How Digital Content Marketing of E-commerce Retailers Influence Their Sales Performance? An Empirical Study from the Integrated Marketing Perspective

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Abstract: As an emerging marketing tool of e-commerce platforms, digital content marketing (DCM) has been favored by many retailers. It is unclear how e-retailers combine DCM with traditional marketing tools (e.g., price promotion and display advertising) to improve their sales performance. This paper builds a research model from the integrated marketing perspective to explore this question. With a panel dataset of 36 women's clothing stores on Taobao platform, this study combined machine learning with economic model to test the research model. The empirical results show that the information richness of e-retailers' DCM positively influence their sales performance. More interesting, the interaction between DCM information richness and price promotion negatively impacts the sales performance of high-reputation e-retailers, while the interaction between DCM information richness and display advertising positively impacts the sales performance of high-reputation e-retailers. Finally, the theoretical and practical implications are discussed.

Keywords: integrated marketing communications, enterprise-generated content, e-retailer reputation

1. INTRODUCTION

In recent years, with the increasingly fierce competition among e-commerce retailers, the traditional marketing methods such as price promotions and diaplay advertising have been unable to meet the needs of retailers for customer traffic. Currently most of e-commerce platforms are providing digital content marketing tools for retailers to attract customers. For example, Taobao.com launched Weitao sub-platform for its retailers to perform content marketing. As a new marketing method, content marketing is very different from traditional marketing methods in terms of cost input, user experience, and marketing effects.

When facing new content marketing tools and various traditional marketing tools, a big problem for e-commerce retailers, especially C2C small and medium-sized e-retailers with limited marketing resources, is that how to execute their digital marketing strategies. Integrating different marketing tools can be produce maximize profits for e-retailers. There are few academic studies on the integration of different marketing tools for e-commerce retailers. It is also unclear about the impact of digital content marketing on firms' sales performance.

This research aims to explore how e-commerce retailers integrate digital content marketing with traditional marketing tools (i.e., price promotion and display advertising) to improve their sales performance. The main research contents of this paper are: (1) how digital content marketing of e-commerce retailers impact their sales performance; (2) Whether there is an interactive effect among the three marketing tools of digital content marketing, price promotion and display advertising to influence sales performance.

2. LITERATURE REVIEW AND THEORETICAL FOUNDATION

2.1 Literature review about digital content marketing studies

Digital content marketing (DCM) refers to the marketing communication strategies in which enterprises

communicate valuable content through pictures, text, video, live broadcast and other media to stimulate beneficial customer interaction[1]. Current DCM studies focus on enterprise-generated content (DCM) in the context of social media platforms. DCM is a textual description of products and services of e-retailers online on e-commerce platforms, and it is a reliable information that can alleviate consumer uncertainty. Therefore, DCM has gradually become a new channel for communication between enterprises and consumers.

The existing literature on DCM in the field of marketing mainly focuses on the following three aspects [2]: (1) Content strategy: companies can publish various forms of marketing content on social media, but different content will produce different effects. Yan Xing and Chang Yaping[3] divided corporate Weibo content into two categories: task-oriented and social, and explored the mechanism of different types of content triggering user comments. (2) The impact of DCM on consumers' behavioral feelings: Enterprises explore and meet consumers' psychological needs through the interaction of DCM with consumers. Some scholars explore the influence of users on brand cognition or behavioral willingness based on the theory of user perception. For example, Pentina et al.[4] studied the influence of information in Facebook and Twitter on consumers' personal shopping preferences. (3) The impact of DCM on enterprise performance: Content marketing published by enterprises on social media can gain user recognition at a lower cost, and even affect economic benefits. Duboff and Wilkerson[5] proposed to measure the marketing effectiveness of social media by calculating ROI. The above literature review on corporate content marketing shows that the existing literature focuses on the direct impact of DCM in the context of social media, and few studies explore the integration of content marketing and other marketing methods.

2.2 Theoretical foundation

When a firm faces multiple marketing resources with limited marketing costs, it is crucial to evaluate the relative effectiveness of marketing resources and determine the best combination strategy to achieve better sales performance. The concept of "Integrated Marketing Communication (IMC)" was first proposed by Schultz[6], which believes that companies should try to coordinate and control multiple marketing methods to generate more customer-centric information.

Previous integrated marketing communications research has focused on the effects of integration between traditional media and between traditional and online media on users' brand perceptions and firms' sales performance. For example, Chang and Thorson[7] found that TV network ad integration had a greater impact than ads from a single source (TV or web). However, as e-commerce platforms begin to expand their functions by integrating social media modules, scholars have begun to incorporate social media into the study of integrated marketing communications. However, the current study only focuses on the effect of user-generated content of social media on the user behavior of the platform. For example, Hang et al.[8] found that the integration of social media (Facebook) with online review platforms (Yelp.com and TripAdvisor.com) can increase the number of user online reviews and reduce the number of negative reviews. However, such user-generated content is beyond the control of e-retailers, so the existing literature lacks a e-retailer-oriented research perspective, so it cannot provide direct guidance for e-retailers' marketing decisions. At the same time, most of the existing integrated marketing research is aimed at a certain type of enterprise, and the integration effect produced by different enterprises is inconsistent even if they use the same marketing mix, and the existing literature rarely considers the influence of the characteristics of the research individual on the integration effect.

3. RESEARCH MODEL AND HYPOTHESIS
3.1 Research model

Due to the problem of information asymmetry in the transaction activities in the context of e-commerce platforms, in order to reduce the information asymmetry between the two sides of the transaction, the e-retailers

will carry out various forms of marketing activities to transmit the potential quality information of the products to consumers, so as to reduce the information asymmetry between the two sides of the transaction, reduce uncertainty in consumer purchasing decisions and facilitate smooth transactions. Therefore, this paper establishes an integrated model of the marketing methods of e-commerce platforms to explore the integrated marketing effects of different marketing methods.
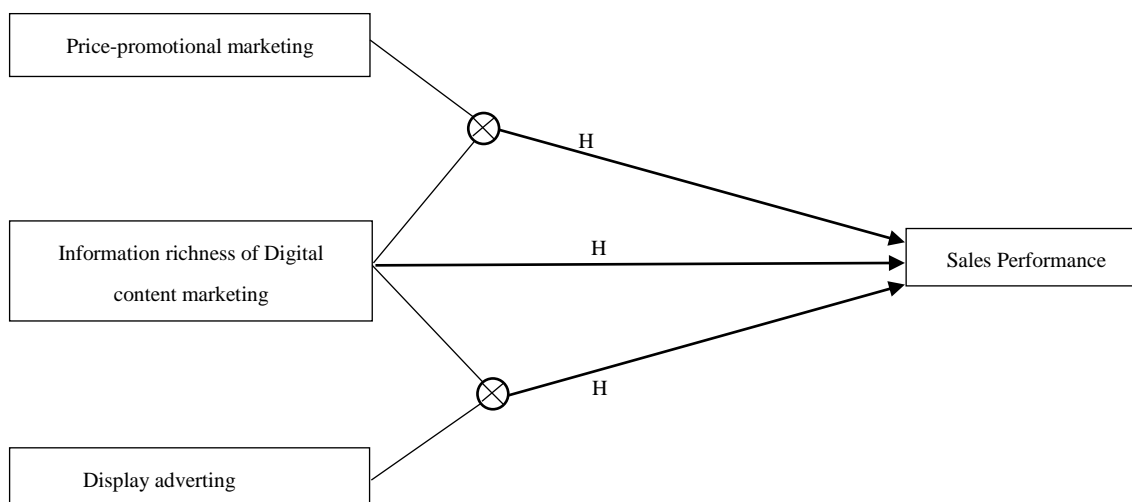

Figure 1. Research model

Table 1. The definitions of research variables

Variable	Definition	Reference
Information richness of digital Content Marketing	The amount of information contained in the digital content published by an e-retailer on its official community account of the e-commerce platform.	Kumar et al.[9]、 Goh et al.[10]
Price-promotional marketing	The number of times that an e-retailer performs promotional activities at a price lower than the normal sales price of the product in a fixed sales cycle.	Kotler et al.[11]、 Alba et al.[12]
Display advertising	The number of diaplay advertising spaces placed by an e-retailer on the platform.	Aiken and Boush[13]、 Feiyu Zhao[14]
Sales Performance	The number of products sold by an e-retailer in a fixed sales cycle reflects the economic effect that the e-retailer obtains.	Kumar et al.[17]

3.2 Research hypothesis

E-retailers need to spend time and effort to write the text description of the product. If there is a big deviation between the text description and the actual product, the e-retailer needs to bear the risk of false description. Therefore, DCM, as a text description of an online product, is considered to be reliable information that can help buyers to alleviate uncertainty about products and e-retailers, thereby increasing purchasing confidence. Angelika et al.[18] found that compared with the standardized product form on product pages, DCM is more flexible and richer, and can further reflect the e-retailer's personality and product characteristics. At the same time, the richer the information contained in DCM, the lower the uncertainty and decision-making risk perceived by users. When the information of DCM is richer, it can better satisfy users' preferences for different types of information to enhance emotional identity and improve their purchasing decisions.

H1. *The more information richness of DCM, the higher sales performance e-retailers obtain.*

The multi-source perception effect believes that the more information sources, the greater the perceived reliability of consumers. However, Li et al.[19] argue that consumers' multiple touchpoints may distract consumers, resulting in a decline in revenue within each channel. Su[20] pointed out that although price and objective product information are the main influencing factors for consumers to decide to purchase, the increase

of objective product information will lead to an increase in retailers' value expectations, thereby reducing consumers' choice of low-priced retailers. Therefore, when consumers are exposed to these two kinds of information at the same time, the existence of rich DCM may make consumers abandon price promotions, resulting in a decrease in the investment income.

H2.   There is a negative interaction effect between the information richness of DCM and price promotion (i.e., substitution effect) on e-retailers' sales performance.

DCM can help consumers alleviate uncertainty about products and e-retailers. On the e-commerce platform, consumers will decide whether to click on diaplay advertising links based on the detailed information about the e-retailer's products or services provided by DCM to consumers. Therefore, when consumers are exposed to both DCM and paid advertisements, according to the multi-source perception effect, when the information released by e-retailers on social media is sufficient and positive, the quality signal attribute of paid advertisements is strengthened. Therefore, DCM can enhance the impact of diaplay advertising on the sales performance of e-retailers.

H3.   There is a positive interaction effect between the information richness of DCM and display advertising (i.e., complementary effect) on e-retailers' sales performance.

4.   METHODOLOGY

4.1 Research samples and data collection

As a small and medium-sized C2C store, women's clothing stores on Taobao's platform have relatively limited marketing resources, and it is necessary to conduct marketing integration to reduce their operating costs. At the same time, because women's clothing stores are experiential products, consumers cannot accurately judge the quality of products due to lack of pre-order experience and need to rely on external product information. Therefore, e-retailers pay more attention to the use of platform marketing tools to promote consumers' understanding of products. The relevant data will be richer. Based on this, this article chooses it as the research object.

This article uses crawlers to obtain a total of 31,126 Weitao tweets from 36 women's clothing stores on Taobao platform from January 1, 2018 to April 30, 2018, including: release time, tweet content, number of views, number of likes, the number of comments and other information. And obtain the operation data of the research sample stores in the corresponding time period from the third-party statistical platform (Tao Data), including: daily sales, dynamic sales rate, through train (paid keywords), diamond booth, price promotion, store launch time, DRS Rating and other information. The final study sample dataset contains marketing mix and sales data (in one day) of a total of 36 e-retailers from January 1, 2018 to April 30, 2018. The dataset has a total of 4320 records.

Among the data obtained, the DRS score intuitively reflects the past buyer's evaluation of the seller's products and services, and is an important indicator of the e-retailer's reputation. According to the DRS score, this paper divides the sample data into "high reputation" and "low reputation" e-retailers for separate research.

4.2 Measurement

Topic distribution of content published by e-retailers: At present, there have been researches on applying machine learning and natural language processing technology to data processing of social media. We use the LDA algorithm provided in the Gensim toolkit to perform topic modeling to obtain the topic distribution of content published by e-retailers. Using perplexity and the elbow rule, the optimal number of topics was determined to be 15, and after 500 iterations, the topic word distribution was generated after training. The measurement methods of all variables are shown in Table 2:

Table 2.   Variable measurement

Variable	Measurement	Reference
Dependent Variable		
Sales Performance($Sale_{it}$)	The total number of products sold by shop i on day t	Kumar et al.[17]
Independent Variable		
Information richness of digital content marketing (DCM_{it})	The Hirschmann-Herfindahl Index (HHI) is used to calculate the topic richness. $$DCM_k=1-\sum_{k=1}^{n} P_K*P_K \qquad (1)$$ The closer the value is to 1, the richer the topic, where P_k is the probability distribution of the k-th topic in the tweet content.	Ordenes et al.[21][22]
Price Promotion ($PRICE_{it}$)	The sum of the number of products that shop i participated in a series of price promotions on Taobao on day t	Alba et al.[12]
Display Advertising (AD_{it})	The number of all paid ad slots placed by shop i on day t	Lu et al.[23]
Regulated Variable		
E-retailer Reputation(DRS_{it})	Dummy variable, the DRS score of shop i is higher than the industry average of 1, and lower than the industry average of 0	Huifang Li[16]
Control Variable		
E-retailer Scale(PD_{it})	The sum of the quantity of all product categories (spu) in shop i on the t day	Lu et al.[23]
E-retailer Experience(EXP_{it})	The difference between shop i on day t and the time it went online	Kumar et al.[17]

5.   DATA ANALYSIS AND RESULTS

5.1 Descriptive statistics and correlation analysis

This article uses STATA 14.0 statistical analysis software to perform descriptive statistics and correlation analysis on the variable data of the sample, as shown in Table 3. The correlation results show that information richness of digital content, price promotion, display advertising, e-retailer reputation, e-retailer scale, e-retailer experience all have different degrees of significant correlation with sales performance.

Table 3.   Variable measurement

Variables	Obs	Mean	S.D.	Min	Max	1	2	3	4	5	6	7
1.Sales	4320	7404.861	15301.43	3	285271	1						
2.DCM	4320	0.7237	0.0413	0	0.8501	0.037**	1					
3.PRICE	4320	3.2408	15.2748	0	239	0.095***	0.033	1				
4.AD	4320	484.7953	844.1656	0	6718	0.335***	-0.045**	-0.041**	1			
5.PD	4320	589.0754	444.5803	7	2892	0.509***	0.032**	0.001	0.411**	1		
6.EXP	4320	2897.141	903.4075	860	4444	-0.257***	0.015	0.078**	-0.202	-0.359*	1	
7.DRS	4320	0.4595	0.4984	0	1	-0.205***	0.017	0.035*	-0.157**	-0.291*	0.280	1

5.2 Econometric model analysis

The sample data of this study belongs to the long panel data and contains both cross-section and time dimensions. Therefore, the fixed effect test was first carried out. The results showed that only individual fixed effects exist. Therefore, individual dummy variables are added to the model to control individual heterogeneity. Before the model calculation, in order to detect the multicollinearity between the variables, the variance inflation factor test (Variance Inflation Factors, VIFs) was performed. The results showed that the average value of the variance inflation factor of each variable of each model did not exceed 2, which was much smaller than The recommended value of 10 indicates that the parameters are unlikely to be affected by multicollinearity[24]. At the same time, the perturbation items of the data were tested and found that there were heteroscedasticity between groups, autocorrelation within groups, and simultaneous correlation between groups. To solve this problem, this paper uses the least squares method (OLS-PCSE) calibration model with panel calibration standard errors, and allows each panel to have its own autoregressive coefficient.

5.3 Data analysis results

This study used stepwise hierarchical regression to test the research hypotheses. To avoid the multicollinearity problem, all variables included in the interaction term are centrally processed before doing the interaction effect. First, perform regression on all sample data, and the regression results are shown in the following table:

Table 4. Regression analysis results

Variable	Sales Performance					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
DRS	5.117	3.478	1.545	3.485	1.55	1.409
EXP	6.249	1.169	1.039	1.172	1.048	0.86
PD	0.731***	0.599***	0.596***	0.599***	0.596***	0.224***
DCM		0.037***	0.037***	0.038***	0.038***	0.039***
PRICE		0.225***	0.227***	0.225***	0.227***	0.224***
AD		0.199***	0.199***	0.200***	0.200***	0.200***
DCM*PRICE			-0.019*		-0.019*	-0.022**
DCM*AD				0.002	0.001	0.001
PRICE*AD						-0.016
Intercept	4.531	5.781	5.949	5.776	5.938	6.174
N	4320	4320	4320	4320	4320	4320
R2	0.8081	0.8106	0.8142	0.8103	0.8136	0.8398

Based on the previous regression analysis of all the sample data, according to whether the e-retailer's reputation is higher than the industry average, the sample data is divided into two groups of high reputation and low reputation for regression analysis. The results are shown in Table 5:

Table 5. Supplementary analysis

Variable	Sales Performance											
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	High Reputation	Low Reputation	High Reputatio	Low Reputation	High Reputation	Low Reputation	High Reputation	Low Reputation	High Reputation	Low Reputation	High Reputation	Low Reputation
DRS	1	0	1	0	1	0	1	0	1	0	1	0
EXP	4.566	1.338	2.798	0.522	2.731	0.234	2.935	0.599	2.596	0.584	2.551	1.038
PD	0.372***	0.767***	0.325***	0.641***	0.322***	0.636***	0.333***	0.645***	0.328***	0.642***	0.331***	0.530***
DCM			0.032***	0.043***	0.036***	0.042***	0.043***	0.044***	0.047***	0.042***	0.046***	0.012*
PRICE			0.241***	0.206***	0.244***	0.207***	0.240***	0.206***	0.243***	0.207***	0.249***	0.134***
AD			0.248***	0.159***	0.247***	0.159***	0.237***	0.158***	0.237***	0.158***	0.243***	0.097***
DCM*PRICE					-0.027**	-0.009			-0.028**	-0.011	-0.029**	-0.007
DCM*AD							0.020**	-0.025**	0.020**	-0.026**	0.020**	-0.015**
PRICE*AD											0.025	-0.061
Intercept	2.734	5.755	3.483	6.622	3.866	6.634	3.281	6.522	3.718	6.854	3.776	6.134
N	2040	2280	2040	2280	2040	2280	2040	2280	2040	2280	2040	2280
R²	0.6605	0.8308	0.6806	0.868	0.701	0.8681	0.707	0.87	0.7132	0.8702	0.7137	0.892

Note:*p<0.1;**p<0.05;***p<0.01

Through the above supplementary analysis of the sample data, it can be found that for e-retailers with different reputation levels, the interaction of different marketing methods has significantly different effects on

sales performance. Specifically, for high-reputation e-retailers, price promotion will weaken the positive impact of DCM information richness on sales performance (substitution effect), and diaplay advertising will enhance the positive impact of DCM information richness on sales performance (complementary effect), So both assumptions 2 and 3 are true. For e-retailers with low reputation level, the interaction term between DCM information richness and price promotion frequency has no significant effect on sales performance, but there is a significant substitution effect between DCM information richness and diaplay advertising intensity.

Table 6 summarized the results of our research hypothesis.

Table 6.   Summary of research hypotheses

Hypothesis	Hypotheses	Results		
		Total Sample	High Reputation	Low Reputation
H1	The more information richness of DCM, the higher sales performance e-retailers obtain.	Support	Support	Support
H2	There is a negative interaction effect between the information richness of DCM and price promotion (i.e., substitution effect) on e-retailers' sales performance.	Support	Support	Not support
H3	There is a positive interaction effect between the information richness of DCM and display advertising (i.e., complementary effect) on e-retailers' sales performance.	Not support	Support	The reverse is true

5.4 Robustness checks

This article will conduct a robustness test from two aspects. First, in the context of e-commerce online platforms, the impact of the interaction between price promotion and diaplay advertising on sales performance is unknown. Therefore, this study adds the interaction between the two to the model, namely Model 6 to see if it will affect the results of other variables. It can be seen from Table 4 that the magnitude and direction of the coefficients of the original direct impact and interaction estimation results have not changed much, and the significance level remains unchanged. Moreover, the interaction between price promotion and diaplay advertising is not significant for the total sample e-retailers, high-reputation e-retailers, or low-reputation e-retailers.

Secondly, in order to avoid the unstable results caused by the deviation of the sample data estimation method, this research adopts the comprehensive FGLS method to conduct robustness analysis to verify the robustness. The analysis results show that no matter what type of e-retailer, DCM richness, price promotion, and diaplay advertising have a significant positive effect on sales performance $p<0.01$) (significance level is slightly different), and the results of the interaction effect model It is almost the same as the OLS-PCSE estimation result (except for the slightly different significance level).

6.   DISCUSSION AND IMPLICATIONS

The research conclusions of this paper mainly include the following four aspects. First, in the context of e-commerce platforms, the DCM information richness of retailers can significantly improve sales performance Second, for high reputation e-retailers, the interaction between DCM information richness and price promotion frequency has a significantly negative impact on sales performance (i.e., substitution effect). Third, for high reputation e-retailers, the interaction between DCM information richness and display advertising has a significantly positive impact on sales performance (i.e., complementary effect). Fourth, for low reputation e-retailers, the interaction between DCM information richness and display advertising has a significantly negative impact on sales performance (i.e., substitution effect).

The research significance of this article includes the following two aspects. Theoretically, this research reveals the integration mechanism of three different marketing methods in the context of e-commerce platforms,

and expands the empirical research of integrated marketing communication in the context of e-commerce platforms. And put forward feasible ideas to quantify the return on investment of marketing information from the perspective of information theory, and explored the potential impact of individual characteristics of e-retailer reputation on the effect of marketing integration, providing a new research method for follow-up research. In practice: for the current e-commerce platform e-retailers, how to reasonably allocate marketing resources according to their own characteristics, and integrate emerging content marketing methods into the original marketing system, so as to seize a new round of sales growth opportunities. The research conclusions of this paper have certain guiding role.

In addition, this article has some limitations, which still need to be further improved in following research. The sample data source of this article is from women's clothing store that is an experiential product, which does not include other product types, and ignores the impact of product characteristics. Following research can collect more types of e-retailer data for research. Second, in the future, the research method of configuration theory can be further used[25] to explore the combinative effect of multiple factors (more than three) from inside and outside the platform on the sales performance of platform e-retailers.

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