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Video Ads in Digital Marketing and Sales: A Big Data Analytics Using Scrapy Web Crawler Mining Technique

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The survival of the global economy is rooted in the production of goods, rendering of valuable services, and formulation and implementation of favorable trade policies. These goods and services supported by related policies however, must reach prospective customers unblemished in good time, through planned advertisement strategies. Advertisement over the years has evolved from the traditional one-on-one to technology induced ones such as digital marketing and sales. Technological advancement has diversified advertisement into a multi-faceted and dynamic channel with enormous growth and prospects. In this paper, we made a significant effort to identify

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actual online data to justify why short video (SV) adoption is essential in e-commerce and digital marketing. A total of 23589 datasets were drawn from three global B2C and C2C websites using the scrappy web crawlers to investigate a resilience model in the relationship between SV advertising adoption, quality signals, customer satisfaction, price fairness, and sales in digital marketing. Whereas shop location is vital in traditional shopping, logistics service quality overrides its influence in online shopping settings.

Keywords: Scrapy, short video ad, quality signals, big data, logistic service quality, digital marketing.

1. INTRODUCTION

The rapid growth in technological progress and the Internet has led to new ways of e-marketing and online shopping. The number of online shops worldwide has increased, as well as the quantum of online shoppers. [1]. The traditional online advertising synonymous with pop-up, banner, and e-mail advertising has extinct from today's e-commerce. Technological advancement in recent times has diversified advertising into a multi-faceted and dynamic channel with enormous growth and prospects [2]. Currently, the sophistication of online advertising includes search marketing, pay-per-click, pay-per-action, rich media, contextual advertising, geo-targeting, behavioral targeting, social marketing, video advertising, and user-generated online video. Advertising also appears in online games, in-line text, social media, blogs, mobile formats, display advertising, promoted videos, brand Channel, shopping services ads, search ads, and short videos (SVs). SVs, in particular, has dominated many B2B, B2C and C2C e-commerce platforms in recent times (Lai, Lai, & Chiang, 2013). Businesses are leveraging the engaging characteristics of online SV advertising to builds brands and providing 24/7 shopping experiences to customers, which influences consumers' purchasing intends directly [3,4].

Away from text and static pictures, audio-visuals (SV) advertising has brought a shift to online advertising. When consumers watch videos with different appearances of information about the product or brand, they attempt to deepen their impression [5]. Short videos continue to benefit a wide variety of different business functions. Not only is SV the most common in increasing user understanding, but it increases dwell time, sales, traffic and reduces support queries. Consumers continue to value SV content highly as part of their buyer journey. Viewers commonly use video as a starting point to build their knowledge about a product or service. It is also interesting to mention that video acts as a 'tipping point' for an overwhelming majority of consumers as a decisive factor to buy a product or download a piece of software [6]. In general, SVs signal product quality, reduces product uncertainty, and are a perfect extension of electronic word-of-mouth (eWOM). eWOM is a germane remark made by people who intend to purchase, purchasing, or had purchased a product or service. The remarks are readily available to potential customers [7]. Some SV ads include excerpts from actual customers, which are a perfect extension of an eWOM.

Unlike generic video ads, SVs encompass other characteristics such as informational, humorous, and ad length. It is short. Mostly less than a minute. According to Millward & Logic [8] 15-second ads appear to be as strong as 30-second ads for awareness and brand association, while 30-second ads did best at persuasion and conveying emotion, similar to TV ads. SVs are mostly product-specific and maybe entertaining. Ads are memorable when humorous and related to the message [9]. Other studies also found that the more an ad is perceived as entertaining and informative, the more positive the overall rating the ad receives [10]. It implies that the combination of humor and information can positively affect attitude toward the ad and the related product [11].

In measuring service quality, prior research relied on the (service quality) SERVQUAL dimensions. However, SERVQUAL emphasis functional and process dimensions that may not be adequately addressed in content validity. It has also been noted that there are difficulties in implementing SERVQUAL dimensions due to its poor predictive validity [12]. It is, therefore, necessary that actual online data drawn by some machine learning algorithm is engaged to explain this all-important trend of doing business. This study proposed a model establishing the specific importance of short video (SV) adoption as a paradigm shift from text and image advertising and sales. We equally tested the interactive effects of customer service satisfaction, quality signals, and SV and sales, as shown in Fig. 1.

2. SHORT VIDEO ADVERTISING AND SALES

The effectiveness of advertising remains a vital issue in marketing research. Advertising generally causes three common effects; affect, cognition, and experience. These effects lead to behavioral impacts like loyalty and product purchase [13,14]. Many studies suggest a positive impact of video ads on brand awareness and sales [15]. The link between advertising expenditure and sales has been consistently supported. Literature notes at least two basic measuring advertising effectiveness [16,17,18]. First, diagnostic marketing metrics (customer satisfaction, loyalty, awareness, preference, among others). The second is based on evaluative marketing metrics (sales, profits, market share, cash flow, return on investment, firm value, and all that relates to profitability) [19,20]. The current study focuses on the latter (evaluative marketing metrics). Mainly, we focused on the link between SV advertising and financial outcomes (sales) and hypothesized that:

H1: The presence of short videos will have positive impacts on the product's overall sales.

2.1 Short Video Advertising and Quality Signals

Images and text that pre-dominated e-commerce advertising is static while videos are dynamic. A seller can leverage videos to better present and represent target products [21,22]. This dynamic presentation has a tendency to generate traffic and receive a better price and faster sales [23]. Video advertising provides technical supports to consumers. Scholars have revealed that product support is essential for customers to obtain maximum value from products, increase sales revenue, and positively affect customer satisfaction [24,25]. Technical support is interactively embedded in short videos between customers, employees, and other individuals, and the focal product aims to assist and support customers' everyday practices [26]. This support increases customer satisfaction and sales [27]. Based on this evidence, we proposed that;

H2: The presence of short video will positively impact the product's quality signals

The gains in quality perceptions of products are slow, gradual, and must be built over time. Companies must commit to developing and communicating strategies that reveal the actual quality improvements to consumers in the long run through informative and appealing advertising [28,29]. Advertising is a rational phenomenon that works as a device to signal the high quality of a brand or goods. Researchers have argued that other factors such as price, brand, and user experience besides advertising are matters in signaling product quality [28]. The content and informative characteristics of video ads are, therefore, essential [29,30].

However, in duopoly markets and where there is price rivalry, the role of advertising as the more appropriate signaling method is supreme [31]. The retail market and e-commerce, in particular, are becoming extremely competitive. When two firms producing similar products and quality are unknown to customers, price and advertising become the sources of reliability for the customer. Consumers in such a case are left with interpreting the price-advertising tactics of both firms in making purchase and referral decisions [31]. Price alone may prevail for sufficient differentials in inter-brand quality. However, the joint price and advertising signals prevail in a duopoly, or among two unknown firms, among similar known products, especially when marginal quality differential [32,33]. Informative advertising, therefore, clears doubts in consumers when prices are high [34,35]. Other high extrinsic indications include collective cues in signaling product quality [36]. Collective cues are components of eWOM which are embedded in short video advertising. Based on the efficiency of advertising and price in signaling product quality and reducing uncertainty, we hypothesized that;

H3: Product quality signals will positively impact sales

H4: Quality signal will positively mediate the impact of the relationship between the presence of short video and Sales

H5: Quality signal will positively impact customer satisfaction

2.2 Service Quality and Customer Satisfaction

Customer satisfaction is the degree of satisfaction a customer gets after purchasing relative to the prior anticipated satisfaction. The more a customer is satisfied, the more the probability of repeat buying, referral, and positive WOM behavior [37]. Creating superior value and satisfaction is the key to customer satisfaction, directly resulting from service quality. Service quality is usually referred to as the measure of how well the level of service delivered correlates with consumers' expectations [38]. Service quality is, thus, a vital determinant in the success or failure of e-commerce. Service quality has become necessary in many ways for most organizations in meeting their ultimate goal [39]. The ultimate goal of ads is to improve their performance and profitability by satisfying customers [40]. Service quality is necessary because the relationship between customer satisfaction and business performance is not always evident [41,40]. Service quality increases customer retention, attractiveness, hit rate, stickiness, improves eWOM, and increases the comparative advantage in e-commerce [42]. A well-developed body of research exists on the short, medium, and long-term behavioral relationships that support the relationship between satisfaction and financial performance, and profitability. So are the empirical studies on the positive effects of service quality, customer loyalty, and sales or profitability It is also noted that satisfied customers are generally less price-sensitive and are less likely to switch for an alternative even when the company increases price. Existing evidence points to the importance of satisfaction and how some companies are beginning to reconsider the extent to which to invest in customer satisfaction and customer care research [39,43]. It is established that customer satisfaction indicates possible future revenue and the necessary foundation for retaining existing customers [44,45]. Unlike good quality, it is not easy to measure service quality. However, customer service satisfaction is a good measure of service quality [45]. We, therefore, propose that;

H6: The presence of short videos will have positive impacts on customer satisfaction.

H7: Customer satisfaction will have positive impacts on a product's overall sales.

H8: Customer satisfaction will positively mediate the impact of the presence of a short video on sales.

2.3 Price

Price remains an imperative component in consumers' purchase decision marketing [46]. Cost and Price is a popular and overly subscribed concept in consumer experience literature [47,48]. Consumers lookout for clarity, accuracy, truthfulness, and complete pricing information about the product they intend to purchase. Prices are perceived to be fair if consumers believe that the vendor will not try to take undue advantage even in extreme circumstances [49]. Standards usually turn out to be similar products or the total outcome of value derived from the product or service [50]. The rule-of-thumb is that raising prices to maintain profit is fair and unfair to raise prices to increase profit. However, maintaining prices when cost declines may play a dual entitlement role [49,51]. It is also argued that price constitutes a direct financial risk, constraining purchase, where more expensive products are more risk consumers. However, the perception of less risk or performance and quality of more expensive products is prevalent among consumers. Literature has established that price directly affects consumers' purchase [52]. From the evidence found in the literature about the impact of price on sales and purchase decision making, we hypothesize that;

H9: Price will moderate the impact of quality signals on sales.

H10: Price will moderate the impact of customer satisfaction on sales.

H11: Price will moderate the impact the presence of short video ads has on sales.

3. METHODS AND DATA COLLECTION

Data from Tmall, Taobao, and JD e-commerce platforms are the backbone for our hypotheses testing. The Alibaba e-commerce marketplaces (including Taobao and Tmall) and JD.com are not only the biggest customer-experience websites in China but are listed among the global B2B and C2C ahead of eBay, Rakuten, Walmart, and Shopify [53]. Tmall, in particular, has been identified are the world's leading B2C platform as of 2019 [54]. We believe that data from these platforms represent the marketing trend in China and Asia, and globally.

All the online shops, products, and vendors on the selected websites are defined by standard quantitative metrics to assess, compare, and track their service performance and production qualities. Specifically, data about Service Ranking (the overall numerical measure of the degree of actual satisfaction a customer gets after purchasing relative to the prior anticipated satisfaction), product descriptive ranking (the numerical measure of how well the level of service delivered correlates with consumers' expectations logistic ranking (Logistics ranking involves the scores associated with the quality of planning, control, and implementation of the active movement, handling, and storage of related information, services, and goods from the vendor to the customer's preferred destination), price, sales, and the present of not of video ads were collected. We also collected the product category and location. A total of 23589 actual online data were used in testing for the hypotheses after data cleaning. The product categorization followed the predefined classification of Tmall (women/underwear, men's/sports, watch/ glasses/ Jewelry, phone/digital/computer, among others), the same as the other platforms where data was gathered. The location definition was based on urban, rural, and regional development data from the 2018 China Statistical yearbook. This data is publicly available at the official website of the National Bureau of Statistics of China for economic indicators [55]. Data from each shop and product was collected monthly from September 2018 to February 2019, and the monthly averages of the numerical Figures were computed. A typical Chinese-English translated Tmall page is presented in Fig. 2.

We built a web crawler to collect and store the datasets from the websites. A web crawler is a program script that analyzes and browses the World Wide Web systematically and automated manner to extract information such as URLs, images, and videos from web pages. We used the focused crawling approach as we are interested in specific information.

We first identified an initial set of URLs known as seed URLs. Then scanned the web links structure and recorded the web URLs containing the commodities details. Next, I downloaded the web pages for the seed URLs, stored the needed files, and extracted new links present in the downloaded pages. The extracted URLs are compared with the seed URLs to confirmed whether or not they are related. This process is iterated to download and store the required information. In our case, the web crawler, also known as a spider or robot, moves from page to page by scanning the graphical structure of the web pages. Finally, we stored the data into a database ready for statistical analysis.

All URLs and user IDs are hash-mapped and encrypted. In defining the variables, the presence of video ads was coded as a binary (1 indicates the presence of a video ad, else, 0). The actual data for the rest of the variables were collected. The flow of data collection is presented in Fig. 3. We proceeded to clean the dataset. The user ID and URL pairs were used to eliminate all duplicated datasets. Datasets of missing records were equally removed. We also eliminated products that adopted or stopped using SV midway within the data collection window. A total of 23589 datasets were used to support our assumptions.

To ensure that our dataset meets all the assumptions needed for regression, we performed initial normality tests as specified for testing our hypotheses. We first transformed all the continuous datasets to a logarithmic form to avoid data misrepresentations. The logarithmic transformation is necessary as continuous data is likely to skew [56]. This transformation will also smooth large values and possible [57]. We tested for the variance inflation factor (average VIF = 1.786) and confirmed that the data is normally distributed. All path estimations are based on 10,000 bootstraps of samples at a 95% confidence interval, specified by Hayes [58]. The basic statistics and measurements are presented in Table 1.

4. RESULTS

Table 2 shows the zero-order bivariate correlation matrix of the key variables. As expected, all the variables except price and location (a controlled variable) have positive correlations with each other. An indication that an increase in price causes a reduction in sales and customer satisfaction. It is also necessary to note that all the variables have correlation coefficients smaller than 1.

We specified the Ordinary Least Square (OLS) Regression to test our hypotheses. The choice is influenced by the fact that the dataset used in this study is large enough and has met all the preconditions needed for its use [59,60]. PROCESS macro vs. 3.4 was used to test both simple and serial moderated meditation paths. In doing so, we specified a 95% bias-corrected confidence interval based on 10,000 bootstrap samples [59]. We reported the unstandardized B coefficients. Considering that our independent variable (Short video ads) is dichotomous, it would not be appropriate to standardize it as it produces coefficients without any real meanings.

An eleven-step hierarchical regression to check whether or not SV, quality signals, and customer

satisfaction are related to sales even after controlling for the influence of product category, location, and logistic service quality is proposed.
In Table 3, all the controlled variables explained about 15% variances, while SV explained about 26% variance in quality signals seen in model 2 (β=.715, p = .000). This provided support for H2. In model 4. A total of 34% variance was explained by SV in conjunction with the controlled variables in customer satisfaction (β=.985, p = .000), supporting H6. We found about 62% variance explained when quality signals were added in model 5 (β=.811, p = .000). This confirms H5.

In Table 4, the results of a hierarchical regression on sales as the dependent variable are presented. In model 7, LSQ (β=.894, p = .000) strongly influenced the total variances explained by all the controlled variables (R^2 = 0.122). On the other hand, the location was not significant and produced nearly no impact on the change in SV adoption. Unlike physical shops, locations are less considered in online shopping when logistic service quality is high — a possible explanation for the nonsignificant and minimal impact of location in our model. Adding SV produced a 42.7% change in variance in support of H1 that proposed that SV will have positive evaluative impacts on the product's overall sales. In model 9, quality signals positively impacted (β=.585, p = .000), increasing the total variance explained in sales with a collective change of 86.7%. Customer satisfaction added in model 10 contributed to an 86.7% variance in sales (β=.526, p = .000). Although the price added about 1.5% to the variance explained (from 86.7% to 88.2%), it is vital to note that a price increase produced a retrospective effect on sales (β= -.268, p = .000).

A serial moderated mediation is presented with a holistic view of the study framework and the interactive results shown in Fig. 4. Based on model 89 of PROCESS macro [61]. SV, moderated by price and after controlling for LSQ, location, and product category, produced a significant direct effect of 0.725 to support H1. The overall framework explains a 90.1% change in sales was, as illustrated in Fig. 4. We provide a detailed report of the direct, moderation, and mediation effects in Table 5.

At 95% confidence intervals, all the direct paths produced significant positive effects. The results of the analysis in Table 5, indicate that SV has a positive and significant effect quality signals (a_1 =.715, LL = .692, UL = .738) with 26.3% variance which supports H2. Next, the controlled significant effect of SV on customer satisfaction (a_2 =.764, LL = .741, UL = .788) provided a strong backing for H2. Quality signals showed to be a critical in explaining customer satisfaction in e-commerce websites (d1 =.811, LL = .799, UL = .824) to back H5. A total of 61.7% variance in customer satisfaction is explained due to the controlled moderated-mediation of SV via quality signals.

An interactive effect of quality of service and price (M_1w = .111, LL= .091, UL = .108) indicates the possible wiliness of consumers to accept some level of price increase that comes with products with higher quality signals. A proof for H9. An increase in price without the needed quality signals resulted in a significant customer dissatisfaction (M_2w = -.202, LL = -.210, UL = -.194). Similarly, an increased in price has a negative effect on sales (xw = -.207, LL = -.225, UL = -.189). In both cases, H10 and H11 were supported with a price increase, significantly negatively impacting customer satisfaction and sales.

We proceeded with the indirect moderated paths, where +1SD means the effects at one standard deviation above the mean of the moderator. M of w means the moderated indirect path and the mean of the moderator, and -1SD stands for the effect at one standard deviation below the mean of the moderator.

Next, the moderated indirect effects of short video on sales via quality signals is significant (+1SD: β = .463, LL =.065, UL = .083; M of w: β = .110, LL = 102, UL = .117; and -1SD: β = .154, LL =.146, UL = .161). This effect is, however, weak at +1SD (β= 0.074). Customer satisfaction places a significant mediation role between SV and sales whiles being moderated by price (+1SD: β= .463, LL =.447, UL = .480; M of w: β= .393, LL =.379, UL =.407 and -1SD: β= .308, LL =.296, UL =.318). The effect is stronger at one standard deviation above the modal mean.

Finally, the indirect effect of serial moderated mediation of SV on sales through quality signals and customer satisfaction is presented. All three levels at which the moderated path was measured produced significant positive effects (+1SD: β= .352, LL =.340, UL = .364; M of w: β= .305, LL =.289, UL =.309 and -1SD: β= .232, LL =.226, UL =.241). The effect is, however, stronger at one standard deviation above the mean of the moderator. We found an overall stronger moderated mediation of short video sales through customer satisfaction, followed by quality signals and customer satisfaction. The weakest of the indirect moderated effect of short video ads on sales is through quality signals. It is possible that even though it is important to propel product quality signals, that should lead to overall customer satisfaction. The slope of the interaction is shown in Fig. 5. This interaction predicts sales. The slope in "A" indicates that as price increases, sales decreases. In "B" and "C" the slopes indicate that's as customer satisfaction and quality signals increase, sales valume increases. However, the slope increasingly reduced as price Increases.

Table 1. Measures and Descriptive Statistics

Variables	Observed Measures	Min.	Max.	Mean	Std. Dev
Product Category	Product Category	1	10	5.38	1.80
Location	Location	1	31	11.75	6.50
Short Video ads (SV)	Video	0	1	.58	.49
Logistic Services Quality (LSQ)	Logistic Ranking	1.10	5	4.78	.32
Quality Signals (QS)	Description Ranking	.20	5	4.51	1.02
Customer Satisfaction (CS)	Service Ranking	.20	5	3.48	1.35
Sales	Sales	1	473206	1713.29	8705.06
Price	Actual Price	.20	280900	490.23	3834.30

N=23589

Table 2. Measure, Descriptive Statistics, and Correlations of key variables

Variables	1	2	3	4	5	6	7	8
Product Category	-							
Location	.173**	-						
Short Video ads (SV)	-.077**	.031**	-					
Logistic Services Quality (LSQ)	-.064**	-.008	.129**	-				
Quality Signals (QS)	-.180**	-.027**	.394**	.348**	-			
Customer Satisfaction (CS)	-.172**	-.028**	.527**	.282**	.741**	-		
Sales	-.068**	-.015*	.154**	.075**	.085**	.187**	-	
Price	.097**	.029**	-.056**	-.187**	-.212**	-.140**	-.021**	-

**p = 0.05; ** p = 0.01; N = 23589*

Table 3. Hypotheses testing

	DV = Quality Signals		DV = Customer Satisfaction		
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Prod. Cat.	-.090#	-.075#	-.116#	-.088#	-.027#
Location	.001	-.002*	.002	.004#	-.003**
Log. Ser. Qty	1.071#	.936#	1.139#	.884#	.125
Short Video ad		.715#		.985#	.764#
Quality Signals					.811#
Adj. R^2	.146	.263	.103	.340	.617
Mean VIF	1.031	1.028	1.031	1.026	1.125
Hypothesis support		Yes		Yes	Yes

Note: Results without the moderation effects of price

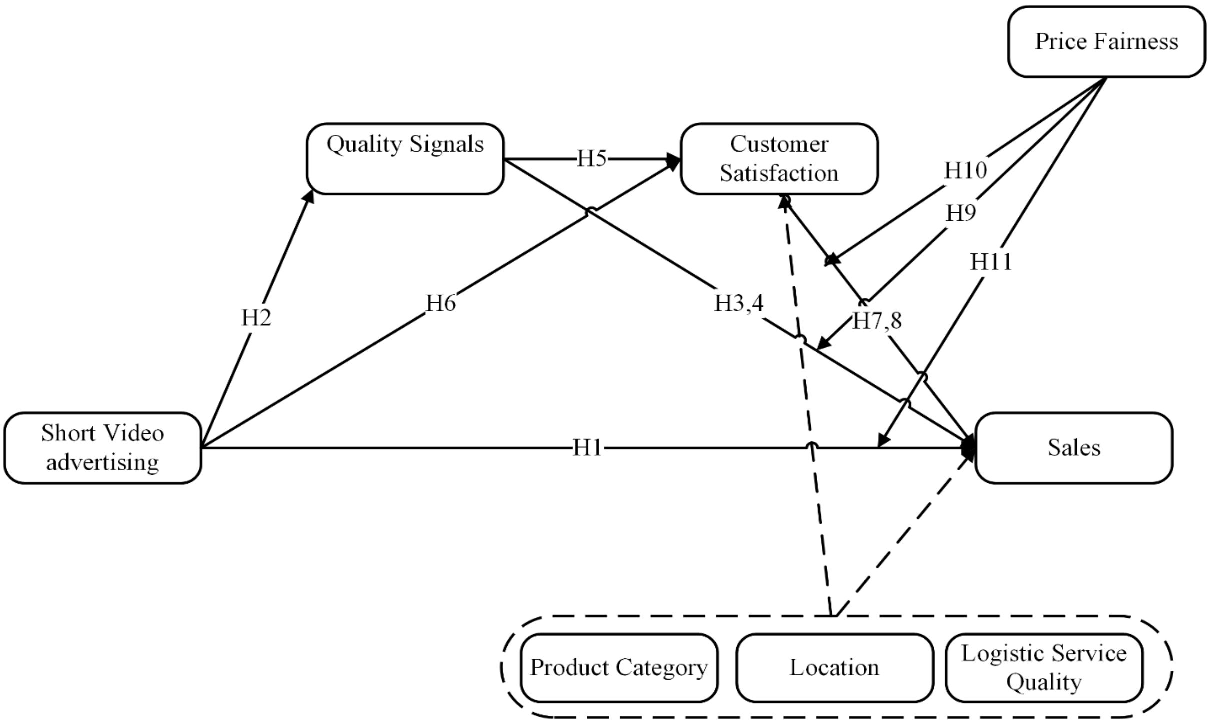

Fig. 1. Research Framework

Fig. 2. A typical Chinese-English translated Tmall Website

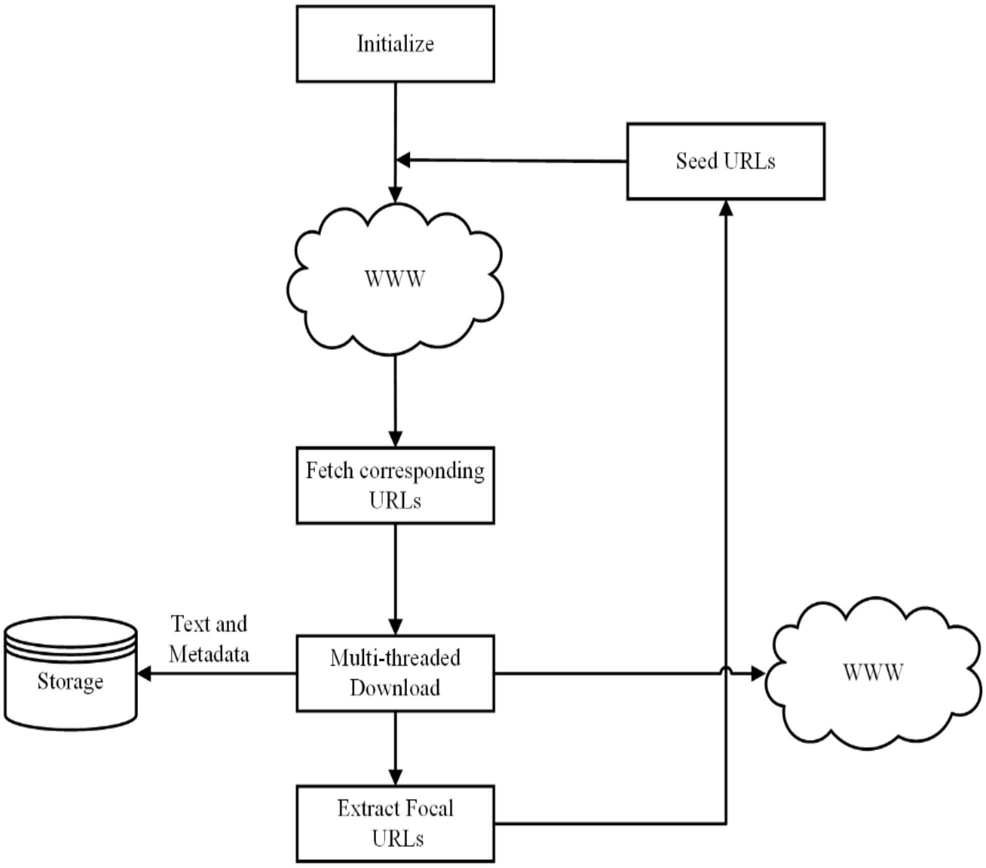

Fig. 3. The Flow of data collection

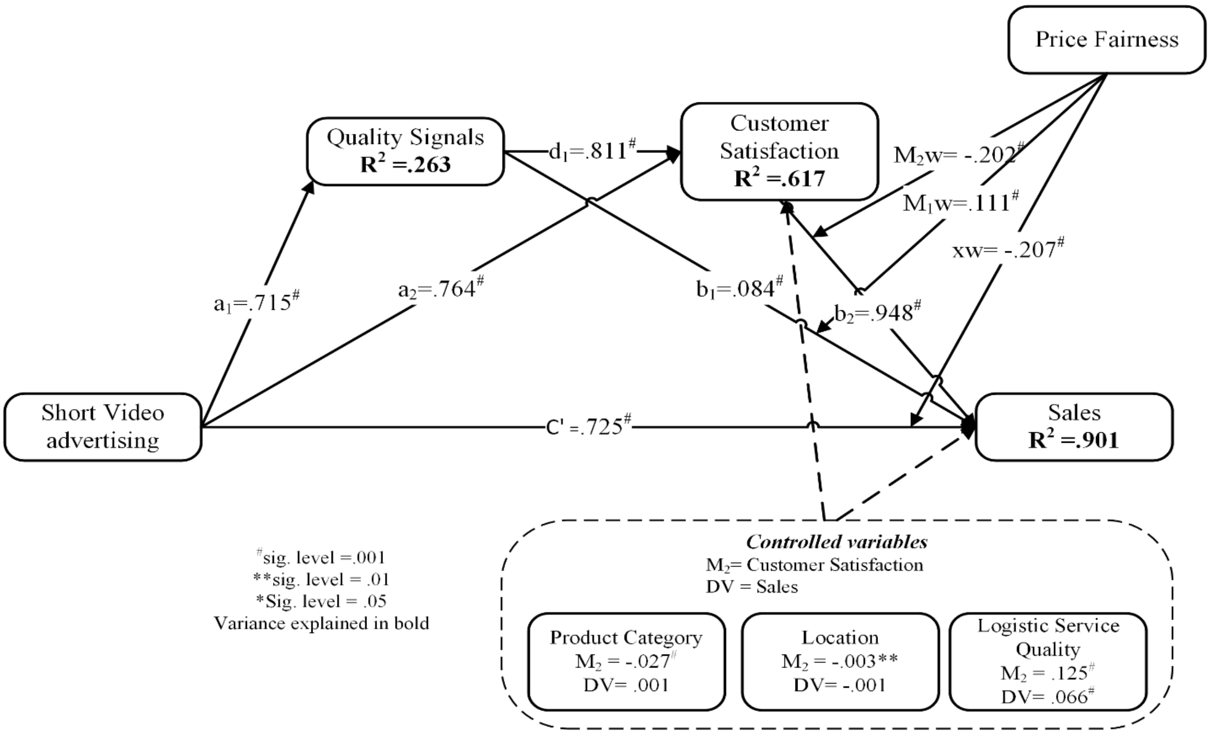

Fig. 4. Serial moderated mediation

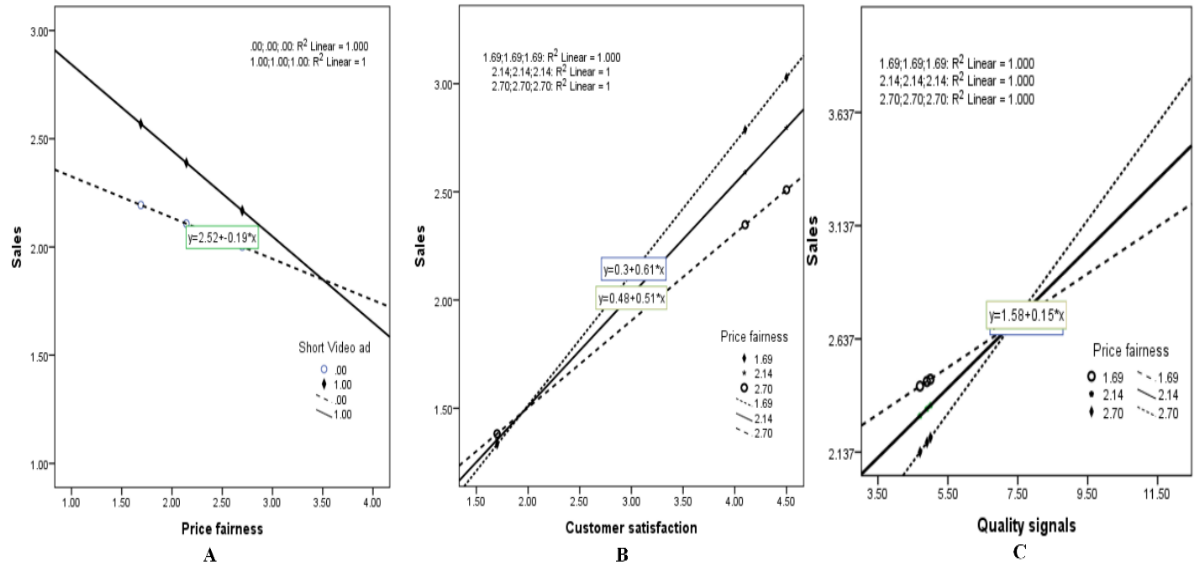

Fig. 5. Short video ads, quality signals and customer satisfaction as functions of price fairness
This interaction predict sales; The slope in “A” indicates that us price increase, sales decreases. In “B” and “C the slope indicate that as customer satisfaction and quality signals increase, sales volume also increases. Howerer the slope is increasingly reduced as price increases

Table 4. Hypotheses testing

		DV = Sales			
Variables	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**
Prod. Cat.	-.106#	-.082#	-.038#	-.024	-.003
Location	.001	-.004#	-.002#	-.001**	-.001
Log. Ser. Qly	.894#	.676#	.128#	.063#	.064
Short Video ad		1.151#	.733#	.331#	.324#
Quality Signals			.585#	.158#	.137#
Cus. Sat				.526#	.493#
Price					-.268#
R2	.122	.427	.680	.867	.882
Mean VIF	1.031	1.023	1.125	1.665	1.431
Hypothesis support		Yes	Yes	Yes	Yes

Note: Results with the moderation effects of price

5. DISCUSSION

5.1 Key Findings

The focal aim of the present work is to investigate a resilience model in the relationships between short video advertising adoption, quality signals, customer satisfaction, price, and sales, using a serial moderated mediation analysis. The present findings expand on the results of previous studies on the effectiveness of advertising in general and short video advertisings directed towards signaling product qualities and technical support in particular.

We have demonstrated the importance of SV beyond the perceived ease of use and technical support that dominated literature to establish its impact on sales via quality signals and customer satisfaction using a rigorous and carefully collected actual online dataset.

First, the results confirmed the significant positive impact of the adaptation of SV on sales. SV ads are significant drives for purchase in the online marketplace. This finding thus upholds claims that SV, as short as they are, are as useful as TV ads for awareness, brand, persuasion, and conveying emotional messages. It is also in line with the claims that SVs may have striking characteristics, satisfy hedonic needs, reduce product uncertainty, and signal product quality [62,63].

Table 5. Serial moderated mediation to identify direct and indirect effects between short video ads and sales

Effect	Path	B	SE	95% CI LL	95% CI UL	Hypothesis support
Direct effect of SV on QS	a_1	$.715^{\#}$	.012	.692	.738	Yes
Direct effect of SV on CS	a_2	$.764^{\#}$	.012	.741	.788	Yes
Direct effect of QS on CS	d_1	$.811^{\#}$	.006	.799	.824	Yes
Direct effect of QS on S	b_1	$.084^{\#}$	.012	.061	.108	Yes
Direct effect of CS on S	b_2	$.725^{\#}$	.022	.683	.768	Yes
Direct effect of SV on S holding QS and CS constant	C'	$.725^{\#}$	.005	.246	.266	Yes
Interaction of SV and PF	xw	$-.207^{\#}$	.009	-225	-.189	Yes
Interaction of QS and PF	M_1w	$.111^{\#}$	.000	.102	.120	Yes
Interaction of CS and PF	M_2w	$-.202^{\#}$	.004	-.210	-.194	Yes
Indirect SV>QS>Sales	+1SD	.074	.005	.065	.083	Yes
	M of w	.110	.004	.102	.117	
	-1SD	.154	.004	.146	.161	
Indirect SV>CS>Sales	+1SD	.463	.008	.447	.480	Yes
	M of w	.393	.007	.379	.407	
	- SD	.308	.006	296	.318	
Indirect SV>QS>CS>Sales	+1SD	.352	.006	.340	.364	Yes
	M of w	.299	.005	.289	.309	
	-1SD	.233	.004	.226	.241	

B = Unstandardized B coefficients; SE = standard errors; CI, bias-corrected and accelerated 95% confidence interval; LL = lower limit; UL = upper limit; SV = Short video ads; QS = Quality signals; CS = customer satisfaction; PF= Price; S = Sales 10,000 bootstrap samples.
[a] location, product category, and logistic service quality. # $p < .001$. N = 23589

Second, the results support our hypothesis that proposed a significant positive impact of SV on quality signals. After controlling for location, product category, and logistic service quality, SV provided a sufficient change in the quality signal of products. However, prior studies did not draw their evidence from actual online datasets but have revealed that product support is essential for increasing sales revenue and positively affects customer satisfaction.

Next, drawing upon the perspective of signaling theory, we proposed a positive impact of quality signals on customer satisfaction (H5). The findings supported this accession. As noted in the literature, the everyday support customers derive from SV, and the quality signals they carry have the tendency to increase customers' satisfaction and sales. Our findings demonstrated this assumption even better with an actual online dataset.

Creating superior value and satisfaction is a crucial marketing concept. Customer satisfaction is primarily measured by service quality. Service quality is, thus, a vital determinant in the success or failure of e-commerce. Many companies are said to reconsider the extent to which to invest in satisfaction and customer care research. SV is such a marketing investment to improve the overall satisfaction of customers. The results presented in this work supported the proposition that SV has a significant positive impact on customer satisfaction. Further, this level of satisfaction has proven to be a plausible measure for mediating SV and sales. These results are not different or isolated but supported claims that customers' satisfaction is the most significant indicator of possible future revenue and the necessary foundation for retaining existing customers.

The possible effects of price as an imperative component in consumers' purchase decision marketing were considered. The results pointed to an exciting outcome. When quality signals are high, customers are willing to pay slightly high prices for the commodity as the interactive effect of price on the relationship between quality signals and sales is significantly positive, though marginal. However, customers' level of satisfaction is very likely to go down when prices are increased without an accompanying quality signal. The perception of high risk or less performance and quality of more expensive products is likely prevalent among consumers if there are no quality signals. An indication that the willingness of customers to pay more for a product that guarantees less risk is high. This uncertainty in online purchasing can only be guaranteed through quality signals embedded in SV.

Based on the results, we also proposed that the clarity, accuracy, truthfulness, and completeness of pricing information about a product supersedes prior satisfaction in the case of an upward adjustment in prices. We are basing on this to provoke an in-depth debate on what drives customers' acceptance of upwards price adjustment in online marketplaces.

We acknowledged the influence of other variables in determining customer satisfaction and sales in online shopping places. Literature supported the assumption that some product categories, such as apparel and baby products, generally receive increased online sales, whereas other categories, such as handheld and small appliances, experience low online sales [64]. The store location is also a known stimulus in marketing. [65]. However, the influences of these controlled variables are less and, in most cases, non-significant as far as online marketing is concerned. Our results, instead, pointed to the significant impact of logistics service quality LSQ. When LSQ is high (timely, safe, and affordable), location and product categories are less relevant in online sales.

Finally, the entire model with the controlled variables helps delineate the full picture in which both quality signals and customer satisfaction shape sales in an online marketplace as far as SV adoption is concerned.

5.2 Implications for Research

SVs have gain popularity in e-commerce in recent times. In general, SVs signal product quality reduces product uncertainty and is a perfect extension of electronic word-of-mouth (eWOM). SERVQUAL dimensions dominated research of these phenomena. Authors of such studies acknowledged the possible gaps in using SERVQUAL dimensions and the lack of actual online secondary datasets. This study provided an alternative to understanding and measuring the variables mentioned above.

This study is one of the very few, if not the first, to have tried to deal with the data type and measurement concerns in the literature on studying the relationship between customer satisfaction, quality signals, and sales. Even though our variables may not be exhaustive enough, they shed significant light on this aspect of online shopping.

Online advertising and video advertising, in particular, have dominated e-commerce research in recent times. Nevertheless, research on SVs advertising is still in its embryonic trajectory. Many e-commerce websites are yet to adopt SV ads. Amazon, for an instant, adopted the automatically played back SV ads based on the internationally recommended 50/2 minimum visibility rate of MRC (Media Rating Council) and IAB (Interactive Advertising Bureau) only at the beginning of 2019 [66,67]. Therefore, the current study provides a possible reference and standard for related future studies with actual online SV datasets.

Away from what is documented in e-commerce literature on the influence of shop location on purchase decisions and sales [68,69]. we have proposed instead that the store location is less significant in purchase decisions in online shopping. This is, however, true when logistic service quality is guaranteed. It is a call on academia to reexamine this direction not in isolation but with relevant variables such as LSQ.

Variables on secondary data available on e-commerce websites are limited as compared to questionnaire instruments. Our model is a plausible reference as far as short video ads, logistic service quality, quality signals, customer satisfaction, and sales are concern. The model is flexible and allows for modification and the introduction of new variables. It should, however, be noticed that the findings presented in this work are founded on the data collected from Chinese e-commerce websites. The phenomenon could be significantly different from the West and other parts of the world. Further examination of the model based on data from other cultural settings might be necessary for the generalization of the results.

Finally, from a narrative perspective, this study describes the process by which short video ads promote sales through the critical mediating role of customer satisfaction and quality signals moderated by price after controlling the effects of a few crucial variables.

5.3 Implications for Practice

Our study also has some practical implications. First, research on advertising effectiveness, customer satisfaction, quality signals, and sales are not new. Nonetheless, very few studies combined in a single study to understand their interaction in an online shopping context. More so, understanding the interaction of these variables is mostly studied from psychological and belief perception points of view. We made a significant effort to identify online data to justify why SV adoption is essential in e-commerce. E-vendors can now leverage this to focus on what matters.

Second, our results indicated that the mere adoption of SV is not enough to drive higher product sales. We identified key variables that mediate, moderate, and control this relation. This understanding will help industry players to align their resources appropriately to achieve higher sales. Specifically, the results suggest that an improved logistics service will impact sales more positively than store location. The results of this work, combined with previous research suggest that consumers are more willing to accept an upward adjustment in price if it comes with product clarity, accuracy, truthful (quality signals), and technical support information. It is an antipasto on what to consider in a price adjustment.

Finally, our research upholds the claims that customer satisfaction is crucial for the success of electronic commerce and extends this understanding in line with quality signals based on signaling theory. This implies that building an online environment towards the satisfaction of consumers is as important as building an institutional setting with the IT-enabled mechanisms for the online marketplace. Since most e-commerce websites have successfully created a stable institutional environment, it is more urgent and essential for e-commerce companies and market providers to establish a value-added environment using short videos that carried hedonic characteristics yet defines and signal product qualities.

6. CONCLUSION

From the perspective of the signaling theory, this paper explores the impact of SV ads on sales through the mediation powers of customer satisfaction and quality signaling. Key variables were controlled in the arrival of the results, and so was the price moderation effect. A research model that describes the SV-sales relationship was developed and tested with the support of over twenty-three thousand five hundred datasets from 3 top global e-commerce websites. First, we re-conceptualize and validates the concept of quality signal in line with SV ads. We also made a frantic effort to collect actual online data (data recommended by several previous works).

Finally, this paper discloses the significant positive effects of SV on quality signals, suggesting an effective way of communicating product-specific and technical support to consumers in online and social commerce marketplaces.

7. LIMITATIONS

This work has some limitations. First, data were collected within six months, which will not necessarily be the story throughout the year.

Next, the adoption of SV is similar to the adoption of technology, affected by industry type, culture, among others. This study, however, only focuses on shops in mainland China. Even though these shops are among the global e-commerce giants, extending the research beyond the current setting is vital. Other variables such as experience, capital, comments that could influence the adoption of SV ads are worth considering.

Also, different e-commerce platforms have unique strengths. While Pin Duo Duo (Much more) is known for cheaper commodities, JD is noted for express delivery and logistic quality. Applying this model in a comparative study will be necessary to confirm if the results cut across all platforms or are limited. The time-serials approach will also shed more light on the patterns existing in different seasons and months of the year, looking at SV ads and sales. Thus, future research can explore this direction.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Alam SS, Yasin NM. What factors influence online brand trust: Evidence from online tickets buyers in Malaysia. Journal of Theoretical and Applied Electronic Commerce Research, 2010;5(3):78–89. Available:https://doi.org/10.4067/S0718-18762010000300008
2. Boone G, Secci J, Gallant L. Emerging Trends in Online Advertising. Doxa Comunicación: Revista Interdisciplinar de Estudios de Comunicación y Ciencias Sociales; 2007.
3. Lai Y, Lai C, Chiang H. The Advertising Effectiveness of Advertising Message and Product Placement on Video Advertisement 2 Literature Review. 2013. (May 2009):112–121.
4. Briggs R. A road map for online marketing strategy. Admap. 1998;27–31.
5. Drèze X, Hussherr F-X. Internet Advertising : Is Anybody Watching. Journal of Interactive Marketing. 2003;17(4):8–23. Available:https://doi.org/10.1002/ dir.10063.
6. Demand Metric. the state of Video Marketing; 2017. Retrieved from http://awesome.vidyard.com/rs/273-EQL-130/images/Demand Metric State of Video Marketing 2017.pdf
7. Hennig-Thurau T, Qwinner PK, Walsh G, Gremler DD. Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? Journal of Interactive Marketing. 2004;18(1):38–52.
8. Millward B, Logic D. IAB Digital Video Ad Effectiveness Case Study; 2008. etrieved from http://www.iab.net/dv_effectiveness
9. Cline TW, Kellaris JJ. The Influence of Humor Strength And Humor–Message Relatedness on Ad Memorability: A Dual Process Model. Journal of Advertising, 2007;36(1):55–67.
10. Janssens, W, Pelsmacker PD. Emotional or informative? Creative or boring? The effectiveness of different types of radio commercial. International Journal of Advertising, 2005;24(3):373–394.
11. Stysko-Kunkowska, MA., Borecka, D. Extraversion and Evaluation of Humorous Advertisements. Psychological Reports, 2010;106(1):44–48.
12. Bienstock, CC., Mentzer, JT., Bird, MM. Measuring physical distribution service quality. Journal of the Academy of Marketing Science, 1997;25(1):31–44. Available:https://doi.org/10.1007/BF02894507
13. Breuer, R., Brettel, M, Engelen A. Incorporating long-term effects in determining the effectiveness of different types of online advertising. Marketing Letters, 2011;22(4):327–340. Available:https://doi.org/10.1007/s11002-011-9136-3
14. Davidavičienė V. Effectiveness Factors of Online Advertising. The 7th International Scientific Conference "Business and Management 2012". Selected Papers, 2012;(April):822–830. Available:https://doi.org/10.3846/bm.2012.106
15. Yim, MY-C., Yoo, S.-C., Till, B. D., Eastin, M. S. In-Store Video Advertising Effectiveness. Journal of Advertising Research, 2010;50(4), 386–402. Available:https://doi.org/10.2501/S0021849910091634
16. Ampomah, EK., Nyame, G., Qin, Z., Addo, PC., Gyamfi, EO., Gyan, M. Stock Market Prediction with Gaussian Naïve Bayes Machine Learning Algorithm. Informatica, 2021;45(2). Available:https://doi.org/10.31449/inf.v45i2.3407
17. Lehmann, DR. Metrics for making marketing matter. Journal of Marketing. 2004;68(4):73–75.
18. Mintz O, Currim IS. What drives managerial Use of marketing and financial metrics and does metric use affect performance of marketing-mix activities. Journal of Marketing; 2013. Available:https://doi.org/10.1509/jm.11.0463
19. McAlister, L., Srinivasan, R., Jindal, N., Cannella, AA. Advertising Effectiveness: The Moderating Effect of Firm Strategy. Journal of Marketing Research. 2016;53(2):207–224. Available:https://doi.org/10.1509/jmr.13.0285
20. O'Sullivan, D., Abela, A. V. Marketing performance measurement ability and firm performance. Journal of Marketing; 2007. Available:https://doi.org/10.1509/jmkg.71.2.79
21. Addo, PC., Fang, J., Liangqiang, L. Green advertising and purchase decisions in live-streaming B2C and C2C interactive marketing. International Journal of

Information and Management Sciences. 2020;31(2):191–212.
Available:https://doi.org/10.6186/IJIMS.202006 31(2).0005

22. Clement Addo, P, Fang, J., Asare, AO., Kulbo, NB. Customer engagement and purchase intention in live-streaming digital marketing platforms. The Service Industries Journal, 2021;1–20.
Available:https://doi.org/10.1080/02642069.2021.1905798

23. Krishnan SS., Sitaraman R. K. Understanding the effectiveness of video ads: A measurement study. In Proceedings of the ACM SIGCOMM Internet Measurement Conference, IMC 2014;149–162.
Available:https://doi.org/10.1145/2504730.2504748

24. Gajic, N., Boolaky, M. Impact of technical support on customer satisfaction: Case of automotive Available:paints. SAGE Open, 2015;5(4):1–19.
https://doi.org/10.1177/2158244015611457

25. Saccani, N., Songini, L., Gaiardelli, P. The role and performance measurement of after-sales in the durable consumer goods industries: An empirical study. International Journal of Productivity and Performance Management, 2006;55(1):259–383.
Available:https://doi.org/10.1108/17410400610653228

26. Grönroos, C. Service logic revisited: who creates value? And who co- creates? European Business Review, 2008;20(4):298–314.
Available:https://doi.org/10.1108/09555340810886585

27. Kaura, V., Prasad, SD., Sharma, S. Service quality, service convenience, price and fairness, customer loyalty, and the mediating role of customer satisfaction. Marketing Intelligence and Planning; 2015.
Available:https://doi.org/10.1108/IJBM-04-2014-0048

28. Akdeniz, MB., Calantone, RJ., Voorhees, CM. Signaling quality: An examination of the effects of marketing- and nonmarketing-controlled signals on perceptions of automotive brand quality. Journal of Product Innovation Management, 2015;31(4):728–743.
Available:https://doi.org/10.1111/jpim.12120

29. Dolan, M. Ford Closes Gap With Japanese on Quality Issue. The Wall Street Journal; 2008.
https://www.wsj.com/articles/SB122481292908765489

30. Erdem, T., Keane, M. P., Sun, B. A dynamic model of brand choice when price and advertising signal product quality. Marketing Science; 2008.
Available:https://doi.org/10.1287/mksc.1080.0362

31. Fatima, S., Kaushal, DSK., Wong, L., Shahbaz, M., Kok Li-Ming, A., Wai, TB, Faghani, E. Impact of advertisement on buying behaviours of the consumers: Study of cosmetic industry in Karachi City. SSRN Electronic Journal, 2013;4(2):1–15.
Available:https://doi.org/10.7763/IJSSH.2014.V4.334

32. Samar, F., Samreen, L. Impact of advertisement on buying behaviours of the consumers: Study of cosmetic industry in Karachi City. International Journal of Management Sciences and Business Research, 2015;4(10):125–137.
Available:https://doi.org/10.21917/ijms.2018.0108

33. Fluet, C., Garella, PG. Advertising and prices as signals of quality in a regime of price rivalry. International Journal of Industrial Organization, 2002;20(7):907–930.
Available:https://doi.org/10.1016/S0167-7187(01)00075-3

34. Barigozzi, F., Garella, PG., Peitz, M. Advertising and prices as signals of quality: competing against a renown brand; 2006.
Available:http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.499.5406&rep=rep1&type=pdf

35. Erevelles, S., Roy, A., Yip, L. SC. The universality of the signal theory for products and services. Journal of Business Research, 2001;52(2):175–187.
Available:https://doi.org/10.1016/S0148-2963(99)00069-7

36. Mastrobuoni, G., Peracchi, F., Tetenov, A. Price as a Signal of Product Quality: Some Experimental Evidence. Journal of Wine Economics, 2014;9(2):135–152.
Available:https://doi.org/10.1017/jwe.2014.17

37. Choi, D, Chung, CY., Young, J. Sustainable online shopping logistics for customer satisfaction and repeat purchasing behavior: Evidence from China. Sustainability (Switzerland), 2019;11(20).
Available:https://doi.org/10.3390/su11205626

38. Santos, J. E- service quality: a model of virtual service quality dimensions. Managing Service Quality: An International Journal, 2003;13(3):233–246. Available:https://doi.org/10.1108/09604520310476490
39. Van Der Wiele, T, Boselie P., Hesselink, M. Empirical evidence for the relationship between customer satisfaction and business performance. Managing Service Quality: An International Journal, 2002;12(3):184–193. Available:https://doi.org/10.1108/09604520210429259
40. Yeung, MCH., Ging, L. C., Ennew, C. T. Customer satisfaction and profitability: A reappraisal of the nature of the relationship. Journal of Targeting, Measurement and Analysis for Marketing. 2002; 11(1):24–33. Available:https://doi.org/10.1057/palgrave.jt.5740064
41. Terpstra, M., Verbeeten, F. H. M. Customer satisfaction: Cost driver or value driver? Empirical evidence from the financial services industry. European Management Journal, 2014;32(3):499–508. Available:https://doi.org/10.1016/j.emj.2013.07.001
42. Zeithaml, VA. Service quality, profitability, and the economic worth of customers: What we know and what we need to learn. Journal of the Academy of Marketing Science, 2000;28(1):67–85. Available:https://doi.org/10.1177/0092070300281007
43. Anderson, EW. Customer satisfaction and price tolerance. Marketing Letters; 1996. Available:https://doi.org/10.1007/BF00435742
44. Guo, L., Xiao, JJ., Tang, C. Understanding the psychological process underlying customer satisfaction and retention in a relational service. Journal of Business Research, 2009; 62(11):1152–1159. Available:https://doi.org/10.1016/j.jbusres.2008.10.020
45. Keiningham, TL., Perkins- Munn, T., Aksoy, L., Estrin, D. Does customer satisfaction lead to profitability? Managing Service Quality: An International Journal, 2005;15(2):172–181. Available:https://doi.org/10.1108/09604520510585352
46. Herrmann, A., Xia, L., Kent, MB., Huber, F. The influence of price fairness on customer satisfaction: An empirical test in the context of automobile purchases. Journal of Product and Brand Management, 2007;16(1):49–58. Available:https://doi.org/10.1108/10610420710731151
47. Bolton, L. E., Warlop, L., Alba, J. W. Consumer Perceptions of Price (Un)Fairness. Journal of Consumer Research, 29(4), 474–491; 2003. Available:https://doi.org/10.1086/346244
48. Munnukka, J. Pricing method as a tool for improved price perception. Journal of Revenue and Pricing Management, 2006;5(3):207–220. https://doi.org/10.1057/palgrave.rpm.5160021
49. Available:Diller, H. Price fairness. Journal of Product and Brand Management, 2008;17(5):353–355. Available:https://doi.org/10.1108/10610420810896103
50. Xia, L., Monroe, K. B., Cox, J. L. The price is unfair! A conceptual framework of price fairness perceptions. Journal of Marketing, 2004;68(4):1–15. Available:https://doi.org/10.1509/jmkg.68.4.1.42733
51. Mehmet, D., Yağci, İ. the Impact of Perceived Price Fairness and Consumer Ethnocentrism on Conumers' Purchase Intentions: an Exploratory Assessment. Cilt, 2010;19(3):131–148. Available:http://dergipark.ulakbim.gov.tr/cusosbil/article/viewFile/5000001454/5000002145
52. Lu, B., Fan, W., & Zhou, M. Social presence, trust, and social commerce purchase intention: An empirical research. Computers in Human Behavior, 2016;56:225–237. Available:https://doi.org/10.1016/j.chb.2015.11.057
53. Adam, L. The 7 Largest E-Commerce Companies in the World; 2019 Available:https://www.fool.com/investing/the-7-largest-e-commerce-companies-in-the-world.aspx
54. Chen, C., Liu, Z., Zhou, J., Li, X., Qi, Y., Jiao, Y., & Zhong, X. How much can a retailer sell? Sales forecasting on tmall. In Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 2019;204–216. Available:https://doi.org/10.1007/978-3-030-16145-3_16
55. National Bureau of Statistics of China. China Statistical Yearbook; 2018.

Retrieved December 13, 2019
Available:http://www.stats.gov.cn/tjsj/ndsj/2018/indexeh.htm

56. Feng, C., Wang, H., Lu, N., Chen, T., He, H., Lu, Y., Tu, X. M. Log-transformation and its implications for data analysis. Shanghai Archives of Psychiatry, 2014; 26(2):105.
Available:https://doi.org/10.3969/j.issn.1002-0829.2014.02.009
57. Bründl, S., Thomas, H. Why do users broadcast? Examining individual motives and social capital on social live streaming platforms. In PACIS. 2006;332–140).
Available:https://aisel.aisnet.org/pacis2016/332/
58. Hayes, AF. Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation. Communication Monographs, 2018;85(1): 4–40.
Available:https://doi.org/10.1080/03637751.2017.1352100
59. Bellini, S., Cardinali, M. G., Grandi, B. A structural equation model of impulse buying behaviour in grocery retailing. Journal of Retailing and Consumer Services, 2017;36(February):164–171.
Available:https://doi.org/10.1016/j.jretconser.2017.02.001
60. Todman, J., Dugard, R. Approaching multivariate analysis. New York: psychological press; 2007.
61. Hayes, A. Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. (D. A. Kenny & D. L. Todd, Eds.), New York, NY: Guilford (2nd ed.). New York: The Guilford Press; 2018.
62. Arnold, MJ., Reynolds KE. Hedonic shopping motivations. Journal of Retailing, 2003;79(2): 77–95.
Available:https://doi.org/10.1016/S0022-4359(03)00007-1
63. Kim, Y., Krishnan, R. On Product-Level Uncertainty and Online Purchase Behavior: An Empirical Analysis. Management Science. 2015;61(10):2449–2467.
Available:https://doi.org/10.1287/mnsc.2014.2063
64. Kim, J., Forsythe, S. Factors affecting adoption of product virtualization technology for online consumer electronics shopping. International Journal of Retail and Distribution Management. 2010;38(3): 190–204.
Available:https://doi.org/10.1108/09590551011027122
65. Yeung, RMW., Yee WMS. Chinese New Year Festival: Exploring consumer purchase intention at the flower market in Macau. International Journal of Hospitality Management, 2010;29(2):291–296.
Available:https://doi.org/10.1016/j.ijhm.2009.10.006
66. Amozon. Amazon Video in Search Ads (Beta); 2019.
Retrieved December 27, 2019,
Available:https://advertising.amazon.com/resources/ad-specs/en/video-in-search
67. Niggenaber C. More Success on Amazon – A Closer Look at the New Video Ads; 2019.
Retrieved December 27, 2019,
Available:https://blog.mynd.com/en/success-amazon-video-ads
68. Abu Kausar M., S. Dhaka, V, Kumar Singh, S. Web Crawler: A Review. International Journal of Computer Applications, 2013;63(2):31–36.
Available:https://doi.org/10.5120/10440-5125
69. Addo, PC., Jiaming, F., Kulbo, NB., Liangqiang, L. COVID-19: fear appeal favoring purchase behavior towards personal protective equipment. The Service Industries Journal, 2020;40(7–8):471–490.
Available:https://doi.org/10.1080/02642069.2020.1751823

APPENDIX A

Sample Clawing Codes

Pipeline

```
# -*- coding: utf-8 -*-
import codecs,json
import pymysql
import redis
# Define your item pipelines here
#
# Don't forget to add your pipeline to the ITEM_PIPELINES setting
# See: http://doc.scrapy.org/en/latest/topics/item-pipeline.html
class TmallPipeline(object):
   def __init__(self):
      self.file = codecs.open('data.csv', 'wb', encoding='utf-8')
      self.Redis_conn = redis.StrictRedis(host='127.0.0.1', port=6379, db=0)
      self.conn = pymysql.connect(
        host="127.0.0.1", port=3306, user="root", passwd="", db="clawer", charset='utf8mb4')
   def process_item(self, item, spider):
      if spider.name == 'tmall':
         #line = item['name'] + ', ' + item['link']
         #self.file.write(line)
         name = item['name'].strip() + ":" + str(item['price']) + ":" + item['ind'].strip()
         link = item['link']
         self.Redis_conn.set(name, link)
         return item

      if spider.name == 'details':
         # line = str(item)
         # self.file.write(line)
         ind = item['ind'].strip().decode('utf-8')
         name = item['name'].strip()
         company = item['company'].strip()
         video = item['video']
         img_count = item['img_amount']
         desc_rank = item['desc_rank']
         server_rank = item['server_rank']
         logistics_rank = item['logistics_rank']
         location = item['location'].strip()
         price = item['price']
         sales = float(item['sales'])
         comments = float(item['comments'])
         sql = u"insert into
tmall(ind,name,company,video,img_count,desc_rank,server_rank,logistics_rank,location,price,sales,c
omments) values ('%s','%s','%s','%s','%s','%s','%s','%s','%s','%f','%f','%f')" % (
         ind, name, company, video, img_count, desc_rank, server_rank, logistics_rank, location, price,
sales, comments)
         self.conn.query(sql)
         self.conn.commit()
   def close_spider(self, spider):
      self.conn.close()
            self.file.close()
```

Scrappy

```
import scrapy
from ..items import DetailsItem
import redis
from scrapy.conf import settings

class ItemSpider(scrapy.Spider):

    name = "details"
    start_urls = [

#"https://detail.tmall.com/item.htm?spm=a220m.1000858.1000725.1.714b7bf3mQkIwQ&id=56504329
3587",

#"https://detail.tmall.com/item.htm?spm=a220m.1000858.1000725.35.714b7bf3mQkIwQ&id=5656544
35718",

#"https://detail.tmall.com/item.htm?spm=a220m.1000858.1000725.35.714b7bf3mQkIwQ&id=5656544
35719"

#"https://item.taobao.com/item.htm?ft=t&spm=a220m.1000858.1000725.1.714b7bf3mQkIwQ&id=565
043293589"
    ]
    cookie = settings['COOKIE']
    headers = {
        'Connection': 'keep-alive',
        'User-Agent': 'Mozilla/5.0 (X11; Linux x86_64) AppleWebKit/537.36 (KHTML, like Gecko)
Chrome/52.0.2743.82 Safari/537.36'
    }

    def get_urls(self):
        url_list = []

        pool = redis.ConnectionPool(host='127.0.0.1', port=6379, db=0)
        r = redis.StrictRedis(connection_pool=pool)

        keys = r.keys()
        for key in keys:
            # print key
            name, price, ind = key.split(':')
            url = 'http:' + r.get(key)
            url_list.append([url, float(price), ind])
            # r.delete(key)
        return url_list

    def start_requests(self):

        url_list = self.get_urls()
        for url, price, ind in url_list:
            # print url
            yield scrapy.Request(url, cookies=self.cookie, meta={'price': price, 'ind': ind},
callback=self.parse)

    def parse(self, response):
        # with open("check.html", "wb") as f:
        #     f.write(response.body)
```

```
        detailitem = DetailsItem()
        detailitem['ind'] = response.meta['ind']
        detailitem['name'] = response.xpath("//h1")[1].xpath("./text()").extract()[0].strip()
        # detailitem['price'] = response.xpath("//span[@class='tm-price']/text()").extract()[0]
        detailitem['price'] = response.meta['price']
        detailitem['company'] =
response.xpath("//div[@id='shopExtra']/div[@class='slogo']/a/strong/text()").extract()[0]
        video = response.xpath("//video").extract()
        if video:
            detailitem['video'] = 1
        else:
            detailitem['video'] = 0

        detailitem['img_amount'] = 0
        #img_bar = response.css("ul.tb-thumb tm-clear")
        for img in response.xpath("//a[@href='#']/img").extract():
            detailitem['img_amount'] += 1

        div_main = response.css("div.main-info")
        details_array = div_main.xpath("./div[@class='shopdsr-item']")
        detailitem['desc_rank'] = details_array[0].xpath("./div/span[@class='shopdsr-score-
con']/text()").extract()[0]
        detailitem['server_rank'] = details_array[1].xpath("./div/span[@class='shopdsr-score-
con']/text()").extract()[0]
        detailitem['logistics_rank'] = details_array[2].xpath("./div/span[@class='shopdsr-score-
con']/text()").extract()[0]
        detailitem['location'] = response.xpath("//li[@class='locus']/div/text()").extract()[0]
        # for details in detailitem:
        #     print details, ':', detailitem[details]
        print response.xpath("//span[@class='tm-count']")
        # detailitem['sales'] = response.xpath("//span[@class='tm-count']")[0].xpath('/text()').extract()[0]
        # detailitem['comments'] = response.xpath("//span[@class='tm-
count']/text()")[1].xpath('/text()').extract()[0]
        detailitem['sales'] = 0
        detailitem['comments'] = 0
        yield detailitem
```


Peer-review history:
The peer review history for this paper can be accessed here:
https://www.sdiarticle4.com/review-history/73785