p,t_n} = Price_{p,t_n}$ is the price of product p at time n.

3.2.3 Model formulation

We formulated two estimation models with GEE to answer the research questions. In the first model the dependent variable is $G_{p,t_{n+1}}$ because we wanted to validate the relationship between the incremental difference (increase) in the number of tags and the incremental difference (increase) in sales for the current time (see equation 1). For the second model the dependent variable is $G_{p,t_{n+2}}$ since we wanted to verify the incremental difference (increase) in the number the number of tags which could provide nowcasting to predict the next immediate future period of increment difference (increase) of product sales (see equation 2). The two models' equations are described below.

$$G_{p,i,t_{n+1}} = \sum_{tag=\mathrm{i}}^{j} \beta_i * \Delta Log(Tag)_{p,i,t_{n+1}} + \alpha * P_{p,t_{n+1}} + \delta * D_{p,t_{n+1}} + \varepsilon \tag{1}$$

and,

$$G_{p,i,t_{n+2}} = \sum_{tag=\mathrm{i}}^{j} \beta_i * \Delta Log(Tag)_{p,i,t_{n+1}} + \alpha * P_{p,t_n+1} + \delta * D_{p,t_n+1} + \varepsilon \tag{2}$$

We then performed GEE with SPSS by transforming the data set into a panel data format.

4. RESULTS

4.1 Correlation Analysis

To answer RQ1 and RQ2, we performed a correlation analysis to ascertain the discriminate strength of the review tags and their association with product sales, price and discount rate using differences model parameters. Table 4 depicts the descriptive statistics of the means, standard deviations, correlation coefficients and significance levels among the variables. For the investigation period, most of the products' sales are declining on a moving average basis and are offering huge discounts to attract sales. Overall the mixtures of products contain high variation in price, discount rate and overall sales.

4.2 Current tag to estimate immediate sale

To answer RQ3, we validated the relationship between differential tag changes from time n to time n + 1 and differential sales changes for the corresponding time from n to n + 1. We performed GEE with $G_{p,i,t_{n+1}}$ as the dependent variable and $\Delta Log(Tag)_{p,i,t_{n+1}}$ with positive review tags as the independent variables. We obtained the results shown in Table 5.

The results show that among all the positive review tags, Food Taste, Food Quality, Packaging, Delivery Service, Food Price and Emotion are all significant with $p < .05$ and all β estimates are positive. Purchase influence is significant at $p < .1$ only. Interestingly Price, Food Smell and Customer Service are not significant

Table 4. Descriptive statistics and Correlation matrix for the variables

Parameters	Min	Max	M	SD	1	2	3	4	5	6	7	8	9	10	11	12
Price	1.00	135.00	26.80	15.16												
Discount	0.00	0.88	0.44	0.15	-.245**											
Sales(N+1)-Sales(N)	-107788	42032	-443.36	4584.28	0.014	-0.007										
(Sales(N+1)-Sales(N))/Sales(N)*100	-64.04	158.24	-3.18	17.10	0.010	-.117**	.386**									
Food Taste	-8.48	8.55	-0.48	2.78	-0.041	-.093**	.119**	.217**								
Food Quality	-7.90	7.71	-0.62	2.26	-.103**	-0.041	.240**	.222**	.206**							
Packaging	-5.95	6.39	-0.28	1.23	0.029	-.079**	.077**	.139**	.221**	.198**						
Delivery Service	-6.65	5.95	-0.49	2.01	-.090**	-.085**	.272**	.287**	.548**	.559**	.285**					
Food Smell	-5.25	3.99	-0.17	0.90	-0.006	-0.022	.075**	.075**	.148**	.208**	0.016	.278**				
Food Price	-6.76	6.81	-0.16	1.89	-.105**	-0.006	.241**	.230**	.440**	.469**	-0.012	.588**	.308**			
Customer Service	-7.06	7.06	-0.13	1.38	0.031	-.054*	0.011	.059*	.166**	.162**	-.112**	.222**	0.044	0.042		
Purchase Influence	-5.68	4.86	-0.35	1.45	-0.041	-.081**	.276**	.255**	.467**	.483**	.246**	.647**	.244**	.510**	.179**	
Emotion	-8.55	8.55	0.01	1.17	0.007	0.030	.095**	0.021	-.353**	-0.004	-0.019	-0.009	-0.021	0.026	-0.027	-0.005

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

in estimating current growth of sales. However, food smell and customer service are positively correlated with growth of sales with a small effect size of r = .075 and r = .059 respectively of p < .01. Notice that price has no effect in predicting growth of sales while offering a huge discount improves sales growth which is typical for snack products. Price promotion indicates that products with high price are being offered at huge discounts (1-Chinese discount rate).

4.3 Current tag to nowcasting next period sales

To answer RQ4, we validated the relationship between differential tag changes from time n to time n + 1 and differential sales changes for the corresponding time from n to n + 1. We performed GEE with $G_{p,i,t_{n+2}}$ as the dependent variable and $\Delta Log(Tag)_{p,i,t_{n+1}}$ of positive review tags as the independent variables. We obtained the results shown in Table 6.

From the results, *Food Taste* and *Delivery Service* are the only two review tags that are significant with *p* < .01 to predict the growth of sales for the next immediate period. *Purchase Influence* and *Emotion* were significant at *p* < .1. This shows that these tags are valuable predictors for nowcasting to the next immediate period. Other tags are not so useful to predict sales in more distant periods, suggesting that the snack product properties are dynamic in Tmall.

5. DISCUSSION

Our investigation demonstrates that the tag mechanism in Tmall is actually playing a role in affecting food product sales on the e-commerce platform. Specifically, positive tags contribute to product sales, and tags of different types (aspect tags) individually have different weights in promoting sales respectively. In addition, some tags are more capable of serving as predictors for future product sales.

Our research fills in the gap of exploring the effect of the tag mechanism on product sales. The only existing research on Tmall tags was done by Liu Jingfang (2016), investigating the impact of tag-based review summarization on experience products and searched products in terms of perceived usefulness and system satisfaction but not for predicting sales. Our research suggests tags' positive effect on promoting product sales, while Liu's work focused on the improvement of customer's feelings in the purchasing process.

Our research pays more attention to the relevant relationship between tags and sales, and further to different effects of each aspect tag. Reading reviews to learn more about a product before purchase is essential for most buyers. However having thousands of reviews to browse will incur physical search cost and cognitive search cost (Q. Liu et al., 2011). Tags are essentially a mechanism that provides key phrase summarization of customer reviews that offer personal sentiment and judgment on products' properties. In this way, the tag mechanism serves as a way to overcome the customer's search cost of finding those reviews relevant to their favored product property and helps them to make faster decisions. Yatani, Novati, Trusty, and Truong (2011) study concluded that a system offering brief overviews of many reviews can accelerate the customer's decision process. Hence the tag mechanism in e-commerce sites is highly recommended.

Our findings also provide indirect evidence that there is a significant positive correlation between review volume and product sales, since essentially the difference changes in the aspect tag reviews parameter reflects volume change of certain types of reviews. This phenomenon can be explained by two theories. One is the uncertainty elimination effect. According to Chen et al. (2011) a greater volume of reviews reduce the customer's uncertainty about product properties and contribute to their purchase decision. In our case, the aspect tags provide easy access to better eliminate customer uncertainty about their most important product property, therefore leading to an increase in sales. The other theory is the awareness effect. A greater volume of reviews diffuses the existence of a product more easily, and thereby makes more people see the product and choose to purchase it (W. Duan et al., 2008).

The aspect tags that are significant in the current study are viewed as salient features in promoting product sales from the buyer's perspective. A possible explanation may be attributed to the nature of food features and the desired expectations from customers. Respectively, it is intuitive that *Food Taste* and *Food Quality* are both important criteria for customers, since a food product's core features are its taste and quality. These features include not only flavor and texture, but hygiene and freshness which would greatly influence people's desire to eat food, and especially for snacks which people consume more for their appealing taste rather than staple foods for satisfying hunger. On the other hand *Packaging, Delivery Service and Food Price* are essential decision factors not limited to food products that have a direct impact on sales. Packaging refers to the physical appearance of a product when a consumer sees it. Packaging designs can increase consumer intention to purchase (Schnurr, 2019). Delivery service refers to time spent on delivery and the condition of a product during the process of delivery. For food products, high quality and efficient delivery services are a key factor in consumer satisfaction (Suhartanto, Dean, Leo, & Triyuni, 2019). *Food Price* generally consists of customer opinions on whether the product provides value for money, which is certainly affecting their purchasing decision while assessing products (Buch-Andersen, Andreasen, Jørgensen, Ehlers, & Toft, 2019).

6. CONCLUSION AND FUTURE RESEARCH

In this paper, we explored the relationship between review tags, a mechanism to collect reviews with similar key content phrases and display them to customers, and the sales of products. Using real data from Chinese e-commerce platform Tmall and snack seller Bestore, we obtained specific insight into snack product sales mechanisms. To validate whether review tags of different semantic expressions would affect sales differently, we classified all review tags according to their meaning into 9 types. We performed GEE on our repeated observations of a longitudinal data set of review tags and sales volume, because GEE provides good robust parameter estimates. The results show that review tags concerning food taste, food quality, packaging, delivery service, food price and emotion would have a significant impact on sales. The result implies that customers pay considerable attention to these product properties when deciding whether to purchase in the immediate time frame. The second result indicates that review tags concerning food taste and delivery service are good predictors for a sales nowcasting model, which may help improve sales performance. Hence, our findings also offer real evidence for e-commerce platforms (e.g. Amazon, eBay) that do not have similar review tag mechanisms to consider implementing such features as they are useful in generating sales and contribute to reliable forecasting.

The current study is not without limitations. First, our classification of review tags are novel so require further validation and to establish standards and criteria as there has been little previous relevant work that we can compare with. Although our classification produces meaningful results, it would be also more reliable for later research to produce standardization across different product types other than snacks. Second, while we focused our analysis on 264 Bestore snack products, there are some mainstream varieties of snacks that Bestore does not sell, for example chocolate. Hence, our conclusions can only be generalized to similar snack ranges unless further analysis can be performed on a wider variety of snack products.

Although we obtained meaningful results about which types of review tags would influence sales, future research could explore how to design corresponding algorithms and visualizations to persuade potential online buyers to purchase the products. Future research can also look into designing interaction log experiments with real people from actual purchases to test different tag algorithms and visualizations. In addition, it seems very promising to try incorporating review tags as factors into sales prediction models, since our work implies their potential power as predictors. Apart from this, since reviews collected by review tags are the core elements that are making a difference, this offers great motivation for later research to add more review' features to prediction models.

Table 5. Parameter estimates of current sales

Parameters	B	SE	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald χ^2	Sig.
(Intercept)	2.09	2.03	-1.88	6.06	1.06	0.30
Price	0.02	0.03	-0.04	0.08	0.42	0.52
Discount	-9.72	3.38	-16.35	-3.08	8.25	.004***
FoodTaste	0.56	0.20	0.17	0.95	7.87	.005***
FoodQuality	0.58	0.22	0.16	1.01	7.24	.007***
Packaging	0.79	0.39	0.03	1.54	4.15	.042**
DeliveryService	0.83	0.31	0.22	1.44	7.03	.008***
FoodSmell	-0.38	0.48	-1.31	0.55	0.65	0.42
FoodPrice	0.66	0.29	0.08	1.23	4.95	.026**
CustomerService	0.00	0.31	-0.62	0.62	0.00	0.99
PurchaseInfluence	0.71	0.37	-0.02	1.45	3.61	.058*
Emotion	0.81	0.34	0.14	1.48	5.56	.018**
(Scale)	260.55					

***, **, and * Mean difference is significant at the ≤.01, ≤.05, and ≤.1 levels, respectively.

Table 6: Parameter estimates for nowcasting sales

Parameter	B	SE	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald χ2	Sig.
(Intercept)	-2.01	1.93	-5.80	1.78	1.08	0.30
Price	-0.02	0.03	-0.09	0.05	0.33	0.56
Discount	-1.62	3.34	-8.17	4.93	0.24	0.63
FoodTaste	0.57	0.20	0.18	0.96	8.11	.004***
FoodQuality	0.11	0.23	-0.35	0.56	0.21	0.64
Packaging	0.50	0.39	-0.26	1.26	1.66	0.20
DeliveryService	1.33	0.32	0.70	1.96	17.02	.000***
FoodSmell	-0.71	0.49	-1.67	0.26	2.04	0.15
FoodPrice	0.00	0.28	-0.55	0.55	0.00	0.99
CustomerService	0.33	0.33	-0.32	0.98	1.01	0.31
PurchaseInfluence	0.81	0.42	-0.01	1.63	3.77	.052*
Emotion	0.72	0.39	-0.04	1.48	3.47	.062*
(Scale)	255.58					

***, **, and * Mean difference is significant at the ≤.01, ≤.05, and ≤.1 levels, respectively.

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